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RESEARCH ARTICLE

An improved packing equivalent circuit modeling method with the cell-to-cell consistency state evaluation of the internal connected lithium-ion batteries

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Abstract

The existing equivalent modeling methods reported in literature focuses mainly on the battery cells and do not take the packing consistency state into consideration, which exists on the internal connected cells of the lithium-ion battery pack. An improved equivalent circuit model is constructed and reported in this manuscript for the first time, which can be used to characterize the working characteristics of the packing lithium-ion batteries. A new equilibrium concept named as state of balance is proposed as well as the calculation process, which is realized by considering the real-time detected internal battery cell voltages. In addition, this new equilibrium concept aims to obtain more information on the real-time consistency characterization of the battery pack. The improved adaptive equivalent circuit model is investigated by using the improved splice modeling method, in which the statistical noise properties are corrected and the additional parallel resistance-capacitance circuit is introduced. The parameter correction treatment is carried out by comparing the estimated and experimental detected closed circuit voltages. Furthermore, the tracking error is found to be 0.005 V and accounts for 0.119% of the nominal battery voltage. By taking the packing consistency state and temperature correction into consideration, the accurate working characteristic expression is realized in the improved equivalent circuit modeling process. Finally, the model proposed in this manuscript presents a great number of advantages compared to other methods reported so far, like has the high accuracy, and the ability to protect the security of the lithium-ion battery pack in the power supply application.

KEYWORDS

equivalent circuit modeling, lithium-ion battery, packing equivalent, state of balance, temperature correction, Thevenin

1 | INTRODUCTION

The voltage and capacity of the single lithium-ion battery cell is very limited as a result they should be connected together and used as packs that are suitable for the industrial energy power supplies, especially for the Unmanned Aerial Vehicles (UAVs).[1] As the material and process variations cannot be avoided, the imbalance phenomena exits among the internal connected cells of the lithium-ion battery pack,[2] which makes the balance state evaluation to be necessary for power supply applications.[3] As a result, it is quite difficult to obtain accurate working state descriptions of the lithium-ion battery packs using the current power supply conditions.[4] The existing modelling methods reported in literature so far cannot resolve the life shortening, thermal runaway and other issues in the lithium-ion battery packs for reliable power supply purposes.[5] The existing research has carried out a great work by improving the safety level of the lithium-ion battery pack effectively.

Considering the high specific energy and safety demands, the lithium cobalt oxide batteries have been investigated extensively for the auxiliary power application[6] because of its equity and environmental protection advantages.[7] Moreover, it can be used in high temperature conditions with a high degree of safety.[8] The battery cell voltage can describe the working state to a certain extent[9] and the internal equilibrium state of the lithium-ion battery pack can be characterized, which can improve its safety in the industrial power supply applications.[10] The iterate calculation modeling was obtained by using the co-estimator,[11] according to which the on-line working state estimation could be also investigated.[12] Then, the on-line remaining energy status named as State of Charge (SOC) was also predicted,[13] which plays an important role in the Battery Management System (BMS). Multi-timescale power and energy assessment was also investigated for the lithium-ion battery and supercapacitor hybrid systems.[14] The working state estimation was investigated for the lithium-ion battery pack, in which the equilibrium state was consistent by implying the battery cell voltages, reflecting its actual energy state adequately.[15] Because of the difficulty in the packing state estimation of the lithium-ion batteries, the real-time performance and its adaptability are not precise enough.

Moreover, a great number of research papers have been extensively reported to overcome the balance state security issues. The power capability evaluation was conducted by investigating the multi-parameter constraints estimation constraints.[16] An online frequency-tracking algorithm was proposed[17] and the dynamic estimation process was also obtained.[18] The state-space model with noninteger order derivatives was constructed[19] along with the H-infinity-filter-based SOC estimation method.[20] The estimation method was also studied by using the stress measurement.[21] The electrochemical model-based estimation algorithm was also investigated.[22] The improved SOC estimation method was conducted by considering the current dependence on the internal resistance.[23] Other research groups as well as our research team have carried out in-depth research to enhance the lithium-ion battery pack safety by using the associated BMS equipment. However, there are still some parameters that cannot be considered fully because of the real-time imprecise complex requirement as well as the dynamic adaptability defects, which are mainly due to its indirect measurement characteristics. The reliability of the SOC estimation method was calculated by using the smooth variable structure filter[24] and the online internal resistance measurement.[25] Furthermore, the polynomial equivalent circuit model was constructed[26] for the electrochemical impedance spectroscopy of the lithium-ion batteries. The comparative optimization methods were analyzed for the parameter identification using different Equivalent Circuit Models (ECMs) for lithium-ion batteries.[27]

The related research work was concentrated on the energy transferring consumption policies[28] and the SOC determination methods were analyzed.[29] A data-driven bias-correction-based lithium-ion battery modeling was conducted[30] and the estimation process was also investigated by using the nonlinear fractional model.[31] The space representational degradation was considered along with the impedance modeling[32] and a simplified electrochemical model was built.[33] The iterate calculation was obtained by conducting the evolutionary Gaussian mixture regression[34] and the advanced BMS equipment was designed for the smart grid infrastructure.[35] Moreover, the maximum available power state estimation was conducted by using the Particle-filtering (PF) algorithm[36] and it was also achieved by using the temperature-compensated model.[37] The SOC estimation method was obtained for a latent heat storage[38] and a neural network-based observer was designed.[39] Furthermore, the dual sliding mode observer was built[40] and a comparative study was conducted for different ECMs.[41] These studies expanded the theoretical and experimental study of the energy transformation for the lithium-ion battery packs.

