Equivalent Circuit Model of Lead-acid Battery in Energy Storage Power Station and Its State-of-Charge Estimation Based on Extended Kalman Filtering Method

Wen-Hua Cui, Jie-Sheng Wang*, and Yuan-Yuan Chen

Abstract—**Based on the performance testing experiments of the lead-acid battery in an energy storage power station, the mathematical Thevenin battery model to simulate the dynamic characteristics is established. The constant current intermittent discharge experiments are used for obtaining the initial model parameters values. Then the function relationship is fitted between the various parameters and the remaining power SOC. Combining the electrical characteristic equations in the related mathematical model, the voltage response data are produced in the simulation environment. The obtained data are compared with the actual experimental data of the voltage to get the difference, which is used to obtain the optimum model parameters estimation online based on the unconstrained nonlinear optimization method. Finally, on the basis of the parameter identification results on the mathematical model, the state space equations are established and the extended Kalman filtering method is used for SOC estimation. In the model validation and algorithm simulation implementation, it can be seen form the simulation results that these models and estimation algorithm have high prediction precision and can simulate the real-time dynamic battery, achieve the rapid convergence, and satisfy the need of actual simulation and engineering application.**

Index Terms—**energy storage power station， lead-acid batteries， thevenin model， extended Kalman filtering， state-of-charge estimation**

I. Introduction

WITH the progress of modern society, the electrical energy consumption will continue to increase, but other energy, such as coal, oil and other non-renewable energy sources is decreasing. Thus prompting the development of renewable energy power generation and solving the problem of environmental pollution have become the research focus in China and the world. With the development of renewable energy, more and more researchers focus their attention on energy storage technology. Energy storage technology in a certain extent can effectively regulate the grid connected power generation with renewable energy caused by the changes of network voltage and frequency change, the large-scale and distributed power generation in reliable incorporated into the power grid, improve power grid stability. In the research of energy storage technology, the residual capacity estimation of the storage battery can determine the used power in the energy storage power plant. The residual capacity estimating of the energy storage battery is not only related with battery types, environmental conditions and charge and discharge control factors, but also the battery using time, number of cycles and battery life, and so on.

At present, scholars at home and abroad have proposed a variety of storage battery residual capacity estimation method, but it is not much to get really popularization and application. The general estimation methods are mainly divided into traditional estimation methods, advanced intelligent estimation method and compound estimation method. The traditional estimation methods mainly include the open circuit voltage method, discharge experiment method, resistance method, ampere hour integral method, etc. Among them, the open circuit voltage method is the commonly used method. In a variety of battery performance testing, the open circuit voltage and residual capacity of lead-acid battery has a good corresponding relationship [1]. When finding this kind of corresponding relationship, using the open circuit voltage to predict the residual energy is very accurate. However, the time of different battery from the work state to the stable static state is different. Sometimes some batteries need several hours. So it is difficult to solve the problem how to determine the standing time of different battery. In the case of battery charging and discharging, the voltage at the two ends of the battery can be measured and the open circuit voltage is not measured online. So it is necessary to make the battery static to the steady state. The above description shows that the open circuit voltage method is not online accurately to estimate the residual capacity. Resistance method is to measure the battery impedance to estimate the battery

Manuscript received December 19, 2017; revised April 13, 2018. This work was supported by the the Basic Scientific Research Project of Institution of Higher Learning of Liaoning Province (Grant No. 2017FWDF10), and the Project by Liaoning Provincial Natural Science Foundation of China (Grant No. 20180550700).

Wen-Hua Cui is with the School of International Finance and Banking, University of Science and Technology Liaoning, Anshan, 114051, PR China; National Financial Security and System Equipment Engineering Research Center, University of Science and Technology Liaoning. (e-mail: cwh@ustl.edu.cn).

Jie-Sheng Wang is with the School of International Finance and Banking, University of Science and Technology Liaoning, Anshan, 114051, PR China; National Financial Security and System Equipment Engineering Research Center, University of Science and Technology Liaoning. (Corresponding author, phone: 86-0412-2538246; fax: 86-0412-2538244; e-mail: wang_jiesheng@126.com).

Yuan-Yuan Chen is a postgraduate student in the School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051, PR China (e-mail: chenyuanyuan@mail.iee.ac.cn).

remaining capacity [2]. But the non-chargeable discharge variation of electrolyte, such as volatilization, electrolytic decomposition, and impurity changes over time, will continue to affect the battery internal resistance. Only relying on the relationship between internal resistance and residual capacity to predict the residual capacity will have great error. So this method is seldom used. Ampere hour method is mainly based on the definition of the remaining power. Usually it is defined the percentage of the remaining power as SOC [3-4]. The ampere hour method makes the battery as a black box to calculate the import and consumption of black box. This will because external measurement error and battery total capacity and capacity of the initial value of the given calculation caused by inaccurate.

Advanced intelligent estimation algorithms include neural network, fuzzy control, multiple adaptive regression algorithm, support vector machine algorithm and Kalman filter algorithm, etc. For the neural network method [5-6], the external data, such as the battery voltage, current and temperature of the battery, are collected and fed into the input of the neural network model. Through training, learning and calculation on these data (samples) to realize the on-line estimation and prediction when the NN learning results meet the requirements of SOC prediction performance. This method can realize on-line prediction, but the prediction accuracy will be influenced by the variables of training method and it requires the large amounts of training data. The fuzzy control method [7-8] is similar to the characteristics of nonlinear neural network. Through the establishment of fuzzy rules, the detected parameters (such as voltage, current, temperature, etc.) are carried out the fuzzy processing and fed as the input of the fuzzy rules. Then the fuzzy output results are obtained. The output results (such as SOC) are through anti-fuzzy gelatinization processing to realize the battery SOC estimation. Multivariate adaptive regression (MARS) algorithm [9] is a nonlinear regression method, which determines the functional relationship between variables through the establishment of mathematical model. This can save the training time of many samples so that it is superior to the neural network algorithm. But the establishment of mathematical model and the functional relationship will need some prior knowledge to determine the optimal model. Support vector regression (SVR) algorithm is a nonlinear functional relationship mainly based on large amounts of data [10]. This approach to establish a nonlinear model will has some limitations because of limited data samples. Kalman algorithm [11-15] is the more commonly used forecasting method, which establishes the mathematical model of the system and obtain the optimal estimation on the model states. It realizes the states prediction by using the state equation and output equation based on the established mathematical model. Then the Kalman gain and the actual measured values are combined to carry out the revision. The modifying link can output the optimal correction value. However, the estimation accuracy of the Kalman algorithm depends on the established battery model and the state equation. On the other hand, it is difficult to identify the internal parameters of the battery equivalent circuit model.

