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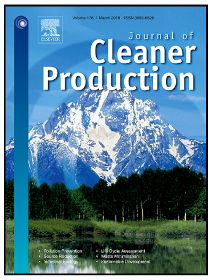

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A novel safety anticipation estimation method for the aerial lithium-ion battery pack based on the real-time detection and filtering

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Abstract – Lithium-ion battery packs have become increasingly important for power supply applications, in which the state of charge estimation and output voltage tracking should be very critical for the safety protection. A novel real-time estimation method is proposed by using the improved extended Kalman filtering algorithm together with the two-order resistance and capacitance circuit network battery model, aiming to solve its security protection issues. Experimental results show that this method can track the voltage signals effectively along with the real-time state estimation in the discharging and charging maintenance operation processes. The battery cell voltage detection accuracy is found to be 1.00mV and the pack voltage measurement error is less than 20.00mV. Meanwhile, the state of charge value can be estimated with a great accuracy of 2.00%, in which the state of balance parameter is considered for the internal connected battery cells. The developed experimental associated battery management system can be used for the working state monitoring in the aerial power supply application of the lithium-ion battery pack.

Keywords: lithium-ion battery pack; safety anticipation; state estimation; voltage track; Kalman filter

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1. Introduction

Lithium-Ion Batteries (LIB) are becoming increasingly popular as a source of energy in a dynamic power system applications, such as electric vehicles, renewable energy systems and satellite power supply systems, which is mainly due to its high energy density, low self-discharge rate and long cycle life advantages, compared with lead-acid, nickel-cadmium and other batteries. The technological developments in batteries are summarized by Hu *et al.* (2017). The LIB cells are assembled into battery pack with typically complex electrochemical devices. Therefore, the working state monitoring and security protection concerns of their working conditions are becoming the core issue for energy management applications of the aerial LIB pack. The accurate estimation of the remaining capacity is essential for optimizing the energy control system targeting at preventing it from over-charge/discharge risks, which is used to ensure its power safety during the service life.

The remaining capacity is characterized by the State of Charge (SOC) estimation. In order to meet the energy and power requirements of the aerial LIB pack, the battery pack usually contains several battery cells connected in series and parallel to provide adequate emergency power and energy. However, the safety issues limit its power applications and the real-time security protection is expected to be the core technology. The over-charge/discharge phenomenon has irreversibly damaged the LIB pack and reduced its performance and life cycle. A great number of researchers have investigated into different perspectives for battery applications as reported by Bruen *et al.* (2016), which promoted the LIB development in great progress for its dynamic and advanced power supply applications. The security issue is expected to be solved by carrying on real-time voltage detection together with the SOC estimation according to the relevant researches shown as follows. The combined in-situ and post-mortem investigation on the local permanent degradation is conducted by Bresciania *et al.* (2016) in a direct methanol fuel cell. In addition, a comprehensive review is proposed by Jaguemont *et al.* (2016) for the LIBs at cold temperatures. The fractional-order modeling and SOC estimation methods are studied by Zhang *et al.* (2016), in which the fractional-order modeling and optimal model parameter identification methods are proposed together with the fractional Kalman filter showing a good estimation performance. The investigation on internal short circuits of LIBs with a ceramic-coated separator is analysed by Kim *et al.* (2015) during the nail penetration process. The safety focused modelling is reported by Abadaa *et al.* (2016) for the LIBs. An advanced machine learning approach for lithium-ion battery state estimation is proposed by Hu *et al.* (2016), in which an advanced SOC estimator is developed *via* machine learning methodology. The SOC value, which reflects the remaining capacity of the battery, cannot be measured directly and should be obtained by indirect estimation methods. To the best of our knowledge this is the first manuscript to report a simple and versatile integration method, which provides a real-time detection and working state monitoring system that can be implemented in the battery management system (BMS) equipment.

The associated BMS equipment is developed on universal, intelligent, personalized, intimate interactive features and practicality. In addition, the safety and efficient energy management also involves security control, battery thermal management, critical data storage and analysis. The energy management method is reported by Lim *et al.* (2016) with automated mechanical transmission. The life cycle assessment method is analyzed by Zackrisson *et al.* (2016) for the lithium-air battery cells. The integration issues are investigated by Saw *et al.* (2016) for implanting the LIB into the battery pack. However, the real-time security monitoring problem is still not completely resolved, which needs effective solutions to a serious impact in the power application process for the security and safety effects. The voltage detection and real-time security forecasting research is conducted, aiming to solve the core issue in the development process of the Battery Management and Test System (BMTS) platform that is based on the improved Extended Kalman Filtering (EKF) algorithm. The SOC estimation of LIB is studied by Aung *et al.* (2016), in which the square root spherical Unscented Kalman Filtering (UKF) algorithm is used in nano-satellite. The understanding capacity fade is analyzed by Beattie *et al.* (2016) in silicon based electrodes for LIBs using three electrode cells and upper cut-off voltage studies. The robust adaptive sliding-mode observer using RBF neural network is proposed by Chen *et al.* (2016) for the SOC estimation.

A probabilistic adaptive estimation is conducted to obtain the accurate and reliable SOC estimation results. Aiming to realize the accurate state estimation of the aerial LIB pack, the two-order Resistance and Capacitance (RC) battery Equivalent Circuit Model (ECM) model is constructed considering the electro-chemical model, obtaining the accurate output voltage and the SOC estimation by using the experimental results. The EKF-based SOC estimation algorithm is developed together with the BMTS platform, which can handle the real-time SOC estimation and solve the actual problems along with the system engineering process noise. Since a large number of battery cells are composed in the aerial LIB pack and its output voltage has obvious nonlinear behavior because of the complex electrochemical characteristics, the real-time monitoring and safety protection are the key technology in the power application of the high-power LIB pack according to various internal and external conditions.

2. Theoretical analysis

The working state characterization is critical for the security protection of the aerial LIB pack, which is carried on by using the two-order ECM in the power supply working process. The working state is a core parameter for the associated BMS equipment of the aerial LIB pack. The dynamic and model-based method with closed-loop characteristic has been used in the working state estimation and projection of the LIB pack. As a key component to the battery power system, the associated BMS equipment is designed to provide the monitor, diagnosis, control and protection features to improve operation effect of the power LIB pack.

2.1. Working state estimation method analysis

The modeling of the battery pack is related to the LIB safety investigation, which analyzes the major achievements of the modeling work. The Open Circuit Voltage (OCV) characterization method is investigated together with the hysteresis assessment. The calculation and estimation process of the intelligence control methods, including fuzzy logic and artificial neural network aspects, has been involved into the working state estimation of the aerial LIB pack. Although they can provide accurate estimation values, their computational cost is too high and they suffer from the complex training process and the imperfect quality of the training data set. The KF-related algorithms, including EKF, UKF require far less computing resources which have been studied in order to solve the real-time security protection problem of the LIB pack. The cell and pack voltages are highly dependent on the charging and discharging current rates, which makes the whole charge and discharge sustain period contemplated with the required safe period. The battery model has been proposed to describe the operating state of the LIB pack by fitting a piece structure, which can be called ECM. A novel dynamic model of LIB is proposed by Mesbahi *et al.* (2018), in which the electro-thermal and ageing aspects are incorporated. A split battery model is proposed by Yang *et al.* (2017), together with which the adaptive SOC estimation is realized. The modeling and optimization method is studied by Gollei *et al.* (2012), which is used in the complex clean energy systems. The electrochemical method requires a large amount and needs to be calculated and adapted in terms of the working electrode and electrolyte. The ECM uses electrical components, such as resistors and capacitors to simulate the LIB characteristics, which requires fewer computing resources, and can simulate the dynamic operation accurately of the battery dynamic response. As a result, the ECM is quite suitable for the intended purpose of security.