Mounts of equivalent modeling strategies were carried out as well, proposing a variety of circuit topologies. A novel thermoelectric model was investigated,[42] attracting a great protection circuit progress. A mixed estimation algorithm was proposed, in which high accuracy values can be achieved in various driving patterns of Electrical Vehicles (EVs).[43] The discrete wavelet transform-based feature extraction was analyzed for the lithium-ion battery consistency by using the experimental voltage signals.[44] The real-time SOC estimation method was conducted in the thermal storage vessels and applied to the smart polygene ration grid.[45] It was also investigated by using the dual exponential function[46] and the impact on the Open Circuit Voltage (OCV) tests were conducted.[47] The temperature-compensated models were conducted by using the Extended Kalman Filter (EKF), which were used as the implantable charger.[48] The co-estimation method was studied for the SOC determination, in which the mixed strategist dynamics was proposed along with the maximum entropy principles.[49] The electrochemical model was conducted by using the charging optimization[50] and the dynamic model was investigated incorporating electro-thermal and aging aspects.[51] A rapid screening and regrouping approach was proposed to manage the large-scale retired lithium-ion battery cells in second-use applications by using the neural network algorithm.[52] Therefore, it is necessary to construct the adaptive model based on the internal mechanism theory, which can achieve the optimum life for f lithium-ion battery packs, protecting the instantaneous power supply capacity and improving its energy utilization.

An improved equivalent circuit model is constructed, which can be used to characterize the working characteristics of the packing lithium-ion batteries. A new equilibrium parameter named as State of Balance (SOB) is constructed, which is introduced into the packing equivalent circuit modeling process. The consistency among the internal connected battery cells in the lithium-ion battery pack is characterized by using this equilibrium parameter. An adaptive model is built by conducting the battery internal principle along with the working state analysis, in which the information acquisition and model-building methods are introduced to establish the working state expression model.

2 | MATHEMATICAL ANALYSIS

The mathematical methods are studied by considering the key factors of voltage, current and temperature, which can improve the energy management effect and safety of the power lithium-ion battery packs. The parametric method is conducted by establishing the equilibrium state evaluation model. The key issues of the adaptive equilibrium parameters are effectively studied to achieve the working state description. A scientific evaluation of the equilibrium parameters and the adaptive models are investigated. Then, the SOB evaluation is embedded into it by using the adaptive model building method, which can provide a basis of reliable lithium-ion battery packing power supply applications.

2.1 | Equivalent circuit description

According to the working state description requirement of the lithium-ion battery pack, the Splice-Equivalent Circuit Model (S-ECM) is constructed by considering the characterization accuracy and computational complexity, which is realized by the combined empirical treatment of existing equivalent models. In order to obtain the accurate mathematical expression of the working characteristics, the different internal effects are simulated by the proposed S-ECM model, aiming to adapt the lithium-ion battery packs at various conditions of the internal battery cells cascade. Considering the working characteristics of the lithium-ion battery pack together with its internal composition, the improved equivalent circuit model is constructed to build the model framework. Furthermore, the effective state-space equation of the S-ECM can be described by conducting the experimental analysis along with its parameter identification. The equivalent mechanism can be described as follows:

1. The electromotive force is derived by using the ideal voltage source U_{OC}. The parallel-connected large resistance R_s can be added next to the electromotive force to characterize the self-discharge effect, which can decrease the equivalent modeling error caused by the self-discharge phenomenon. The Ohm effect is characterized by the serially connected internal resistance R_o.
2. The one-order Resistance-Capacitance (RC) paralleled circuit is used to characterize the polarization effect. The parallel resistance circuit connected with reverse diodes are used on the equivalent modeling basis, aiming to characterize the charge-discharge resistance difference. The resistances of R_d and R_c paralleled circuit connected with reversed diodes are utilized, which will furthermore improve the working state description accurately.
3. The mathematical description of the SOB influence can be carried out by considering the consistency difference between the internal connected battery cells in the packing equivalent model. U_δ is used by conducting the reverse-tandem treatment, which is serially connected with the OCV source U_{OC} to describe the variation on the output voltage $U_L(t)$ that shortens the range of the working voltage period, including upper and lower limits. The time-variable resistance R_δ is used to describe this influence effect of the accumulative increase in the internal resistance R_o, which will increase the heating effect gradually.

By considering the comprehensive effect of these factors, a more effective solution can be provided for the existing working state characterization problems of the lithium-ion battery packs. In this way, a novel S-ECM model is constructed for the lithium-ion battery packs together with its state-space equation as shown in Figure 1.