The composite estimation methods are most commonly used because it can foster strengths and circumvent weaknesses, play to the advantages of various algorithms, and maximize the accuracy of estimation of SOC. The fuzzy control and Kalman algorithm are combined to predict SOC mentioned in the Ref. (8), which mainly introduces the adjustable coefficient on the noise estimation values. Then the theoretical error and the actual error are compared to correct the measurement noise and system noise in order to improve the accuracy of Kalman filter for predicting SOC. The open circuit voltage and ampere hour integral method are integrated in Ref. (16), which adopts the Ah-electric potential method with the weighted factor. Adjusting the weighed factor is to change the weights of two methods so overcome the initial error and accumulative error of shortcomings of ampere hour integral method. The Kalman algorithm and neural network are combined estimate SOC and SOH in Ref. (10) and (17). Fuzzy logic method and the least squares method are integrated based on the relationship between the open circuit voltage and SOC to estimate SOH [10]. Firstly the SOC is estimated. Then the Q-VOC curves from the battery charge and discharge experiments on the different phases are observed. Through the design of fuzzy systems, the Q-VOC curves are the input of the system and the output is SOH. This method need to carry out the battery charge and discharge process continuously. The RBF neural network is adopted to establish the prediction model [17]. The SOC is an independent state variable. A nonlinear model is established by using the data training method and the state equation and output equation are listed. The Kalman algorithm is used to estimate SOC with the measured error about 3%. But when the experiment object once changes, the amounts of data are needed to establish the SOC estimation model.

The valve controlled sealed lead-acid battery is the research object. In order to improve the estimation accuracy of the remaining capacity for energy storage battery, the research on the battery SOC estimation algorithm is carried out in-depth. For verifying the correctness of the established model and the accuracy of battery SOC estimation, MATLAB software is used to carry out simulation experiments for the battery SOC estimation so as to verify the effectiveness of the proposed strategy. The paper is organized as follows. In Section 2, the experimental testing platform for Lead-Acid battery in energy storage power station is established. The equivalent circuit model of Lead-Acid battery is introduced in details in Section 3. The estimation method of battery residual capacity and model validation is described in Section 4. The algorithm verification and results analysis are introduced in Section 5. The conclusion illustrates the last part.

II. Experimental Testing Platform for Lead-Acid Battery in Energy Storage Power Station

The photovoltaic energy integrated power generation system is consisted of the reservoir power plant and the photovoltaic power station. Wherein, the energy storing power plant is mainly used to help to stabilize the photovoltaic power fluctuation and real-time improve the response intermittent of the power generation system. It can increase the stability and reliability of the new energy power generation and network and improve the economic benefit. In addition, the power storage power plant in the power grid can also achieve many function applications, such as cut peak and fill valley, isolated network operation, power compensation, make up the line loss, load regulation, new energy access, improvement of electric energy quality, et al. Thus, it can be seen the importance of power plants in the power system of the reservoir. The photovoltaic energy generation system architecture is shown in Fig. 1, which includes photovoltaic power generation, energy storage power station, user load parts and the energy management system [18].

In the realization of the above functions, the energy storage power station is mainly used to cut peak and fill the valley on the power grid. The photovoltaic energy storage integrated power generation system can access the energy storage power station in to the user power supply system, which mainly realizes the effective management of the users' demands. The storage energy power plants can absorb the power grid harmonics generated by the grid connected photovoltaic power generation, smooth the load of power grid, peak shaving and valley filling, greatly improve the local electric energy quality, reduce the cost of power supply, improve the response time of the system, and improve the stability and reliability of the whole power system operation. The structure of the energy storage power station is shown in Fig. 2 [18].

The power station is composed of battery pack, battery management unit, grid connected control unit PCS, power station distribution unit and monitoring unit of the power station, where the total capacity of storage battery group is 1MWh and the total power of the grid connected control unit is 2MW. Because of the larger PCS capacity, the system selects two grid control units connected in parallel. Then it is connected with battery pack. This structure can improve the safety of energy storage power station. In the energy storage power station, the battery is the weakest link of power station. If it is not controlled effectively, the performance and service life will directly affect the energy storage power station.