2.2. Power storage and supply principle analysis

The LIB unit has three layers and the internal structure is an electrolyte with lithium ions, the components of which have an olivine structure used as a negative electrode material of the battery. The positive terminal of the LIB is connected to an aluminum foil and the graphite is used as the positive electrode material. The negative terminal of the battery connector is constructed by the copper foil. The middle part of the internal structure is separated by the positive electrode and the negative electrode, which allow lithium ions passing through but blocking electrons through the membrane. When the LIB is charged, the lithium ions leave the cathode and travel through the membrane to the anode. Meanwhile, the negative electrons are purchased from an external circuit. When discharged, the lithium ions leave the anode, travels through the separator and embedded in the positive electrode. The LIB pack is composed of serial and parallel connectors to the battery cells, which can be described in Figure 1.

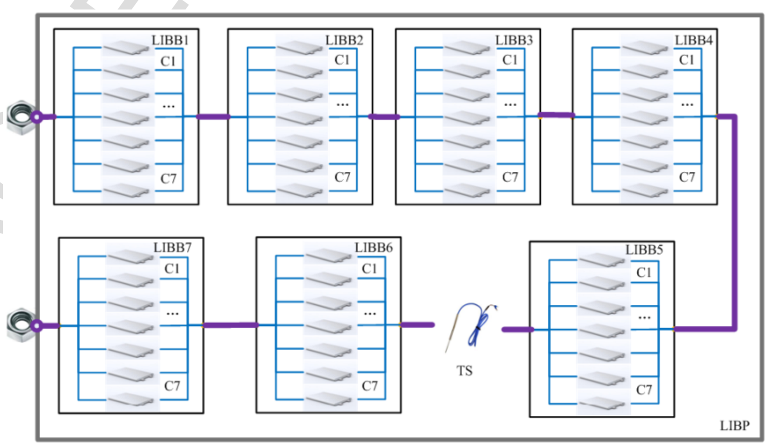

Fig. 1.The internal structure of the aerial LIB pack

The physical meaning of the symbols in the above Figure is described as follows. The symbols of C1, C2, ⋯ and C7 represents the Lithium-ion battery Cells, the number of which varies from 1 to 7. The symbol LIBB1 represents the Lithium-ion battery Bag 1 and the change law also applies to symbols from LIBB2 to LIBB7, through the series structure of which the LIBP(Lithium-ion battery Pack) is formed. The symbol TS represents the Temperature sensor, which is embedded in the LIBP to monitor the temperature. The state estimation model is a common feature of these methods, which is highly dependent on the ECM structure and its parameter identification process. As the LIB power system increases, the accurate and reliable information should be increased significantly in order to ensure the performance of the entire power supply system. The voltage performance monitoring is necessary for avoiding the excessive discharge or charge. That dangerous working conditions in the operating process of the LIB pack may cause permanent internal degradation. As a result, a large number of studies have investigated the status of the detection and control process, which should be designed to guarantee the safety of the power LIB pack. Specifically, the working state estimation is considered to be a key factor of the BMS for supporting the optimal battery performance and safety of the LIB pack. The charging reaction can be described as shown in the first part of Eq.1, according to which the SOC estimation model parameters and real-time model can be carried out along with the cascaded filtering stage. The SOC can be estimated accurately and appropriately in the associated BMS equipment of the aerial LIB pack. In addition, the discharging reaction is shown in the second part of the equation.

$$\begin{cases} \begin{cases} (+): LiCoO_2 \rightarrow xLi^+ + Li_{1-x}CoO_2 + xe^-; \\ (-): xLi^+ + xe^- + 6C \rightarrow Li_xC_6 \end{cases} \\ \begin{cases} (+): xLi^+ + Li_{1-x}CoO_2 + xe^- \rightarrow LiCoO_2; \\ (-): Li_xC_6 \rightarrow xLi^+ + xe^- + 6C \end{cases} \end{cases} \tag{1}$$

The polarization phenomenon will occur in the charge and discharge process of the aerial LIB pack, which is mainly because of the potential difference between the positive and negative electrodes. The cell polarization usually can be divided into ohmic polarization, concentration polarization and electrochemical polarization. The ohmic polarization is also called polarization resistance, which is caused by the electrode material, electrolyte and the contact resistance of the separator resistor. The concentration polarization is caused by the participating lithium-ion reactions, which is smaller than the electrochemical rate made by the diffusion reaction. The electrochemical polarization is less than the movement rate of electrons caused by the electrochemical reaction. Therefore, it is impossible to eliminate the phenomenon of polarization of the LIB, which can be mitigated by the material melioration to improve design and production levels. The battery polarization is mainly affected by the charge and discharge current diversification.

The accurate detection and investigation of the output voltage characteristics for the aerial LIB pack is the guarantee of successful research and development (R & D) of the associated BMS equipment. In order to describe the relationship between the discharge current and the polarization effect, the output voltage of the LIB can be characterized as $U=U_0-\Delta U_1-\Delta U_2-\Delta U_3$, in which the parameter ΔU_1 indicates the ohmic polarization, ΔU_2 is the electrochemical polarization and ΔU_3 denotes the concentration polarization. The polarization will increase along with the discharge current increment. If the output voltage is low, the capacity will reduce and the operating time will be smaller. The modeling error is one of the main problems in the energy control theory, which is used in the adjustments of control algorithms to improve the performance of the system. The two order sequential and electrical ECM is used to approximate the SOC estimation performance. In addition, the state space equation is introduced in the KF-based calculation process.

2.3. **The ECM construction method study**

The battery circuit model type is well known, and will adapt to a wide range of dynamic operating conditions for power supply applications as well as electrochemical reflection properties. The battery aging mechanism is a very complex process, resulting in the characterization difficulty of battery status for major changes of the internal parameters. During the repeated maintenance period, the rated capacity decreases along with the energy retention of the LIB pack, which is due to the active material reduction. Various methods have been proposed for the SOC estimation and each method has its advantages and disadvantages. Most of the discharge test methods can be used together with the ECM construction. There are a variety of algorithms based on the nonlinear state estimation and model-based fusion algorithms. Furthermore, the SOC estimation can be realized by the direct parameter measurement of the voltage, current and temperature. The ECM structure with two-stage RC circuit is designed as shown in Figure 2.

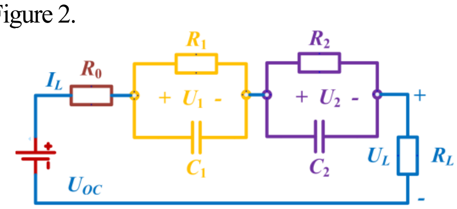

Fig. 2.The ECM with two order RC circuit for the LIB

The physical meaning of the parameters in the diagram is described as follows. The parameter R_0 denotes the ohmic resistance and the two order RC network is designed to describe the dynamic voltage behavior during the charging and discharging maintenance. The parameter U_L denotes the terminal voltage and U_1 and U_2 denote the voltage across the parameters of R_1, C_1 and R_2, C_2. The comprehensive ECM can describe the relaxation effect of the battery behavior during the rest time following each charge or discharge operation. The accuracy of the

SOC estimation depends mainly on the complexity of the model, in which the trade-off between the accuracy and the computational complexity should be considered when implementing the estimation algorithm. To fully utilize the capacity of the estimation process, the ECM shown in the above Figure is adopted, in which an internal resistor and two parallel RC branches have been employed. The electrical equation for the working behavior characterization of the LIBs can be obtained from the structure of the proposed ECM model, which can be described in the first part of Eq.2. Wherein, the parameter U_{OC} denotes the value of the parameter OCV and the parameter I_L denotes the load current which is assumed as positive for the discharge process and negative for the charge process. In order to obtain the discrete format of the state-space equation, the equations can be rewritten as shown in the second part of the equation.