Because of its high accurate and easy calculation advantages, the simulation modeling complexity can be simplified. According to the application conditions and characteristics of the lithium-ion battery pack that are obtained from the experimental analysis, the improved equivalent model can be constructed. The working characteristic expression effect can be improved by using the S-ECM model, which is obtained by improving the original battery equivalent circuit model. The parameters in the model are shown as follows:

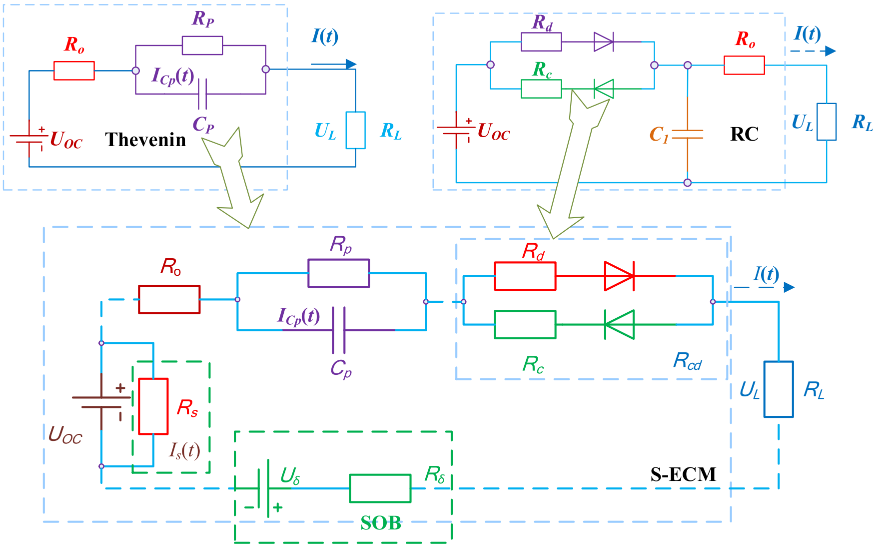

FIGURE 1 The equivalent circuit model of the lithium-ion battery pack

1. U_{OC} is used to describe the OCV varying situation of the lithium-ion battery pack.
2. R_s is utilized to indicate the self-discharge effect.
3. R_o is employed to characterize the voltage drop between the positive and negative poles in the discharge and charge process of the lithium-ion battery pack that is caused by the Ohm effect.
4. The one-order RC parallel circuit is utilized to simulate the relaxation effect on the working process, in which R_p is employed to characterize the polarization resistance and C_p is the polarization capacitance. The parallel circuit of R_p and C_p reflect the production and elimination process of polarization effect in the lithium-ion battery pack.
5. R_d represents the internal resistance difference in the discharge process, and R_c is used to characterize the internal resistance difference in the charging process.
6. U_δ and R_δ are used to characterize the equilibrium state influence due to the difference in the cell-to-cell consistency of the internal connected battery cells.
7. $U_L(t)$ is the Closed Circuit Voltage (CCV) between the positive and negative poles when the lithium-ion battery pack is connected to the external circuit and $I_L(t)$ is the incoming or outgoing current.

2.2 | State of balance evaluation

The consistency characterization method is studied for the lithium-ion battery pack and the structure of the proposed relationship management is constructed in the equalization state evaluation, according to which the correction adjustment is carried out. As the cell voltage is the most direct and effective parameter to be detected for each battery cells, it is used to evaluate the overall balance state in the lithium-ion battery pack. Compared with the capacity and internal resistance, the voltage detection has real-time, fast and easy-implementation advantages, which is quite suitable to investigate the online state evaluation. Therefore, the SOB evaluation of the lithium-ion battery pack can be obtained by using the battery cell voltage U_c, in which the expected voltage value can be calculated as shown in Equation 1.

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

In the above expression, U_{ci} is the i-th battery cell voltage, and n represents the number of the internal connected lithium-ion battery cells. The calculation result $E(U_c)$ represents the expected voltage value of all the internal connected lithium-ion battery cells. The standard deviation δ is an important index to express the difference, so the SOB evaluation research of the lithium-ion battery pack can be conducted by using the standard deviation measurement method with the probability distribution, in which the quantized balance evaluation index can be obtained and applied to the equivalent modeling process. In order to obtain the equilibrium state quantifying target, the inconsistent equilibrium degree parameter can be defined by using the probability and statistical theory. The square value of the standard difference δ can be used to calculate the mathematical description as shown in Equation 2.

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

where in, δ^2 is used to characterize the variance CCV value of each cell in the lithium-ion battery packs (U_{c1}, U_{c2},…U_{cn}), which then describes the voltage inconsistency of the battery cells. According to the difference degree evaluation target, the variation coefficient θ is used to describe the voltage fluctuation influence accurately. The calculation process can be obtained by the standard deviation ratio and its average value, which is shown in Equation 3.

$$\theta = \frac{\delta}{E\left(U_{\mathrm{c}}\right)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{U_{\mathrm{ci}} - E\left(U_{\mathrm{c}}\right)}{E\left(U_{\mathrm{c}}\right)}\right)^{2}} \tag{3}$$

The physical meaning of the symbols for the above expression can be described as follows: θ is used to describe the voltage variation coefficient of the internal connected battery cells and U_{ci} indicates the detected i-th battery cell voltage value. The average voltage value can be calculated to obtain the above evaluation parameters, which can be used to describe the consistency level of the lithium-ion battery pack. The standard deviation can express the discrete degree of the battery cells in the lithium-ion battery pack. When the standard deviation value is small during the SOB evaluation process, the voltage discrete degree of each battery cell is small and the consistency state of the battery cells becomes good.