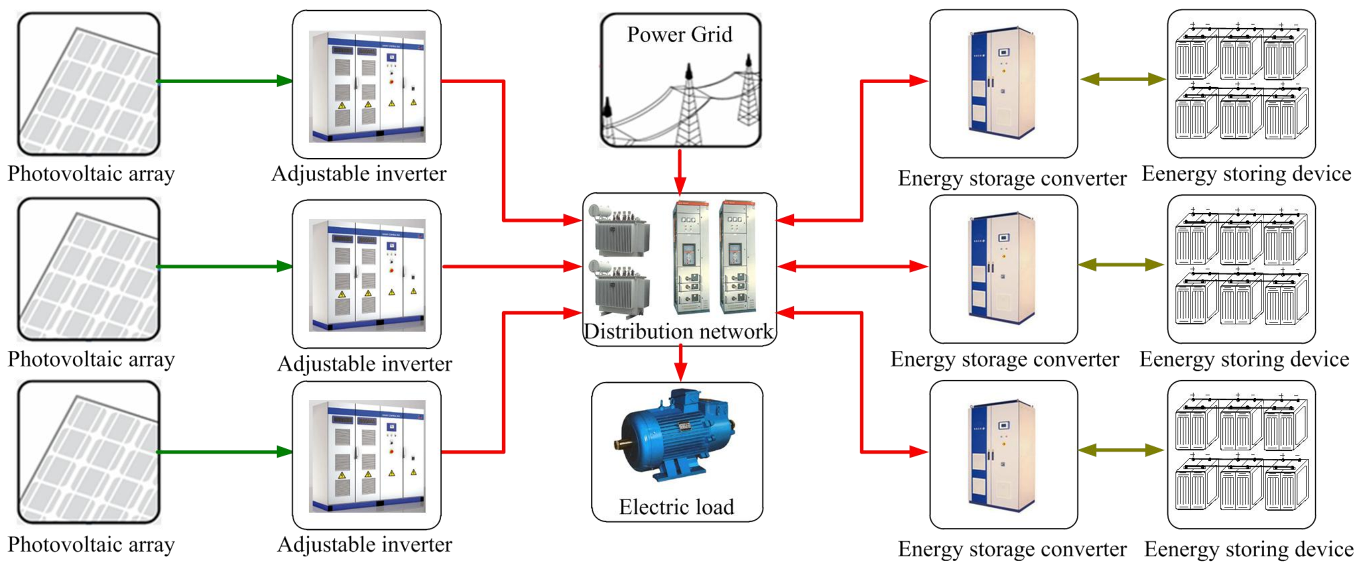


Fig. 1 Energy storage power station (with grid-connected PV applications) architecture diagram.

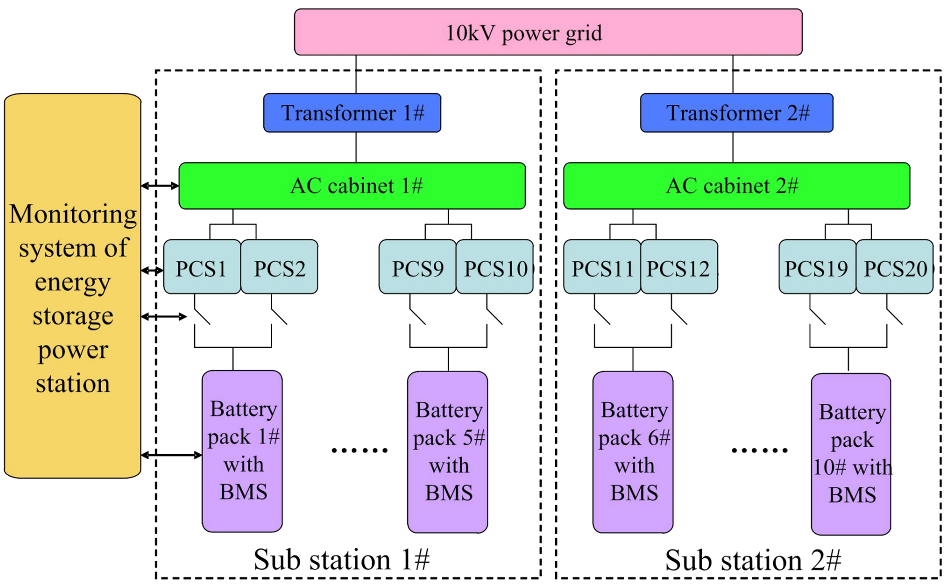


Fig. 2 Energy storage power station system structure.

On the other hand, the storage battery is generally constituted by a string of dozens or even more than a few hundred series of battery group. Due to the mass production of battery and the charge and discharge process, it is easy to cause the voltage, capacity, internal resistance parameter of the each battery in the battery group different. When the battery group reaches the usage requirements, it will cause the improper use of part of the battery group, which leads to the battery overcharge or over discharge and affects the overall capacity of the battery. It is well known that the overall battery capacity general performance is the worst performance of the battery in the battery capacity, which will lead to the excellent battery in early failure before the battery group. Therefore, it is necessary to know the state of each battery in the battery group for timely replacing the bad battery so as to avoid the deterioration of the excellent battery in the battery group and cause resources to waste.

The energy storage battery is the storage equipment of the total storage system and the key segment of the whole photovoltaic energy storage system. With the change of the diurnal variation of solar radiation and confront, when solar energy is not enough (for example rainy days or cloudy), it is an electric supplement on the grid. When the supply of solar energy is strong, it can storage the excess solar energy. Therefore, the power and voltage fluctuation can be smoothed by using the energy storage battery. However, in the usage process, it is found that the storage battery is extremely prone to excessive charge and discharge problems, which results in the battery performance not stable and cannot work properly. Therefore, it is necessary to real-time measure all battery performance parameters, such as voltage, current, temperature and residual capacity variables, in order to avoid the occurrence of this phenomenon. Among them, the residual capacity is the key parameter. Only real-time grasping the battery residual capacity, a reasonable charge and discharge control strategy may be established according to the changes of the environment in order to achieve the rational use of energy storage battery. In a word, it is very important to predict the residual capacity of the storage battery, and the remaining capacity is the key factor to improve the stability and reliability of the whole storage system and the power quality. Therefore, the main work of this paper is to study the estimation of the remaining capacity of the energy storage power station.