$$\begin{cases} \begin{cases} I_L = \dfrac{U_1}{R_1} + C_1 \dfrac{dU_1}{dt} = \dfrac{U_2}{R_2} + C_2 \dfrac{dU_2}{dt}; \\ U_L = U_{OC} - I_L R_0 - U_1 - U_2 \end{cases} \\ \begin{cases} \dfrac{dU_1}{dt} = \dfrac{U_1}{C_1 R_1} - \dfrac{I_L}{C_1}, \dfrac{dU_2}{dt} = \dfrac{U_2}{C_2 R_2} - \dfrac{I_L}{C_2}; \\ U_L = U_{OC} - I_L R_0 - U_1 - U_2 \end{cases} \end{cases} \tag{2}$$

In view of the state space characterization of ECM, a great number of research has been carried out. The electrochemical potentials of cathode materials in LIBs are studied by Lin *et al.* (2016). The voltage relaxation and impedance spectroscopy is analyzed by Schindler *et al.* (2016) for the lithium plating detection on graphitic anodes in LIB cells. The accurate and versatile simulation of transient voltage profile is carried out by Tanaka *et al.* (2015) for the LIB employing the internal ECM. The influence of connecting plate resistance upon LIB performance is studied by Wang *et al.* (2015). The model parameter estimation approach is proposed for the incremental analysis of LIBs without using OCV. The effects of electrode thickness are studied by using the electrochemical and thermal characteristics of LIB. Its discrete format could be rewritten as shown in Eq.3.

$$\begin{cases} U_{1,k} = \exp(-\Delta t/\tau_1) \times U_{1,k-1} + \left(1 - \exp(-\Delta t/\tau_1) \times U_{1,k}\right) \times I_{L,i} R_1 \\ U_{2,k} = \exp(-\Delta t/\tau_2) \times U_{2,k-1} + \left(1 - \exp(-\Delta t/\tau_2) \times U_{2,k}\right) \times I_{L,i} R_1 \end{cases} \tag{3}$$

The security issues of the aerial LIB pack are related to intensive testing to prove all along the value chain, but the failure modes of LIB are related to scientific progress. Because of the significant breakthrough in the computer science, the development of BMS now allows the embedded implementation of more complex operations. In reflecting the remaining capacity of the LIB, SOC is defined as the rate value of the remaining capacity to its maximum available capacity value. The SOC value at the time point t can be calculated by using Eq.4.

$$\begin{cases} U_L = U_{OC} - I_L R_0 - U_1 - U_2 \\ SOC_t = SOC_0 - \dfrac{1}{C_{Rated}} \int_0^t \eta I_{L,\tau} d\tau \end{cases} \tag{4}$$

The parameters used in the above equation can be described as follows. The parameter SOC_t denotes the SOC value at the t time point and the parameter SOC_0 denotes the initial SOC value at the initial time t_0. The parameter C_{Rated} denotes the rated capacity value, which indicates the total available capacity of the LIB. The parameter η is the current efficiency in the discharging and charging maintenance process. The parameter τ is used to indicate the time constant which is initialed as $\tau_1=R_1C_1$ and $\tau_2=R_2C_2$. Δt is used to denote the sampling interval and $U_{1,k-1}$ is the value of the parameter U_1 at k-th step and $I_{L,k}$ is the value of the parameter I_L at k-th step. The comprehensive LIB model can be established easily by combining the ECM and the Ah (Ampere-hour) counting methods together. Herein, the parameters of U_1, U_2 and SOC are chosen as the state variables while the parameter U_L is set as the observable variable. The RLS (Recursive Least Square) filter is used as the first stage in real time to dynamically estimate the parameters of ECM, then the EKF algorithm is used to estimate the parameters by using these working conditions. The EKF algorithm can avoid large estimation errors that may occur along with conventional filtration methods, the reason of which is that it has ability to change over time through Kalman gain to compensate for any possibility of modeling errors. By this recursive Kalman gain equation, the prediction error of the SOC value for the LIB pack is less than 5.00% in the estimation experiments. The proposed method provides a high accurate SOC estimation of real-time applications for the simplicity and feasibility requirements. As a result, the state equation and measurement equation can be expressed as shown in Eq.5.

$$\begin{cases} x_{k+1} = Ax_k + Bu_k + w_k \\ y_{k+1} = Cx_k + Du_k + v_k \end{cases} \tag{5}$$

Wherein, the input parameter u_k is defined as the load current I_L and the terminal voltage U_L of the LIB pack represents the output of the state-space equation. The polarization voltage of LIB is the internal parameter and cannot be measured directly, so it can be used in combination with the SOC estimation as one of the state vector parameters. w represents the process noise and v indicates the observation noise. They are assumed to be uncorrelated to white Gaussian random process with zero mean value. The national observation matrix is defined as shown in Eq.6.

$$\begin{cases} A = \begin{bmatrix} \exp(-\Delta t/R_1C_1) & 0 \\ 0 & 1 \end{bmatrix},\ B = \begin{bmatrix} R1\left(1 - \exp(-\Delta t/R_1C_1)\right) \\ \eta \Delta t/C_{Rated} \end{bmatrix} \\ C = \begin{bmatrix} -1 & \dfrac{dU_{OC}}{dSOC} - I_L \times \dfrac{dR_0}{dSOC} \end{bmatrix},\ D = [-R_0] \end{cases} \tag{6}$$

Because of their closed-loop and online, the EKF-based estimation model has been extensively studied so that work dynamic state estimation error can be limited in the range of available strengths (Aung *et al.*, 2015; Bazinski *et al.*, 2015). The electrochemical operated model of the LIB pack is obtained in-depth to describe the battery output voltage and the following are three commonly used empirical models. (1) The Shepherd model is defined as $y_k=E_0-Ri_k-K_i/x_k$. (2) The Unnerwehr universal model is denoted as $y_k=E_0-Ri_k-K_ix_k$. (3) The Nernst model is described as $y_k=E_0-Ri_k-K_1\ln x_k+K_2\ln(1-x_k)$. Wherein, y_k is the terminal voltage of the LIB pack and E_0 is the initial value of electromotive force. Furthermore, R is the internal resistance of the battery discharge or charge resistance. In order to improve the accuracy of the model, the combination model combined with the above three models can be obtained as $y_k=E_0-Ri_k-K_1/x_k-K_2x_k+K_3\ln x_k+K_4\ln(1-x_k)$. The improved EKF algorithm can be used for parameter identification of the ECM. The linear process of the first order has been intercepted in order to deal with the nonlinear problems, which can bring a large incision error when the working characteristic is nonlinear. As a result, the robust performance and practicality of the SOC estimation cannot be adequately evaluated. Since it is difficult to measure the OCV value directly in its charge and discharge applications, y_k is used instead of using the OCV. Meanwhile, the combination model has small calculation amount and the arithmetic operation is very simple which makes it easy to implement on the single-chip application. As a result, this combination model is employed as the measured equation of the LIB pack.

The measurement equation can be obtained as $y_k=E_0-Ri_k-K_1/x_k-K_2x_k+K_3\ln x_k+K_4\ln(1-x_k)+v_k$ by considering the measurement noise. Among them, the parameter v_k is a normal white noise with zero mean and R_k variance, which is independent with the process noise. K_1, K_2, K_3, K_4 are the proportional coefficient model parameters. The column vector Y is set as $Y=[y_1,y_2,\cdots,y_n]^T$, and the matrix H is set as $H=[h_1,h_2,\cdots,h_n]^T$, in which the parameter h_j is set as $h_j=[1, i_j, 1/x_j, x_j, \ln(x_j), \ln(1-x_j)]^T$. The parameter vector θ is denoted as $\theta=[E_0,R, K_1, K_2, K_3, K_4]^T$ and N is set as $N=[\mu_1, \mu_2, \cdots, \mu_n]^T$. Then, the matrix pattern of the measurement equation can be obtained as $Y=H\theta+N$, in which the parameter θ can be defined as $\theta=(H^TH)^{-1}H^{-1}Y$. The two linear and LIB filtration stage use the ECM to overcome the SOC estimation error problem employed in the process of establishing the proposed limitations. In the first stage, the adaptive Recursive Least Square (RLS) filter has been applied in the real-time ECM parameter identification process, which is based on previous parameter identification results. Next, the model parameters are employed together with the OCV value, which is not sensitive to the noise variance model variations and can compensate the estimation error as it can limit the memory Kalman factors. The advantage of the proposed estimation method is that the estimation accuracy of SOC can be improved over time by updating the model parameters, which reduces the required calculation for the real-time applications.