The equilibrium state of the lithium-ion battery pack can be characterized by the variance calculation along with its coefficient. The variance change describes the distribution of the battery working voltages, in which the variation coefficient is used to characterize the internal battery states of the lithium-ion battery pack. The equilibrium state can be described by introducing SOB into the working state description of different voltage conditions. For the calculation process, the square value of the variation coefficient θ is named as ε which is finally used to evaluate the consistency condition of the lithium-ion battery pack, as the square-root parameter θ will increase the calculation complexity, which is shown in Equation 4.

$$\mathrm{SOB} = \varepsilon = \theta^{2} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{U_{\mathrm{ci}} - E\left(U_{\mathrm{c}}\right)}{E\left(U_{\mathrm{c}}\right)}\right)^{2} \tag{4}$$

In the above expression, ε is used to describe the extent of the voltage inconsistency among the internal connected battery cells in the lithium-ion battery pack and θ characterizes the variation coefficient. U_{ci} is used to describe the i-th measured battery cell voltage, and n indicates the number of the battery cells in the lithium-ion battery pack. The research methods of various key elements are utilized as parts of the technical design in the evaluation model. The parameter correlation method is studied to improve the performance of the lithium-ion battery pack, which is conducted by using the different charge-discharge current rates. The equilibrium state evaluation is studied by conducting the equivalent circuit analysis along with the parameter changes. The preliminary studies are conducted by investigating the experiments, according to which various correlated equilibrium parameters can be identified. Aiming to realize the adaptive multi-input parameter identification, the parametric model-building framework is used to address the equilibrium issue.

The mathematical description of the implementation process is obtained without introducing complex mathematical models. The unique characteristic of the aforementioned equation is that provides a greater feasibility for rapid error analysis to identify results. The observation equation describes the state of the CCV signal in the battery pack. As can be known from the OCV-based parameter identification process, the identification result is closely related to the CCV value. In order to achieve the accurate identification of the target parameters, the CCV is defined as an output parameter of the battery pack. Considering the influence of operating current and temperature conditions, the parameters of the ECM model are analyzed and identified for the battery pack. Combining the state equation and the observation equation, the state space equation needed can be constructed for the working estimation as shown in Equation 5.

$$\begin{cases} \mathrm{SOC}\left(k|k-1\right) = \mathrm{SOC}\left(k-1\right) - \frac{\eta_I \eta_T I(k) T_{\mathrm{s}}}{Q_n} - K_{\mathrm{s}} * T_{\mathrm{s}} \\ U_{\mathrm{L}}\left(k\right) = \left(U_{\mathrm{OC}} - U_{\delta}\right) - \left(R_{\mathrm{o}} + R_{\delta}\right) * I\left(k\right) \\ \qquad -I\left(k\right) R_{\mathrm{p}}\left(1 - e^{-T_{\mathrm{s}}/\left(R_{\mathrm{p}} C_{\mathrm{p}}\right)}\right) - I\left(k\right) R_{\mathrm{cd}} \end{cases} \tag{5}$$

By conducting the above parameter identification principle and process analysis, the parameter identification model can be constructed. The general knowledge of covariance and noise can be taken as a priori known condition, and the additional considerations are made in dependent submodules. After establishing the state equation structure, each factor of the equation needs to be determined experimentally. The parameter identification equation and the identification process are implemented in separate modules. The model parameter values can be calculated through the voltage and current. By constructing its internal working status monitoring structure, the application characterization process is achieved, and the battery operating characteristic information is obtained through the experimental research. The working characteristics and parameter identification of the battery pack are studied, in which each coefficient of the model parameter and its variation rules can be obtained. The initialization of the model parameters in the SOC estimation model are achieved as well.

2.3 | Model building

According to the structure of the equivalent circuit model, the simulation model is built using the Matlab/Simulink platform. Parameter verification and experimental results are taken into the calculation process as shown in Figure 2.