The battery testing platform is mainly composed of batteries, two high precision programmable DC power supply, battery monitoring system and the host computer. The battery test chart and the battery experiment platform are respectively shown in Fig. 3. In the control unit of the whole monitoring system, the main control unit can realize many functions, such as the storage and communication, intelligent analysis, residual capacity estimation, data inquiry, alarm indication, parameter setting and diagnostic. In these functions, the estimation of residual capacity is the most important. The general battery monitoring system can monitor only the battery charging and discharging energy and the remaining power of the battery cannot be simply obtained by subtracting the filling capacity and discharging energy. Therefore it is unable to monitor the real-time remaining capacity of each battery. But the proposed monitoring system is mainly to solve how to achieve the online monitoring of the remaining power for each battery and the whole group battery. The structure of the control unit is shown in Fig. 4, which mainly obtains the data by using the acquisition unit, establishes the mathematical model of the equivalent circuit, and use Kalman estimation algorithm to predict the residual capacity and output the predictive results on the monitoring interface.

III. Equivalent Circuit Model of Lead-Acid Battery in Energy Storage Power Station

A. Thevenin Cell Model

Battery equivalent circuit mathematical model mainly reflects the relationship among the collected information (such as battery voltage, current, temperature, etc.), electrical characteristics (circuit equations) and the battery internal characteristic information (such as battery residual capacity, resistance and electromotive force. etc.). The equivalent circuit of the Thevenin model is shown in Fig. 5.

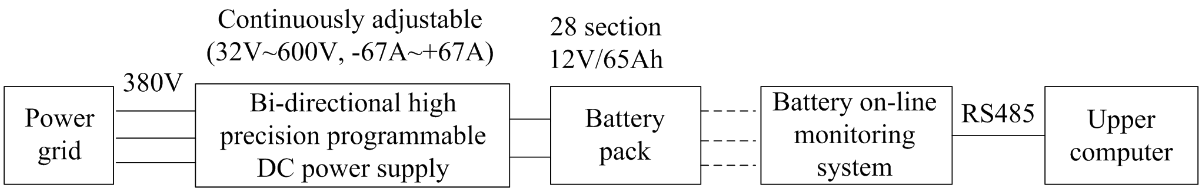


Fig. 3 Block diagram of battery test structure.

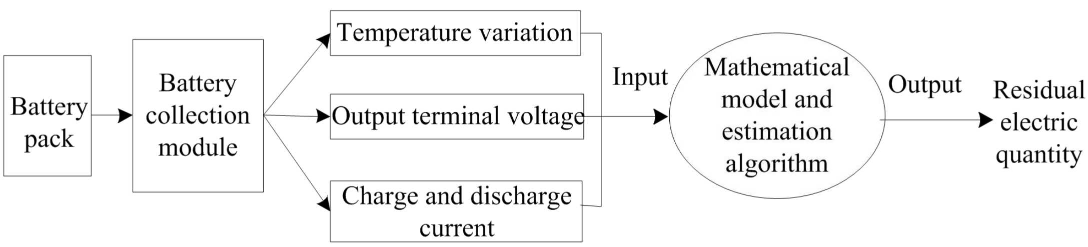


Fig. 4 The control unit.

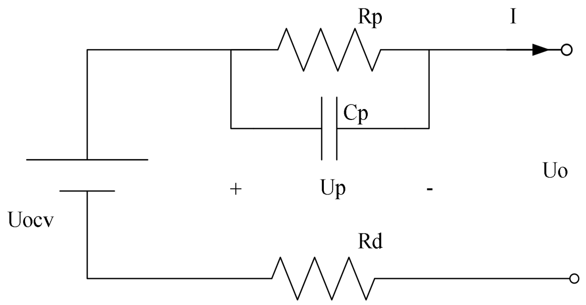


Fig. 5 Thevenin model.

The typical equivalent models commonly include the simple model, Thevenin model and PNFV model, et al. The higher the order of the battery equivalent model, the better the simulated static and dynamic characteristics of the battery and the higher the accuracy. But taking into account the practical engineering application and the degree of difficulty of the algorithm transplanted into the processor, it is necessary to choose a better cell static and dynamic characteristic, not high order number and the battery equivalent circuit model with simple structure. Through comparison, the Thevenin model is selected to carry out the parameters identification in order to establish the precise lead-acid battery equivalent circuit model.

In Fig. 5, Rp and Cp are the polarization resistance and polarization capacitance, respectively. The parallel resistance and capacitance is to reflect the battery dynamic characteristics. Up is the polarization voltage, Rd is the equivalent impedance, $Uocv$ is the open circuit voltage, Uo is the battery terminal voltage, and I is the charging and discharging current of the battery. The electrical expression corresponding to this model is described as follows.