2.4. State estimation and tracking model construction

In order to avoid large estimation error, the EKF algorithm has been introduced in the SOC estimation process which can be realized by using the limited memory. However, it is featured in the error covariance of the LIB supply system by introducing the Kalman gain coefficient. This is important because the performance of the filter depends on the large past data, and the system model is reduced from the distant past measurement information. Thus, the factor will be found in the past data, which helps to minimize divergence in the estimation process and can be realized by the offline optimization based on the discharge test. Meanwhile, the model parameters obtained from RLS stage are transmitted to the output voltage estimation. The ECM is applied and its continuous-time state space equation can be formulated. The LIB has strong time-varying characteristics and the SOC estimation problems can be converted directly from the implicit state of strong nonlinear systems with time varying solutions, which has been proposed and applied to achieve the significant estimation performance. According to the working characteristics of the aerial LIB pack, the SOC estimation framework and output voltage tracking can be constructed. The discrete state-space nonlinear systems can be used in the whole estimation process and can be named in the form of the state equation along with the battery system which are nonlinear equations. It consists of three steps: initialization, prediction and the real-time update along with the measurement correction. Afterward, the algorithm has been used to establish an adaptive SOC estimation framework and the SOC estimation accuracy has higher tracking accuracy and faster convergence ability. The state space model of dynamic estimation system is shown in Eq.7.

$$\begin{cases} x_k = \Phi x_{k-1} + Bu_k + w_k \\ y_k = Hx_k + v_k \end{cases} \tag{7}$$

Among them, the first part of the above equation is named as the state equation and the second part is denoted as the measurement equation. The parameter k indicates the discrete time interval. x_k is the state variables of the system and the parameter y_k is the measurement vector of the system state. u_k is the control signal and w_k is the input noise in which the distribution law obeys to the relationship function $w_k\sim N(0, Q_k)$. v_k is the measurement noise and the distribution law of the relationship function obeys $v_k\sim(0, R_k)$. Because it can overcome the disadvantages, the direct estimation method has become increasingly popular, which is used for deploying model parameters measured by using voltage, current, and temperature to estimate the SOC value. In addition, the flexibility of the estimation model allows further development of it, so that more ECM parameters can be used in the estimation process. Therefore, there is always a trade-off between LIB estimated modeling accuracy and computational complexity. The model should be as simple as possible for the real-time power applications, and the SOC estimation accuracy should be remained within a reasonable range.

The SOC estimation for the residual capacity of the aerial LIB pack is realized by using the KF-based recursive operation. Considering its high reliability, as it is widely implemented the online adaptive estimation model can reduce the SOC estimation error. Two cascaded linear filtering stages are used, in which the Sigma point is utilized to obtain a better distribution of controllability. Then, a unit hyper-sphere model is introduced, which is assigned to the standard ball-point number of independent sigma conversion treatment. The realization of the forecast period is shown as below. The priori estimation is carried out according to the first part of Eq.8, and the priori estimation error covariance can be obtained as shown in the second part of the equation.

$$\begin{cases} \hat{x}_{k|k-1} = \Phi \hat{x}_{k-1|k-1} + Bu_k \\ P_{k|k-1} = \Phi P_{k-1|k-1} \Phi^T + Q_k \end{cases} \tag{8}$$

In addition to its high robustness, stability and accuracy, the proposed method also can significantly improve the voltage detection and SOC estimation accuracy of the LIB, which leads to a more reliable operation and longer battery life. The update phase is executed as follows. The calculation requirement of this method is very low, so that it can be used in different types of application scenarios. It is also possible and easily combined with other technologies, such as the combined estimation model based on the generalizations. However, the drift errors will be accumulated due to unavoidable measuring sensor noise. The initial error can be corrected by using the accurate initial value, which can be obtained by using the OCV-SOC method. The LIB pack is required to have a rest for a long time to reach the stable state. The direct measurement of the battery discharge quantized residual electric amount is used to measure the relative time consuming. As a result, it can be employed for the calibration in the SOC estimation process and directly for the remaining charge amount of measuring requirements. The model-based SOC estimation method is achieved by a variety of estimation algorithms to obtain the accurate and reliable estimation. The accuracy of the battery model is an essential prerequisite in this type of SOC estimation method. By using the high-field battery model, the accurate estimation algorithm can be used by reducing the voltage error of the predicted and measured values. In order to improve the estimation performance, the model-based estimation methods are employed in the SOC estimation process, such as non-linear observer, extended KF, Sigma point KF, adaptive EKF invariant embedding method and sliding mode observer proposals. The online identification method of LIB parameters based on an improved ECM and its implementation is realized. Firstly, the value of Kalman gain can be calculated by using the first part of Eq.9. Secondly, the observation status can be read and achieved as shown in the second part of the equation. Thirdly, the error covariance can be updated by using the last part of the equation.

$$\begin{cases} K_k = P_{k|k-1} H^T \left[H P_{k|k-1} H^T + R_k \right]^{-1} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - H \hat{x}_{k|k-1} \right) \\ P_{k|k} = \left[I - K_k H \right] P_{k|k-1} \end{cases} \tag{9}$$

In the prediction process, the condition in the initial state can be set to sign an initial estimation of the parameter X_{k-1} and the parameter P_{k-1}. Subsequent iterative decision can be obtained by the a priori estimation and prediction for the optimal correction phase at the update stage to predict. Since the output voltage characteristics of the LIB pack show severe non-linear experiences, it should be translated into a linear system step by step. The state and measurement equations based on the Taylor rule are dropped near the optimal estimation point and its high-end systems components expression. Then, the EKF-based estimation method can be conducted along with the conventional linear processing, in which the state equation and the measurement equation are performed as follows. It can be described as a nonlinear state space equation, as shown in the first part of Eq.10.

$$\begin{cases} x_{k+1} = f(x_k, u_k) + w_k \\ y_k = g(x_k, u_k) + v_k \end{cases} \tag{10}$$

The LIB is found to be promising candidates in the electrochemical storage systems, especially due to their excellent energy density and high specific energy than other rechargeable battery technologies. This high energy density is provided from the pre-existing system with a significant breakthrough. This is due to the large potential difference between the positive and negative electrodes, and the measurement equations can be set as shown in the second part of the above equation. Among them, the functions of $f(*)$ and $g(*)$ are a nonlinear functions, which can be extended according to the Taylor rule in the state prior estimation parameter X_k. The available functions of $f(*)$ and $g(*)$ are realized for the linear approximation by ignoring higher-order terms, which are shown in Eq.11.

$$\begin{cases} f(x_k, u_k) \approx f(\hat{x}_{k|k-1}, u_k) + \dfrac{\partial f(x_k, u_k)}{\partial x_k} \Big|_{x_k = \hat{x}_{k|k-1}} (x_k - \hat{x}_{k|k-1}) \\ g(x_k, u_k) \approx g(\hat{x}_{k|k-1}, u_k) + \dfrac{\partial g(x_k, u_k)}{\partial x_k} \Big|_{x_k = \hat{x}_{k|k-1}} (x_k - \hat{x}_{k|k-1}) \end{cases} \tag{11}$$