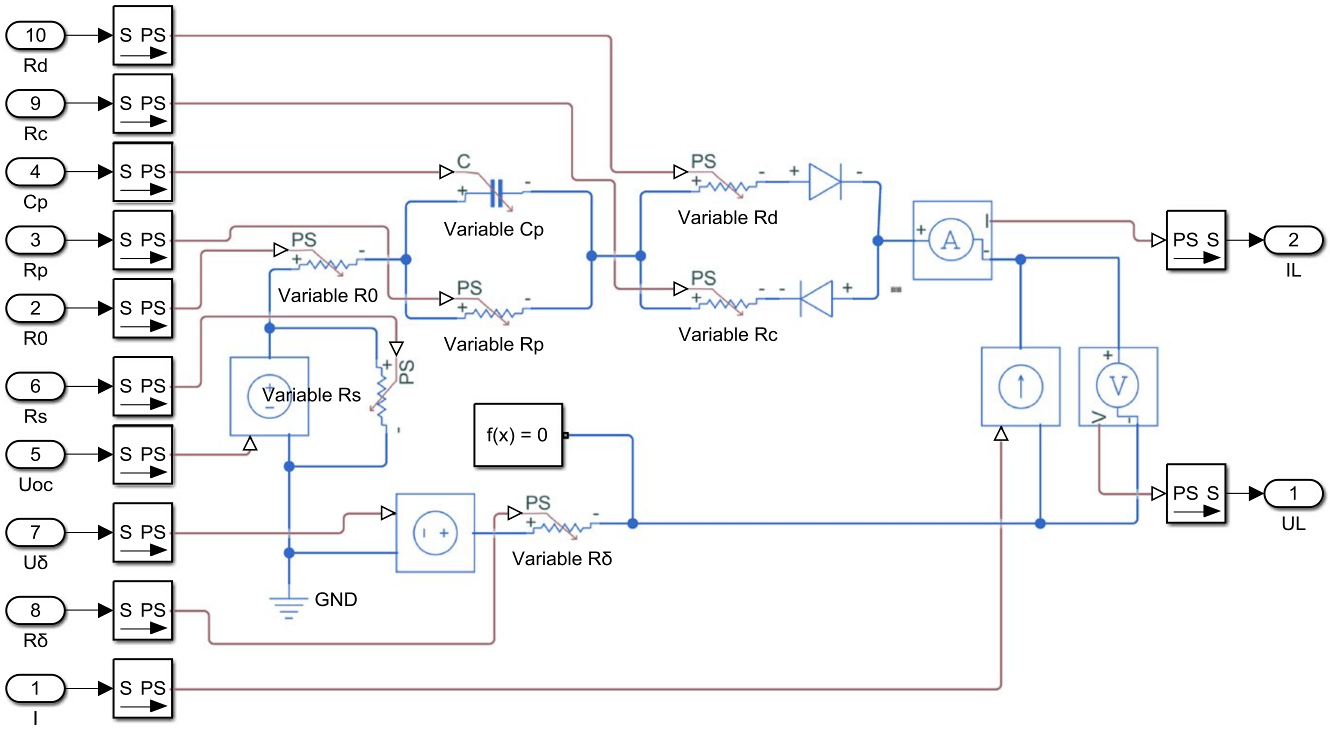

FIGURE 2 The simulation model of the improved equivalent circuit model

It is obtained by considering the real-time varying parameters in the recursive calculation process, which is used to obtain the adaptive time-varying capacity. The model parameter variation law of the S-ECM is analyzed for the applied research of the lithium-ion battery pack to explore the online parameter identification method. According to the judgment and establishment of the working conditions together with the overall imbalance state evaluation, the adjustment can be carried out according to the comprehensive state determination, which is obtained by using the best decision method to find out the first priority battery that needs equalization. Finally, the energy transferring speed and the energy transfer direction is determined by the positive and negative values. The equilibrium parameter is built with battery voltages, in which the parametric equalizer is constructed to analyze the comparative results. The experimental effect is analyzed and compared with other methods, which verifies the constructed equilibrium evaluation effect.

3 | EXPERIMENTAL ANALYSIS

The modeling effect on the experiments is completed to verify the proposed equivalent circuit model. The model parameters are studied to solve the shortened life expectancy, low capacity utilization and low instantaneous power supply degree problems, which have caused frequent thermal imbalance issues. The operating characteristics are analyzed by using the equivalent resistance and capacitance, according to which the parametric variation is prepared for the equilibrium state evaluation. Furthermore, the parameter variation on the interaction is analyzed by using the SOB evaluation among the group working battery cells. The experiments are designed to test the established equivalent model by the parameter correlation and variation characteristics.

3.1 | Platform construction

The electronic and digital power supplies are introduced along with other digital devices. The process field-bus technology has been taken into the experimental Battery Maintenance and Test System (BMTS) platform for the packed lithium-ion batteries. The control strategy is obtained by using the Industrial Personal Computer (IPC), in which the Human Machine Interface (HMI) is used as the monitoring interface. The input components of keyboard and mouse are introduced into the system in order to obtain the manual control. In the BMTS platform, the fourteen-digital-power-charging-supply module is employed for the balance charging purpose and two large power supplies of Taiwan are used for the series charging maintenance. After then, the protection unit is designed to ensure the real-time security protection purpose. The experimental platform has been designed and verified by using the ternary lithium-ion battery packs. The structure is shown in Figure 3.

Aiming to achieve the condition monitoring target of the lithium-ion battery pack in the UAVs, a suitable BMS

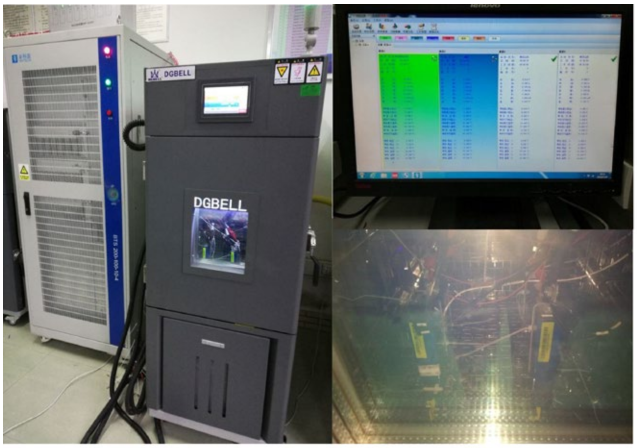

FIGURE 3 The experimental platform

equipment is designed and implemented, in which the STM32 and integrated chip sampling modular are used. The total size of the BMS equipment is set as 50*80 mm, which is smaller than a mobile phone screen and supports the subsequent network expansion. The AVIC lithium battery CFP50AH (rated capacity 50AH, charge cut-off voltage 4.2 V, discharge cut-off voltage 2.75 V) is taken as the experimental object of the Aviation Industry Corporation in China, Ltd. The designed BMS equipment obtains the high-precision real-time detection of each single-battery cell voltage and its accuracy is 1 mV, which features low power consumption and high integration advantages.