$$Uo = Uocv - Up - Rd \cdot I(t) \tag{1}$$

$$\dot{Up} = -\frac{1}{CpRp}Up + \frac{1}{Cp}I(t) \tag{2}$$

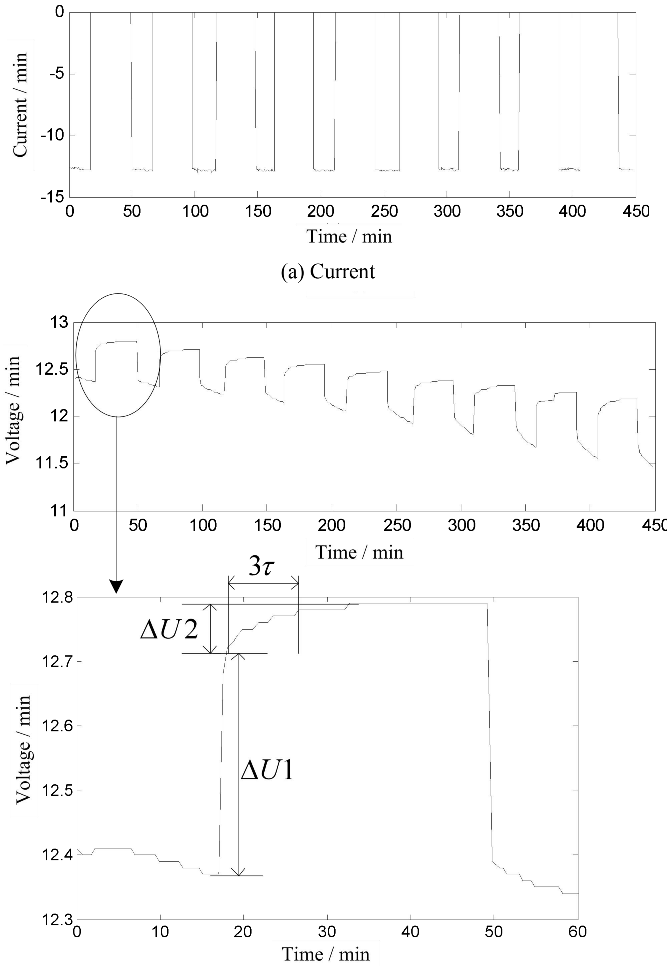
The battery open circuit voltage $Uocv$ has the certain correspondence relationship with the battery SOC under certain conditions, which is often used to set up the initial SOC value. It can be seen from Fig. 5 that the parallel Rp and Cp forms a loop, whose electrical characteristics can reflect the battery charge and discharge dynamic characteristics. Therefore, the Thevenin model is consistent with the principle of choosing a battery. This model can not only reflect the battery static and dynamical characteristics. On the other hand, its structure is relatively simple, the order number is not high and it is easy to implement in engineering. So this kind of battery model is widely applied in the modeling of the battery and the battery equivalent circuit model is used in this paper.

B. Parameter Identification of Battery Model

When the battery equivalent circuit model is chosen, the model parameters need be identified. In this paper, the Kalman filtering algorithm is adopted to estimate the remaining power. Because the estimation accuracy of the Kalman filter algorithm depends on the established state space equations of the battery model, the parameter identification of state space equations is particularly important. But each model parameter is not constant and affected by many external factors, so the identification is more difficult. The fitting relationship between the initialized parameters and the residual energy is mainly to produce the voltage data combined the electrical relationship of the equivalent circuit model of battery. Then the comparison with the experimental data is carried out to obtain the optimal parameter estimation according to the constrained nonlinear optimization method to search minimum value.

The specific algorithm procedure is described as follows. First of all the initial parameters values need be calculated. In accordance with the constant current intermittent charging and discharging experimental method, the voltage response data are obtained by using the resistance capacitance of RC circuit model. The parameters values in the circuit model are initialized according to the voltage zero state or zero input response theory. That is to say the battery remains static 0.5h before every discharge, whose main purpose is to obtain the open circuit voltage $Uocv$ of the battery. Then the DC discharge signal 13A is applied (mainly due to the current 13A having the highest discharge efficiency) with 0.25h duration, whose main purpose is to obtain the remaining power every 10%). The reason to use such data is mainly that the experiments object lead-acid battery being shelved for a long time and its actual capacity not being nominal rated capacity 65Ah due to self-discharge. The battery actual capacity is about 32.5Ah based on the constant current charge and discharge experiment method. Finally, the initial parameters corresponding to the remaining power are obtained after the above experimental procedure at intervals 10%. The pulse characteristics of the battery can also be obtained by the pulse discharge experiment. The battery monitoring system software of the experimental platform can record the change of the battery terminal voltage and charge discharge current.

The simulation results of the discharge current and output voltage are shown in Fig. 6. It can be seen from the terminal voltage waveforms in Fig. 6 that the voltage took place immediately jump when beginning discharge. The reason of the sudden change concluded form the equivalent circuit model results from resistance Rd . That is to say the voltage unlikely and suddenly changes in the resistance capacitance composed of Rp and Cp . Also in the static battery, when the current jumps to zero, the voltage will jump up. After the voltage jumps, the voltage gradually rises with an inertial delay element, which is resulted from the polarization effect of the resistance capacity composed of Rp and Cp . The voltage variation of the delay element is caused by Rp . From the engineering point of view, the voltage rises 94% after 3τ time. Thus the time constant τ and Cp can be calculated. It can be seen from the local enlargement in Fig. 6 the origin of the following three calculation formula. According to the above description, the initial parameters values of the circuit model are calculated. The specific parameter values under different charge states are listed in Tab. 1.



(a) Current

(b) Voltage

Fig 6 Discharge current and the output voltage.

TAB. 1 THE RESULTS OF THE BATTERY MODEL PARAMETER IDENTIFICATION IN A DISCHARGED STATE

SOC	R_d ($m\Omega$)	R_P （ $m\Omega$ ）	C_P (F)	$Uocv$ (V)
0.9	0.0238	0.0085	21373	12.79
0.8	0.0223	0.0085	24306	12.71
0.7	0.0238	0.0069	28116	12.62
0.6	0.0223	0.0092	21521	12.55
0.5	0.0238	0.0085	24235	12.47
0.4	0.0285	0.0085	44470	12.39
0.3	0.030	0.0108	32962	12.33
0.2	0.0346	0.0108	32777	12.26
0.1	0.0354	0.0138	25652	12.19

As shown in Fig. 6, the initial values of all parameters can be calculated by:

$$R_d = \frac{\Delta U1}{I} = \frac{12.68\text{-}12.37}{13} = 0.0238\Omega \tag{3}$$

$$R_p = \frac{\Delta U2}{I} = \frac{12.79\text{-}12.68}{13} = 0.0085\Omega \tag{4}$$

$$C_p = \frac{\tau}{R_p} = \frac{(1/3)*(1597-1052)}{0.0085} = 21373F \tag{5}$$

Secondly, it can be seen from Tab. 1 that each parameter in the model is changeable with the state of charge (SOC) real-time. If parameters of different state of charge are only obtained from a simple look-up table method, it is unacceptable with an interval of 10% SOC to calculate data in the table and the prediction on the values of SOC will have a great error. Thus the look-up table method has not only large error, but also its execution is not smart. In order to accurately estimate SOC, an online adaptive parameters identification model must be adopted. So the least square method is used to fit the electrical parameters and the state of charge (SOC) function. Then the equivalent electrical characteristics equations based on Thevenin model are adopted to obtain the simulation data, which is compared with the experimental data to produce two-order norm of the data difference. Finally the fminsearch function in MATLAB software is used to search the optimal optimum parameters estimation when two-order norm is minimum. By doing so, the parameters are initialized for predicting the remaining power supply

The following four equations mainly use the data in Tab. 1 to obtain the function of each parameter and SOC, and all kinds of coefficients are also used to identify on-line with the above Fminsearch function.