The second-order approximation is employed to provide reasonable accurate discrete state space model. Then, the EKF algorithm is utilized for estimating the output voltage by using the SOC recursive and recursive equations. To simplify the representation of a linear function of the issue, the coefficient is defined as shown in the first part of Eq.12. The recent weight measurements should be increased in the update step of the SOC estimation. Thus, the observation equation can be obtained for the state space model as shown in the second part of the equation.

$$\begin{cases} \begin{cases} x_{k+1} = \Phi_k x_k + [f(\hat{x}_{k|k-1}, u_k) - \Phi_k \hat{x}_{k|k-1}] + w_k; \\ \Phi_k = \dfrac{\partial f(x_k, u_k)}{\partial x_k} |_{x_k = \hat{x}_{k|k-1}} \end{cases} \\ \begin{cases} y_k = H_k x_k + [g(\hat{x}_{k|k-1}, u_k) - H_k \hat{x}_{k|k-1}] + v_k; \\ H_k = \dfrac{\partial g(x_k, u_k)}{\partial x_k} |_{x_k = \hat{x}_{k|k-1}} \end{cases} \end{cases} \tag{12}$$

As can be seen from the above calculation, this algorithm is a mathematical formula by using a series of discrete data recursively to solve the nonlinear filtering problem. It can be employed to estimate the operating state in the power supply process of the LIB pack, and the error covariance in the estimation process is minimized. The priori status values and error covariance should be monitored in the estimation process. Then, the current time status and error covariance values can be obtained. As a result, there is no need to store a large number of estimation parameters, and the actuation of historical data is used to improve the estimation effect for the real-time characteristics. Meanwhile, it has a self-correcting nature, so there will be no cumulative error in the calculation process which makes the SOC estimation more accurate. Thus, the estimation algorithm is very suitable for the working state estimation of the aerial LIB pack. The estimating module can be constructed by using the adaptive adjustment control of the estimated value and the estimation error. The overall structure is shown in Figure 3.

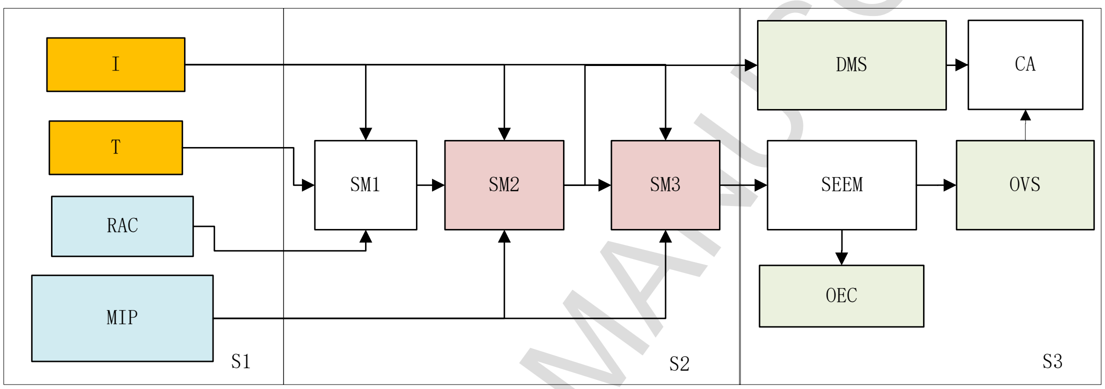

Fig. 3.The model building principle block diagram

The physical meaning of the symbols in the above Figure is described as follows. The entire graph is divided into three parts, S1, S2, and S3, which represent the physical meaning of the input signal sub-module, the monitoring and evaluation sub-module and the output and analysis sub-module. The physical meaning of the symbols in S1 are shown as follows: T(Temperature), I(Current), RAC(Rated capacity), MIP(model identification parameters) . The meaning of the symbols in S2 are shown as follows: SM1(The coulomb efficiency calculation sub module), SM2(SOC and output voltage measurement tracking model) and SM3(Kalman filtering estimation model). The definition of the symbols in S3 are shown as follows: S3(Output and analysis), DMS(Direct measured Signals of SOC and output voltage), SEEM(State estimation and error monitoring), OEC(Output error covariance), CA(comparative analysis) and OVS(Output value of the SOC estimation). The most straightforward SOC estimation method is charged or discharged by Coulomb counting process. Specifically, the estimated SOC indicates the remaining available capacity, which is an outstanding importance in improving energy management. The integration SOC estimating method is commonly used. Its principle is the same method of discharge test, but there is no longer a constant, so it needs to release the power of the integral calculation. The state of charge value SOC_t at t time point can be expressed as shown in Eq.13.

$$SOC(t) = SOC(0) - \frac{1}{Q_n}\int_0^t \eta i_\tau d\tau \tag{13}$$

Wherein, the parameter SOC_0 is the initial power-up SOC value. The parameter Q_n is the rated capacity of the LIB, which can be obtained from a manufacturing specification. Meanwhile, the current in the molecule and the integral term are utilized to represent the total amount of the capacity change during the operation. In addition, the measurement error is inevitable from the current sensor to the noise during operation LIB real-time applications in the process, which will contribute to an additional SOC estimation error. The current parameter i_τ at τ time point will be positive for the discharge period and negative when charged. The parameter η is the Coulomb efficiency. The state equation describes the changes in the state adjacent along with the time point of dynamic systems. Considering the impact of process noise, the state equation can be obtained as shown in Eq.14.

$$x(k) = x(k-1) - (\eta \Delta t / Q_n) i(k) + w(k) \tag{14}$$

Wherein, x_k is the battery SOC value for the k time point. Δt is used for the discrete time interval. i_k is the discrete current. η is the Coulomb efficiency, the value of which is set as η=1/($\eta_i \eta_T$). w_k is the normal white noise with zero-mean and Q_k variance. The analysis process of the real-time voltage monitoring and SOC estimation plays a major role in BMS, so that the power distribution of the battery can be managed effectively.

3. Experiment and analysis

The proposed method has been verified with the referenced experimental results of the EKF and Coulomb counting methods. The results of which show that this method has a lower absolute mean and root mean square error than other traditional methods.

3.1. Experimental study

In order to verify the estimation accuracy and robustness of the proposed SOC estimation model in a different dynamic operating condition, the BMTS platform has been constructed for the aerial LIB pack and the related experiments are performed. The results show that the accurate and robust estimation can be realized by this method. The LIB in working conditions for the terminal voltage and the battery pack voltage signal sampling along with the safety forecasting are particularly important, which can monitor the working conditions of the aerial LIB packs. It provides an important basis to judge which is integrally connected to the high purpose battery power imbalance. The estimation structure and BMTS platform can be built to further evaluate and to verify the performance of the online SOC estimation methods, which is used for the data stores and calculations of the aerial LIB cells and packs in the experiments. The hall current and voltage sensors errors are less than 0.10%. Analog acquisition, communication systems and SOC estimation algorithms are programmed, which ultimately affect the performance of the proposed SOC estimation. The experimental equipment of BMTS is designed as shown in Figure 4.