3.2 | Parameter identification

The typical UAV lithium-ion battery pack is selected as the experimental samples, in which the working state estimation and monitoring process are carried out for the consistency parameter monitoring target. In this way, its characterized accuracy is verified, which improves the equivalent modeling accuracy of the lithium-ion battery pack. Experimental battery packs with different structures are considered in the modeling process, in which its functionality and performance data are introduced into the comparative analysis of different model parameters. And then, the adaptive capacity, correction and optimization of the model parameters are observed, in which the simulated varying current working condition is constructed for the input parameters. The Hybrid Pulse Power Characterization (HPPC) experiments are conducted for the input parameters of the SOC estimation model, which are shown in Figure 4.

The detection time period of the experiment is 600s, in which the pulse width value is 50% and the phase delay is −120. Another current generator is set with the amplitude value of 45*7/4, the period value of 600, the pulse width value of 20% and the phase delayed value of −120. The lithium-ion battery pack is treated as a single battery cell with higher voltage and capacity in the HPPC test to obtain the parameter identification of the packing S-ECM. The parameter values and variation laws are taken into the state-space mathematical description of the ECM. In order to analyze the parameter varying characteristics, the on-line identification method is considered by conducting the explored implementation mechanisms. The parameter identification results are shown in Figure 5.

The credibility is analyzed by conducting the input parameter and the influence of the degree analysis, in which the statistical state-space model is used to improve the working state characterization accuracy.

3.3 | Temperature correction

The Coulomb efficiency effect and temperature correction treatment is introduced into the regulating process to analyze the current correction. The capacity and temperature correction model is built to consort the working environment, in