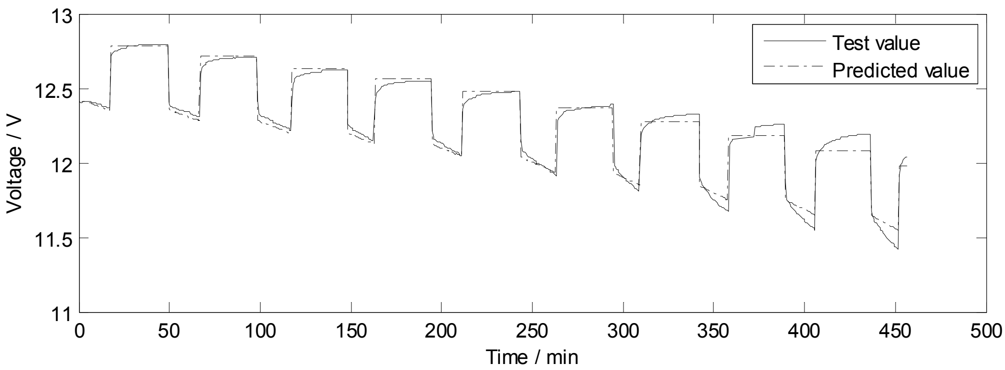
$$R_d = R_d(0) + dR_d(0)*SOC + ddR_d(0)*SOC^2 \tag{6}$$

$$R_p = R_p(0) + dR_p(0)*SOC + ddR_p(0)*SOC^2 \tag{7}$$

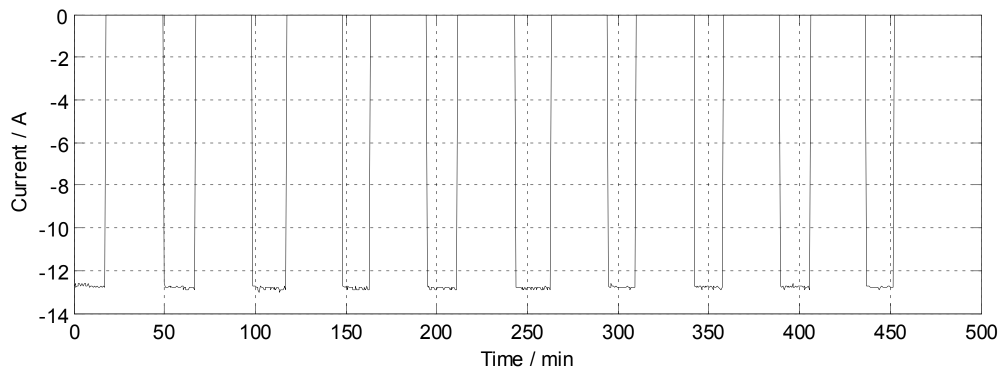
$$C_p = C_p(0) + dC_p(0)*SOC + ddC_p(0)*SOC^2 \tag{8}$$

$$Uocv = Uocv(0) + dUocv(0)*SOC \tag{9}$$

The parameter identification results based on the above search method under MATLAB software are shown in Fig. 7, which includes the obtained voltage output results after the parameter identification and the actual experimental output voltage results. By comparing two simulation carvers, the response of the actual output terminal voltage is indeed consistent with the dynamic response of terminal voltage in the RC equivalent circuit. The estimated value in Fig.7 is obtained by using the fminsearch function to obtain the optimal estimated parameters and the output voltage *Uo* is simulated by using Eq. (1) and (2). It can be seen from the simulation results that the simulation output data has been basically consistent with the experimental data, which shows that the estimated parameters are optimal.



(a) Voltage



(b) Current

Fig.7 Parameter identification Result.

IV. Estimation Method of Battery Residual Capacity and Model Validation

A. Basic Theory to Estimate Battery Residual Capacity

At present, there is no a uniform definition on the SOC. From the perspective of the analysis on the electrochemical cell, the substance concentration in the electrolyte is related with the battery SOC, which is defined as follows.

$$SOC(t)=\frac{(Q-Q_{\min})}{(Q_{\max}-Q_{\min})}\times 100\% \quad (10)$$

where Q is the remaining equivalent power of the battery, that is to say $Q=Q_0-Q_{out}$; Q_0 is the initial capacity of battery; Q_{out} is the released power of battery after a period of t_0 - t_1 ; $Q_{\min}$ is the minimum remaining power at the end of the battery discharging; $Q_{\max}$ is the battery maximum power.

From the point of view of power, the U.S. advanced battery Federation (USABC) defined SOC in the book "electric vehicle battery test manual" as: Under the certain discharge rate of battery, the ratio between the remaining electricity quantity and the rated capacity under the same working conditions.

$$SOC(t)=(1-\frac{Q}{C_I})\times 100\% \quad (11)$$

where Q is the discharge power; C_I is the released power of battery under the constant current *I*. But in the case of variable current or the complex working conditions, the corresponding C_I will change. So in the actual engineering applications, the battery rated capacity Q_N is generally used to replace C_I.