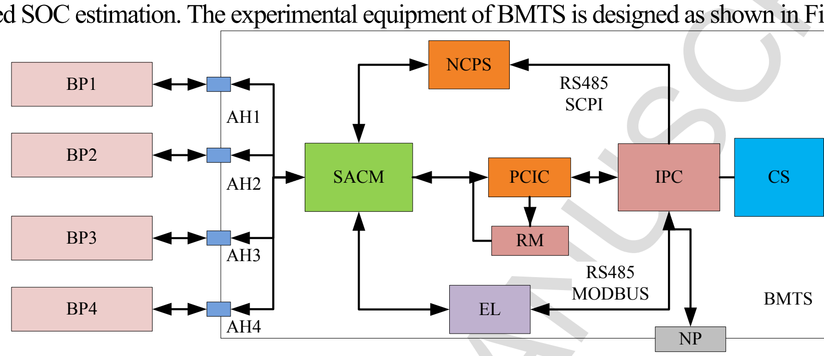

Fig. 4. The BMTS platform structure for the aerial LIB packs

The symbols in the above Figure are described as follows. BP1, BP2, BP3 and BP4 represent the aerial LIB packs. AH1 describes the aerial head 1, and the change law also applies to AH2, AH3 and AH4. SACM denotes the Signal adjustment circuit model and NCPS is the Numerical control power supply. EL represents the Electrical loads. PCIC symbolizes the Peripheral Component Interconnect cards which are embedded in IPC (Industrial Personal Computer) and give control signals to RM (Relay Module). CS signifies the Computer software and NP represents the Network port. The Experimental setup for capacity test cycle is designed by Mendoza *et al.* (2016) and a energy management system is developed by Chiang *et al.* (2016), compared with the system structure is more succinct and suitable for the equipment users. The BMTS takes in the SOC estimation algorithm and the survey, which indicates BMTS has a good performance, and may apply for the aerial LIB pack. It is realized by using the VS2010 platform and C# programming language together with the BMTS equipment development and application. Therefore, good real-time filtering and forecasting results have been achieved. The identical LIB packs with nominal voltage of 3.70 V and nominal capacity of 45.00 Ah are chosen for the experiments, which are cycled with constant current (CC) and dynamic stress test current profiles at room temperature (25.00℃) repeatedly and their discharging capacities are recorded. The parameters of voltage, current, temperature are recorded by the BMTS to create a highly accurate referable SOC value for the evaluation purpose in which the sampling rate is up to 100.00 Hz. The discharging characteristics are investigated to satisfy the estimation of the whole working cycle as shown in Figure 5.

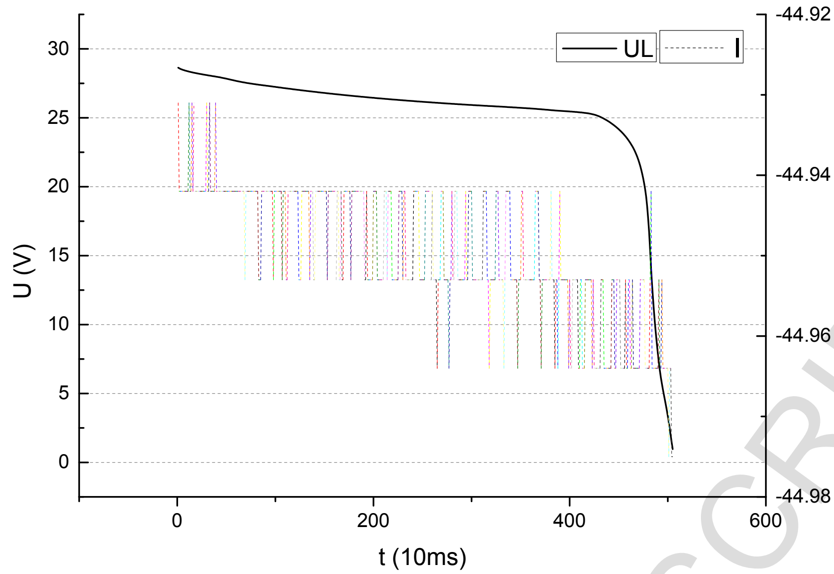

Fig. 5.The over-discharging characteristics of the LIB pack

In order to construct the OCV characteristic curve towards the different SOC value, the LIB pack was initially charged to 100.00% SOC by using the Constant Current (CC) - Constant Voltage (CV) process. Then, the amplitude of $1C_5A$ discharge current is applied to the discharge process of the LIB pack. The terminal voltage was measured during the CC discharge process. The prediction of its security status in real time is effectively carried out by the battery voltage data that is collected in real time together with the data sampling and filtering, aiming to obtain the effective data sampling curve. The voltage levels of the battery with different types are completely different. Even with the same capacity, the energy storage battery may be very different, which will lead to a corresponding difference in life. Therefore, the SOC is defined to indicate the battery as well as it has been reported in literature by Beattie *et al.* (2016) in recent years as the remaining available energy. In addition, it has also been defined as a key parameter of the BMS for the remaining driving range estimation. After the filtration and forecasting process, the initial parameters values are set as follows. The variable parameter X is defined as the prediction value. The initial setting value is set as sampled value directly in order to better participate in the subsequent operation of filtering and estimation. The variable parameter P is used for the covariance, the initial value of which is set as 10.00 in order to better predict the early changes and follow the measured value. The variable parameter Q is the process covariance, the calculation process of which is relatively small and its value is set as 0.00001. The variable parameter R is the measurement covariance, which is set as 0.10. The variable parameter U is the directly measured data. In the non-first operation, the variable parameter X is assigned as the previous time filtering value and the variable parameter P is assigned to be the newly calculated covariance value, combined with a new measured data variable parameter U to calculate the filtering prediction. The14-cell LIB pack terminal voltage raw data and its forecast data are shown in Figure 6.

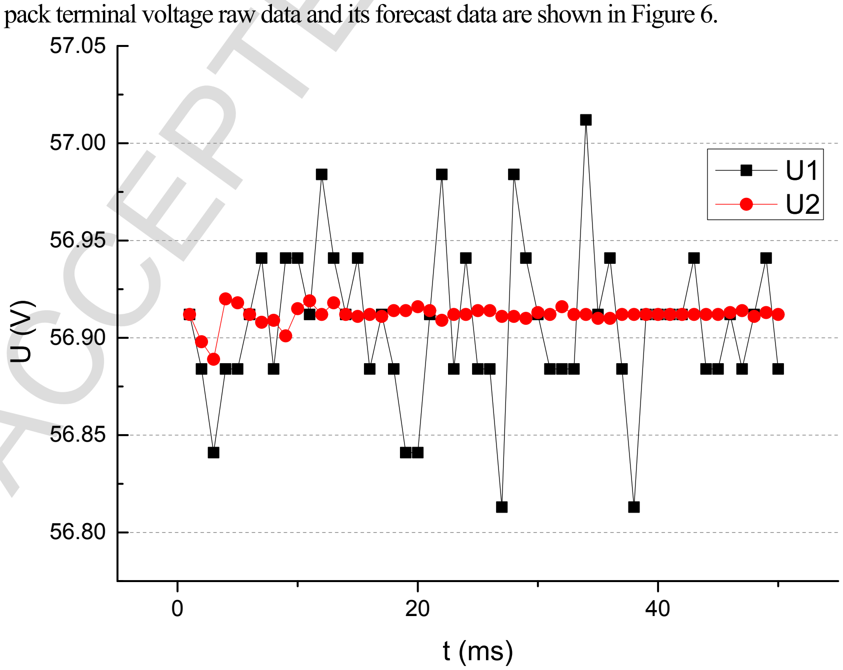

Fig. 6. The terminal voltage filtering results of the LIB pack

The parameter U1 in the Figure above is the real-time sampling voltage value, and the parameter U2 is the voltage value after the filter processing. As can be seen from the above Figure, the filtering effect is obviously good, by which the sampling random noise can be filtered in the pack terminal voltage detection process. The voltage prediction error band of the estimation model is nearly 5 mV, which is much lower than the parameter identification demand of the ECM of the LIB pack. The proposed model has shown excellent characteristic to approximate the real-time detection process. Meanwhile, the LIB function is encapsulated and used to achieve the real-time detection and the cell voltage prediction results. The random error of the measured data is located within 2.00 mV, which has already met the demand of the safety anticipation and balancing adjustment decision. Meanwhile, the time lag characteristics for the data sampling process are investigated, which indicate that the time lag of the fault warning and balanced regulation is less than 5.00 ms by using this method. The time lag has already met their warning time processing and timeliness requirements for the hysteresis characteristics of the aerial LIB pack. This has the same characteristics of the mixed dynamics strategy conducted by Ovalle *et al.* (2016), in which the energy performance characteristics are reported. The Ah algorithm is employed in the discharging experiments for the verification as well, in which the SOC estimation results are analyzed and compared with the obtained experimental estimation results shown in Figure 7.