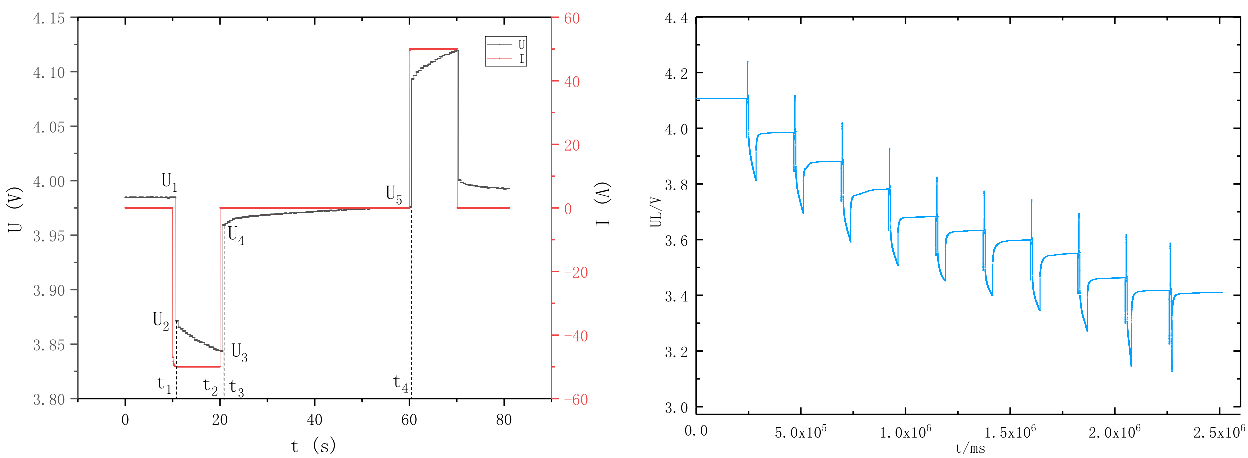

FIGURE 4 The Hybrid Pulse Power Characterization experimental test results

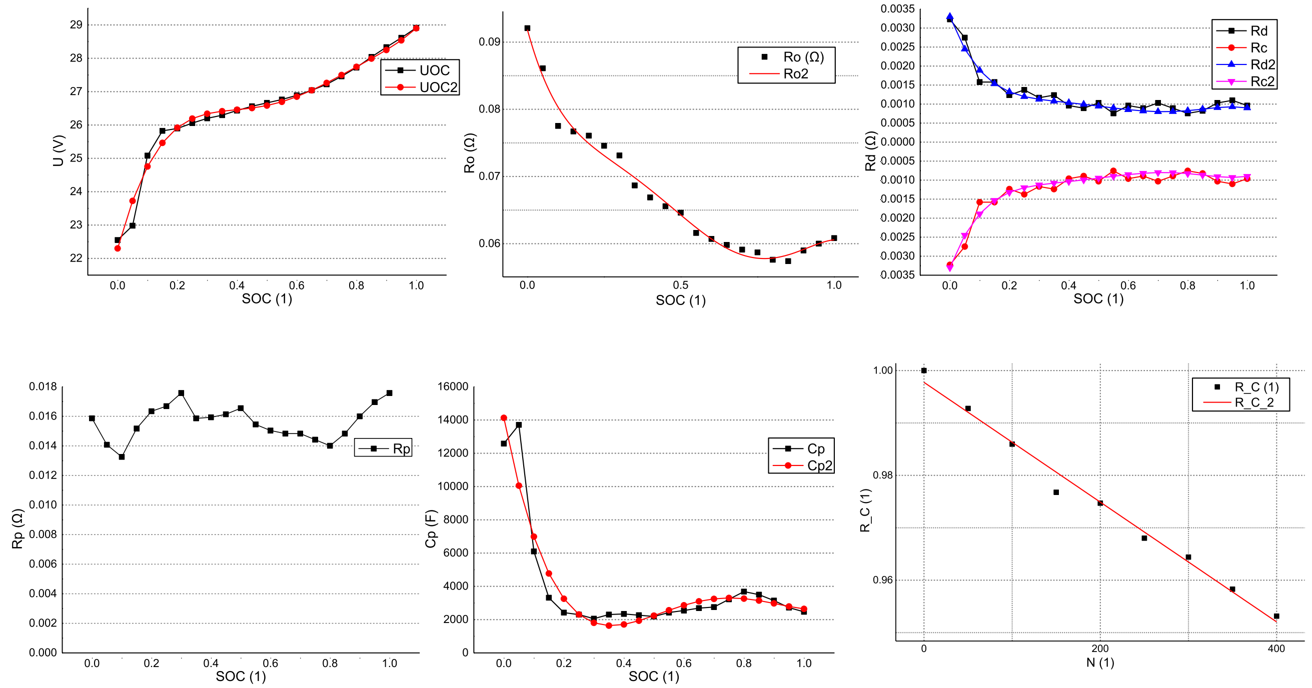

FIGURE 5 The parameter identification results

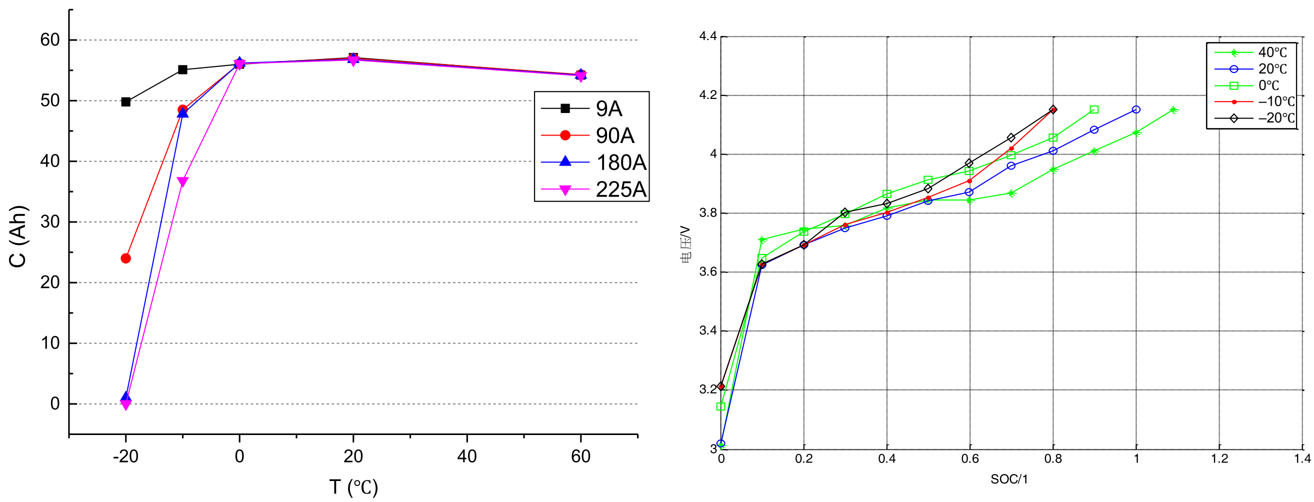

FIGURE 6 The capacity variation toward temperature

which the capacity characteristics are obtained by analyzing the experimental results. Considering the ground to altitude changing process, there will be a great temperature change in the lithium-ion battery pack. Therefore, the working characteristic analysis is conducted at different temperatures and current rates of the lithium-ion battery pack. The discharging characteristics are implemented in different ambient temperatures, including −20.00, −10.00, 0, 10, 20 and 60°C, as well as different currents of 9, 90, 180 and 225.00 A, to study the capacity variation of the test samples. The acquisition of battery capacity can be achieved by the discharging treatment, in which the latest full charged state is turned into the terminal discharge voltage. The discharging capacity law of the lithium-ion battery pack is obtained by the discharging treatment from the full charge state to the empty charge state. The experimental results are shown in Figure 6.

The CC mode discharging capacity restricts the final discharge capacity of the battery cell, which has a huge impact on the total discharging capacity of the lithium-ion battery packs. Under the premise known effect, the specific performance can be obtained through the cycling charge-discharge experiments under high and low temperature conditions. The experimental results show that the battery capacity varies little along with the discharging current rate diversification when the ambient temperature is high. However, the capacity will decrease obviously along with the low ambient temperature. At the low temperature, little electricity can be released when the discharging ratio of the lithium-ion battery pack is high. In this way, the ambient temperature influences on the capacity of the lithium-ion battery pack studied by conducting these experiments. When the ambient temperature is high, the discharge capacity of the battery pack is large. The impact on the discharging capacity of the $1C_5A$ current is obtained, in which the significant difference exists on different current rates and temperatures. And the discharging capacity level decreases when the temperature decreases, the amount of which is also reduced when the temperature is higher than 40°C. The voltage changing characteristics in the charging-discharging process can be obtained together with the voltage variation rule toward temperature.