In the point of energy view, the following definition is more suitable in the complex battery working condition.

$$\begin{aligned}SOC(t)&=(\frac{W_C}{W_N})\times 100\%\\&=(\frac{W_0-\int_0^t \eta E(SOC)Idt}{Q_N * E_N})\times 100\%\end{aligned} \quad (12)$$

where W_0 is initial battery electric energy; $E(SOC)$ is the battery electromotive force ; η is the charging electric efficiency; *I* is the battery charging and discharging current; E_N is nominal battery voltage; W_N is the nominal battery power; W_C is the remaining battery power.

SOC is mainly defined from the above three point view. The classical SOC is defined as:

$$SOC(t)=(\frac{Q_0-\int_0^t \eta Idt}{Q_N})\times 100\% \quad (13)$$

B. Estimation Algorithm of Battery Charge State

(1) Principle of SOC Estimation Based on Extended Kalman Algorithm

In this paper, the Kalman estimation algorithm is used to estimate SOC. The basic principle of Kalman filter algorithm can be described as follows. Firstly, the state equation and output equation of a system are introduced as:

$$X(K)=AX(K-1)+BU(K)+W(K) \quad (14)$$

$$Z(K)=HX(K)+V(K) \quad (15)$$

According to the established system state equation and output equation, the state of K time of the system is predict based on the system's state at K-1 time.

$$X(K|K-1) = AX(K-1) + BU(K) \tag{16}$$

where $X(K|K-1)$ is the predictive value at K time. It is only a not accurate prediction value and should be constantly revised. The prediction value must be corresponding to an error. Thus the error covariance corresponding to $X(K|K-1)$ should be predicted. P is used to express the error covariance at K time.

$$P(K|K-1) = AP(K-1|K-1)A' + Q \tag{17}$$

where $P(K|K-1)$ is the error covariance of $X(K|K-1)$; $P(K-1|K-1)$ is the corresponding error covariance of $X(K-1|K-1)$; A' is the transpose matrix of A; Q is the process noise of the system. Then these predictions are carried out corrections. Combining the predicted values $X(K|K-1)$ and the measured values $Z(K)$, the corrected values $X(K|K)$ of the current state K can be obtained by:

$$\begin{aligned} &X(K|K) = X(K|K-1) + \\ &Kg(K)\cdot(Z(K) - H\cdot X(K|K-1)) \end{aligned} \tag{18}$$

where Kg is the Kalman Gain.

$$Kg(K) = P(K|K-1)\cdot H' / (H\cdot P(K|K-1)\cdot H' + R) \tag{19}$$

As a result, the optimal correction value $X(K|K)$ under K state is obtained. In the same way, the error covariance $P(K|K)$ of the state K is also revised as:

$$P(K|K) = (I - Kg(K)\cdot H)P(K|K-1) \tag{20}$$

where I is the unit matrix. For single model single measurement, I =1. When the forecast is carried out on the next moment, $k = k+1$. Only in this way the iteration is going on until the error covariance reach the minimum and the optimal state value is obtained.

Because the battery is nonlinear, the above discussed Kalman filter algorithm cannot be directly used to estimate SOC. Thus a discrete extended Kalman filter algorithm is adopted to estimate the residual power. Through the above analysis, the Kalman filtering algorithm carries out prediction and correction on the state value of K time at each iteration calculation. The extended Kalman filter is very similar to the Kalman algorithm. The extended Kalman method predicts system's current state by means of nonlinear system. The algorithm procedure is shown in Fig. 8.

The extended Kalman algorithm is composed of two parts. One part is the filter state value calculation and the other part is the calculation of filter gain value. As shown in Fig. 8, the hypothesis space state equation is described as follows.

$$\dot{x} = f(x,u) + w \tag{21}$$

$$y = g(x,u) + v \tag{22}$$

The space state equation is carried out discrete and Taylor series expansion at a state estimation $\hat{x}_K$. The higher order terms are neglected to obtain:

$$x_{K+1} = A_k x_k + \left[f(\hat{x}_K; u_k) - A_K \hat{x}_K \right] + w_K \tag{23}$$

$$y_K = C_K x_k + \left[g(\hat{x}_K, u_k) - C_k \hat{x}_K \right] + v_k \tag{24}$$

where $A_k = \dfrac{\partial f}{\partial x_k}$ and $C_k = \dfrac{\partial g}{\partial x_k}$.

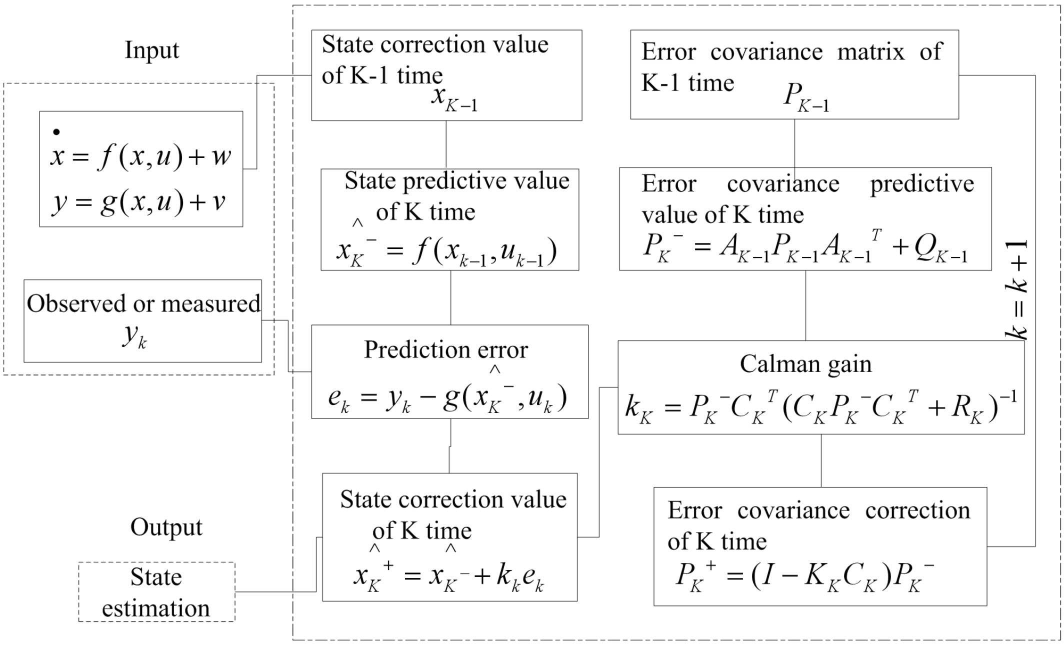


Fig. 8 Implementation flowchart of the AEKF algorithm.