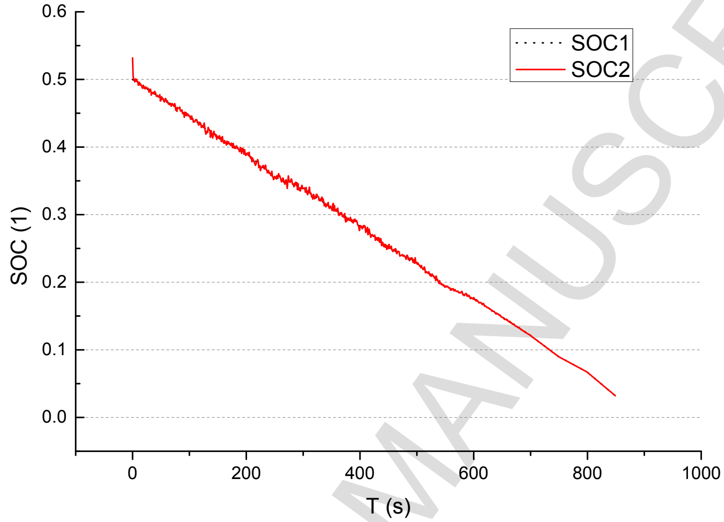

Fig. 7. The SOC estimation results of the aerial LIB pack

The experimental results show that the proposed method can track the voltage signals effectively and realize real-time state estimation during the charge and discharge process. The response time is less than 5.00 ms and the voltage detection accuracy is found to be 0.50%FS, in this case the SOC value can be effectively estimated. The estimation error is found to be less than 2.00%. Meanwhile, the internal imbalance state of the internet connected battery cells can be used for the working condition monitoring in power supply applications. In order to solve the real-time working state detection problem, the effective protection of the power supply safety is realized and the estimation error is shown in Figure 8.

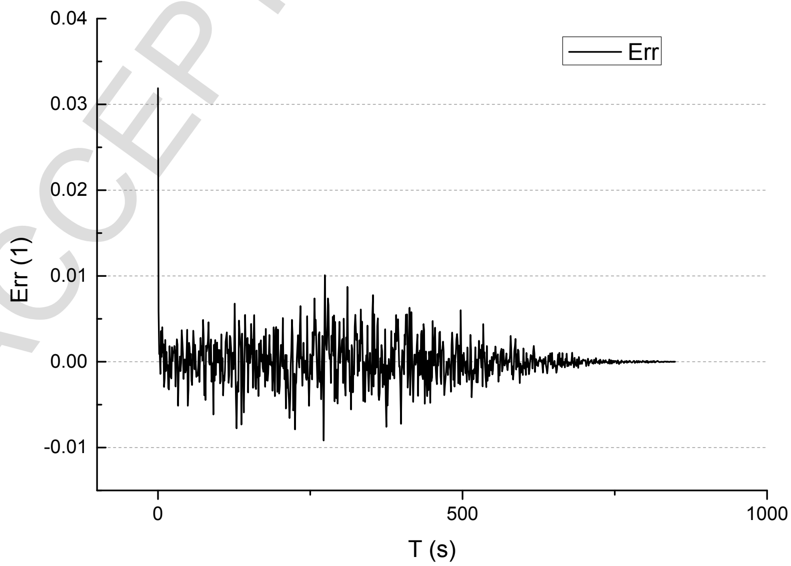

Fig. 8. The SOC estimation results of the aerial LIB pack

The above experimental analysis shows that the model gives an accurate estimation of the SOC values. In addition, when it is mixed with Gauss noise in the CC discharge process, it can make the estimation value quickly converging to the real value. Furthermore, it has a good effect on the initial error correction in the SOC estimation process and can compensate the cumulative error that is caused by the ordinary Ah integral treatment. Typically, when the voltage reaches the OCV steady state condition, it is less than 1.00 mV after several hours. The RC network comprising of two simplified ECM and the estimation will result in the criteria used in the experiment corresponding to the high dynamic current maintenance cycle patterns with significant estimation errors. The results should be constantly updated in the SOC estimation process, in which the covariance estimation error can be obtained.

3.2. Result analysis

Experimental results show that, the battery voltage sampling error is less than 1.00 mV and the complete voltage sampling error is less than 20.00 mV by applying this method. Meanwhile, the predicted time is less than 5.00 ms and the accurate SOC value can be estimated by the Root Mean Square Error (RMSE). The error associated to RMSE is less than 2.00%, which can play a positive role in maintaining the LIB pack applications secure. It is noteworthy that, the estimation error can be large when the battery SOC value is close to zero, which is mainly produced by the nonlinear behavior. However, LIB is rarely discharged to less than 2.00% SOC range. This method achieves good results by meeting the real-time varying voltage characteristics. In addition, the sampling cost which depends on the requirements of the circuit, are effectively reduced. Finally, the proposed SOC estimation method can be successfully applied to achieve the accurate SOC estimation target in the BMS design requirements.

4. Conclusion

The SOC value of the aerial LIB pack has been estimated together with its voltage prediction in the real-time adaptive process of the associated BMS equipment. In addition, it is formed by two order RC circuit and combined with electrochemical model to obtain more accurate predictions. The improved EKF algorithm is employed and the relationship between the input terminal voltage and the models are surveyed. The full battery connections and battery voltages are real-timely detected, by which the series and the output voltage of the LIB pack can be achieved by using the prediction algorithm. Experimental results show that the KF-based method can effectively achieve the packet terminal voltage and battery voltage signal for the sampling, filtering and prediction process of the aerial LIB pack. The SOC value is accurately estimated for the track and trajectory with the inaccurate initial value, in which the estimation error is very small in the practical applications. The SOC estimation method is investigated for the aerial lithium-ion battery pack, in which the aerial auxiliary power supply and pack working conditions are simulated for the SOC estimation effect analysis. The available residual energy characterization is realized for the aerial lithium-ion battery packs, and the subsequent research work makes more in-depth study the following aspects. Firstly, the establishment of expert system for the LIB pack: the energy and security management evaluation method was investigated for the lithium-ion battery pack combining with the application demand of expert system construction. Meanwhile, the expert system should be constructed and gradually improved by using the previous theoretical analysis and experimental researches. Secondly, the industrial applications of the SOC estimation method: the preliminary validation experiments are carried out under laboratory conditions, and the different conditions should be carried out to validate and improve the stability and reliability of the proposed SOC estimation method. Thirdly, the long-term SOC estimation stability and reliability tests should be carried out. This part is cooperated with related lithium-ion battery production and application enterprises. In addition, the application field promotion of the SOC estimation method: the preliminary research work has been carried out mainly for the aerial lithium-ion batteries. Finally, the industrial applications of the battery management subsystem for the power lithium ion battery pack can be realized. In view of the demand for new energy measurement / control the application of lithium ion battery pack for new energy vehicles, the industrial application area of SOC estimation and energy management should be gradually extended.

Acknowledgments

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References

[1] Hu XS, Zou CF, Zhang CP. Technological developments in batteries. IEEE Power and Energy Magazine 2017; 15(5): 20-31.

[2] Bartlett A, Marcicki J, Onori S. Electrochemical model-based state of charge and capacity estimation for a composite electrode lithium-ion battery. IEEE Transactions on Control Systems Technology 2016; 24(2): 384-399.

[3] Jaguemont J, Boulon L, Dubé Y. A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures. Applied Energy 2016; 164: 99-114.