The experimental results show that the CC discharging process can be divided into three stages along with the voltage and SOC variation. The first stage is the initial discharge with a slow-down circuit voltage, which is a certain period of the discharge time along with the obvious voltage drop. The second stage can be observed when it enters into the voltage platform along with the slow voltage variation. The third stage can be described as the discharge stage with the back-end franked treatment (SOC<0.20) toward the dramatic voltage drop, in which the CCV value varies along with different temperatures.

3.4 | Modeling effect analysis

The CCV-tracking results can be analyzed according to the time-varying voltage and current in the experiments, in which the rated capacity of the internal connected battery cell is analyzed together with the parameter sampling interval. Taking the experimental current data as the input signal, the CCV-SOC value is obtained by conducting the Ah integration method. The parameter values of U_{OCV}, R_O, R_P, and C_P are obtained through a functional relationship at this time point, in which the simulated terminal voltage is calculated by using the Thevenin function. The experimental CCV value in the HPPC test is compared with the estimated terminal voltage. The time-varying current is conducted in the discharging process by using the $1C_5A$ current rate. Comparing the CCV value of $U_L(t)$ and the calculated CCV value based on the model operation, the voltage-tracking effect of the output voltage can be obtained as shown in Figure 7.

In the above Figure, U_1 is the HPPC experimental terminal voltage and U_2 is the CCV value obtained by the experimental HPPC current data as the input signal through the model. In the main continuous discharging process, the voltage simulation error increases significantly and the peak appears in the intermittent discharging process after the 9th HPPC test. At this time, the estimated terminal voltage was lower than the real voltage about 0.065 V. The HPPC experimental data and estimation data is taken when SOC = 0.9 was intercepted, in which the comparative analysis can be obtained in the right part of the Figure. The battery weight presets the equalization process to improve the interaction network, and the combination of multi-parameter validation, dynamic change and adaptive optimization are investigated to achieve the improved modular results. The temperature simulation model is constructed, in which the calculation and adjustment can be achieved by using the real-time detection parameters obtained by the charge-discharge variation analysis of the lithium-ion battery pack. The various comparative parameter analysis is conducted to adjust the improvement degree. As can be known from the experimental results, the estimation effect is acceptable and there is no obvious error. As a result, the HPPC experiments are taken as a test set and the voltage-tracking results can reflect the variation characteristics of the lithium-ion battery pack.

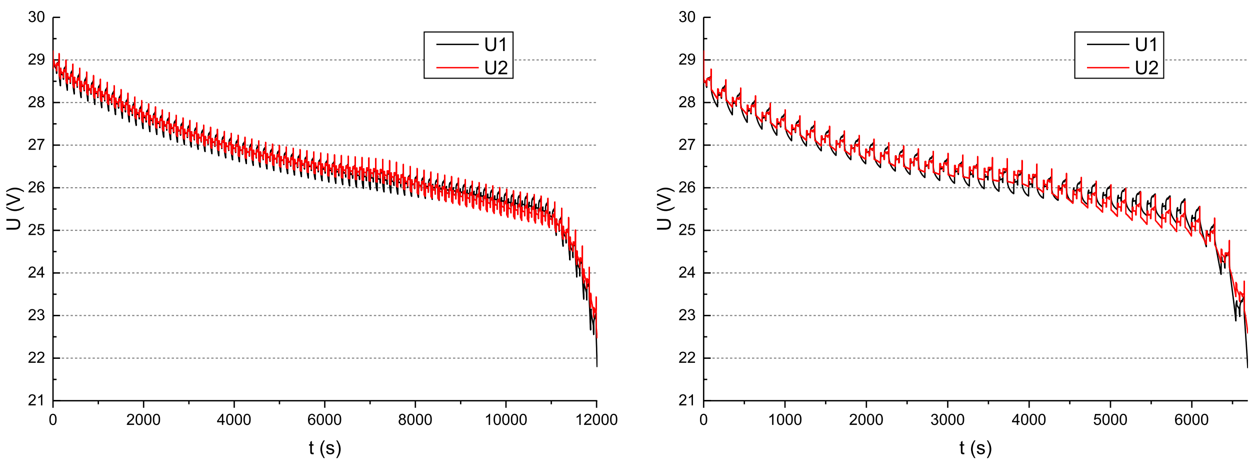

FIGURE 7 The Closed Circuit Voltage-tracking effect of the output voltage

4 | CONCLUSION

A novel equivalent circuit model is proposed and conducted for the power lithium-ion battery pack, in which the equilibrium parameter SOB has been built in order to achieve the security protection, which is the basis of its reliable power supply application. Firstly, the correlation relationship has been investigated between the working performance and its real-time detection parameters of the lithium-ion battery pack. Afterword, the equivalent model of S-ECM has been constructed successfully, according to which the theoretical analysis is carried out for these various measured parameters. An improved equivalent modelling construction method is investigated and the recursion calculation is designed and obtained, in which the model parameters are also identified with the correlative experiments. Then, the correction treatment of the parameter model is conducted in the experimental data acquisition process and the state diversification is monitored in its charge-discharge process. Meanwhile, the mathematical model is built to simulate the effect of the analysis. Finally, the performance of the experimental analysis is tested, in which the same type and batch of the lithium-ion battery pack is chosen under the same conditions. The maximum estimated voltage error in the estimated terminal voltage output is 0.065 V compared with the measured terminal voltage under the HPPC working condition and the current is taken as the input information, which is used for the subsequent power supply applications.

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