[4] Zhang L, Hu XS, Wang ZP. Fractional-order modeling and State-of-Charge estimation for ultracapacitors. Journal of Power Sources 2016; 314: 28-34.

[5] Kim J. Discrete wavelet transform-based feature extraction of experimental voltage signal for Li-ion cell consistency. IEEE Transactions on Vehicular Technology 2016; 65(3): 1150-1161.

[6] Abadaa S, Marlairb G, Lecocqb A. Safety focused modeling of lithium-ion batteries: A review. Journal of Power Sources 2016; 306: 178–192.

[7] Lim K, Bastawrous HA, Duong VH. Fading Kalman filter-based real-time state of charge estimation in LiFePO4 battery-powered electric vehicles. Applied Energy 2016; 169: 40-48.

[8] Saw LH, Ye YH, Tay AAO. Integration issues of lithium-ion battery into electric vehicles battery pack. Journal of Cleaner Production 2016; 113:

1032-1045.
[9] Beattie SD, Loveridge MJ, Lain MJ. Understanding capacity fade in silicon based electrodes for lithium-ion batteries using three electrode cells and upper cut-off voltage studies. Journal of Power Sources 2016; 302: 426-430.
[10] Lin C, Mu H, Xiong R. A novel multi-model probability battery state of charge estimation approach for electric vehicles using H-infinity algorithm. Applied Energy 2016; 166: 76-83.
[11] Hu XS, Li SE, Yang YL. Advanced machine learning approach for lithium-ion battery state estimation in electric vehicles. IEEE Transactions on Transportation Electrification 2016; 2(2): 140-149.
[12] Burgos-Mellado C, Orchard ME, Kazerani M. Particle-filtering-based estimation of maximum available power state in lithium-ion batteries. Applied Energy 2016; 161: 349-363.
[13] Schindler S, Bauer M, Petzl M. Voltage relaxation and impedance spectroscopy as in-operando methods for the detection of lithium plating on graphitic anodes in commercial lithium-ion cells. Journal of Power Sources 2016; 304: 170-180.
[14] Saw LH, Ye YH, Tay AAO. Integration issues of lithium-ion battery into electric vehicles battery pack. Journal of Cleaner Production 2016; 113: 1032-1045.
[15] Chen XP, Shen WX, Dai MX. Robust adaptive sliding-mode observer using RBF neural network for lithium-ion battery state of charge estimation in electric vehicles. IEEE Transactions on Vehicular Technology 2016; 65(4): 1936-1947.
[16] Fridholm B, Wik T, Nilsson M. Robust recursive impedance estimation for automotive lithium-ion batteries. Journal of Power Sources 2016; 304: 33-41.
[17] Dang XJ, Yan L, Xu K. Open-circuit voltage-based state of charge estimation of lithium-ion battery using dual neural network fusion battery model. Electrochimica Acta 2016; 188: 356-366.
[18] Feng XN, Weng CH, Ouyang MG. Online internal short circuit detection for a large format lithium ion battery. Applied Energy 2016; 161: 168-180.
[19] Bruen T, Marco J. Modelling and experimental evaluation of parallel connected lithium ion cells for an electric vehicle battery system. Journal of Power Sources 2016; 310: 91-101.
[20] Zackrisson M, Fransson K, Hildenbrand J. Life cycle assessment of lithium-air battery cells. Journal of Cleaner Production 2016; 135: 299-311.
[21] Gong XZ, Xiong R, Mi CC. A data-driven bias-correction-method-based lithium-ion battery modeling approach for electric vehicle applications. IEEE Transactions on Industry Applications 2016; 52(2): 1759-1765.
[22] Hussein AA, Fardoun AA, Stephen SS. An online frequency tracking algorithm using terminal voltage spectroscopy for battery optimal charging. IEEE Transactions on Sustainable Energy 2016; 7(1): 32-40.
[23] Meng JH, Luo GZ, Gao F. Lithium polymer battery state-of-charge estimation based on adaptive unscented Kalman filter and support vector machine. IEEE Transactions on Power Electronics 2016; 31(3): 2226-2238.
[24] Wang SL, Fernandez C, Shang LP. An integrated online adaptive state of charge estimation approach of high power lithium-ion battery packs. Transactions of the Institute of Measurement and Control 2017; 39 (4): 1-19.
[25] Piao CH, Li ZC, Lu S. Analysis of real-time estimation method based on hidden markov models for battery system states of health. Journal of Power Electronics 2016; 16(1): 217-226.
[26] Pramanik S, Anwar S. Electrochemical model based charge optimization for lithium-ion batteries. Journal of Power Sources 2016; 313: 164-177.
[27] Shi W, Wang JL, Zheng JM. Influence of memory effect on the state-of-charge estimation of large format Li-ion batteries based on LiFePO4 cathode. Journal of Power Sources 2016; 312: 55-59.
[28] Mesbahi T, Rizoug N, Bartholomeus P. Dynamic model of li-ion batteries incorporating electrothermal and ageing aspects for electric vehicle applications. IEEE Transactions on Industrial Electronics 2018; 65 (2): 1298-1305.
[29] Yang JF, Xia B, Shang YL. Adaptive state-of-charge estimation based on a split battery model for electric vehicle applications. IEEE Transactions on Vehicular Technology 2017; 66 (12): 10889-10898.
[30] Wang SL, Fernandez C, Shang LP. Online state of charge estimation for the aerial lithium-ion battery packs based on the improved extended Kalman filter method. Journal of Energy Storage 2017; 9: 69-83.
[31] Wijewardana S, Vepa R, Shaheed MH. Dynamic battery cell model and state of charge estimation. Journal of Power Sources 2016; 308: 109-120.
[32] Zou Y, Li SBE, Shao B. State-space model with non-integer order derivatives for lithium-ion battery. Applied Energy 2016; 161: 330-336.
[33] Sun FC, Xiong R, He HW. A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique. Applied Energy 2016; 162: 1399-1409.
[34] Chiang YH, Sean WY, Wu CH. Development of a converterless energy management system for reusing automotive lithium-ion battery applied in smart-grid balancing. Journal of Cleaner Production 2017; 156: 750-756.
[35] Wang SL, Shang LP, Li ZF. Online dynamic equalization adjustment of high-power lithium-ion battery packs based on the state of balance estimation. Applied Energy 2016; 166: 44-58.
[36] Xiao RX, Shen JW, Li XY. Comparisons of modeling and state of charge estimation for lithium-ion battery based on fractional order and integral order methods. Energies 2016; 9(3): 1-15.
[37] Yang FF, Xing YJ, Wang D. A comparative study of three model-based algorithms for estimating state-of-charge of lithium-ion batteries under a new combined dynamic loading profile. Applied Energy 2016; 164: 387-399.
[38] Gollei A, Gorbe P, Magyar A. Modeling and optimization of electrical vehicle batteries in complex clean energy systems. Journal of Cleaner Production 2012; 34: 138-145.
[39] Wang SL, Shang LP, Fernandez C. Aeronautical lithium cobalt oxide battery capacity check and safety anticipation method study. Journal of Electrical & Electronic Systems 2016; 5 (3): 1-9.
[40] Zhang CP, Wang LY, Li X. Robust and adaptive estimation of state of charge for lithium-ion batteries. IEEE Transactions on Industrial Electronics 2015; 62(8): 4948-4957.
[41] Kuo TJ, Lee KY, Huang CK. State of charge modeling of lithium-ion batteries using dual exponential functions. Journal of Power Sources 2016; 315: 331-338.

1. A novel real-time voltage detection and state estimation method is proposed for the LIB pack.
2. The two order ECM is proposed and constructed aiming to solve the security protection issues.
3. The SOC estimation of the aerial LIB pack is utilizedby using the improved EKF algorithm.
4. The response time of the parameter detection and working state estimation is less than 5ms.
5. The proposed method can realize the real-time protection of the aerial LIB pack effectively.