In the state value calculation process, the state correction result x_{k-1} at time k -1 is used to obtain the prediction value $\hat{x}_{K}^{-}$ according to the Eq. (25). Then the observed value y_k and the corresponding Kalman gain k_k are used to amend the state vector predictive value $\hat{x}_{K}^{-}$ according to Eq. (26) and Eq. (27) to obtain the correction value $\hat{x}_{K}^{+}$ at time k.

$$\hat{x}_{K}^{-} = f(x_{k-1}, u_{k-1}) \tag{25}$$

$$e_k = y_k - g(\hat{x}_{K}^{-}, u_k) \tag{26}$$

$$\hat{x}_{K}^{+} = \hat{x}_{K}^{-} + k_k e_k \tag{27}$$

In the calculation process of gain value, the error covariance correction value p_{k-1} and the system noise variance Q_{k-1} at time k-1 are used to obtain the prediction p_{K}^{-} at k time according to Eq. (28). The measurement noise variance R_k and covariance prediction value p_{K}^{-} are used to obtain the Kalman gain k_k by Eq. (29) and the error covariance correction value p_{K}^{+} at time k by Eq. (30).

$$P_{K}^{-} = A_{K-1} P_{K-1} A_{K-1}^{T} + Q_{K-1} \tag{28}$$

$$k_K = P_{K}^{-} C_{K}^{T} (C_K P_{K}^{-} C_{K}^{T} + R_K)^{-1} \tag{29}$$

$$P_{K}^{+} = (I - K_K C_K) P_{K}^{-} \tag{30}$$

The Kalman filter is adopted to predict and revise the state value of the next moment based on the existing state value, and then to approximate the true value by iteration calculation. According to the known state space equations, the state vectors prediction value , the observation value y_k and the corresponding Kalman gain k_k are used to modify the predicted value $\hat{x}_{K}^{-}$ to obtain the revised value $\hat{x}_{K}^{+}$ (not a real value X (k)). At the same time, the corresponding error covariance p_{K}^{+} and p_{K+1}^{-} at the next moment can be estimated. After finite recycle iterations, the optimal state correction and the corresponding error covariance are obtained. This algorithm gradually makes the optimal correction value $\hat{x}_{K}^{+}$ close to the true value x_K . Its advantage is that there is no relationship with the initial value x_0 . As long as the state space equation is established accurately, this algorithm can make the optimal correction value $\hat{x}_{K}^{+}$ close to the true value x_K even if the error of the initial value x_0 is very large.

(2) State Space Equation and Estimation Algorithm Based on Cell Model

According to the established battery model and electrical expression, the Kalman filter algorithm is used to estimate SOC. But firstly the cell state space equations should be established. Thus by using the SOC definition and the RC circuit models mentioned above, the state space equations are described as follows.

$$\begin{bmatrix} \dot{SOC} \\ \dot{Up} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -\dfrac{1}{C_P R_P} \end{bmatrix} \begin{bmatrix} SOC \\ U_P \end{bmatrix} + \begin{bmatrix} -\dfrac{\eta}{C_N} \\ \dfrac{1}{C_P} \end{bmatrix} [I] \tag{31}$$

$$U_O = \begin{bmatrix} 0 & -1 \end{bmatrix} \begin{bmatrix} SOC \\ Up \end{bmatrix} + [-R_d][I] + [Uocv] \tag{32}$$

where C_N is the nominal battery rated capacity and η is the battery charge discharge efficiency. The state space equations after being carried out discretization and linearization are described as follows (T_S is the sampling time).

$$\begin{bmatrix} SOC_{k+1} \\ U_{P,K+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1-\dfrac{T_S}{C_P R_P} \end{bmatrix} \begin{bmatrix} SOC_K \\ U_{P,K} \end{bmatrix} + \begin{bmatrix} -\dfrac{\eta T_S}{C_N} \\ \dfrac{T_S}{C_P} \end{bmatrix} [i_k] \tag{33}$$

$$U_{O,K} = \begin{bmatrix} 0 & -1 \end{bmatrix} \begin{bmatrix} SOC_K \\ U_{P,K} \end{bmatrix} + [-R_d][i_K] + [U_{OCV,K}] \tag{34}$$

Based on the above discussed estimation method and the established state space Eq. (33) and (34), the coefficients are obtained by using contrast method.

$$x_k = \begin{bmatrix} SOC_K \\ U_{P,K} \end{bmatrix} \tag{35}$$

$$u_k = [i_k] \tag{36}$$

$$A_k = \begin{bmatrix} 1 & 0 \\ 0 & 1-\dfrac{T_S}{C_P R_P} \end{bmatrix} \tag{37}$$

$$C_k = \begin{bmatrix} \dfrac{\partial u_o}{\partial soc} & \dfrac{\partial u_o}{\partial u_p} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial u_{ocv}}{\partial soc} - \dfrac{\partial u_p}{\partial soc} - \dfrac{\partial R_d}{\partial soc} * i_k & \dfrac{\partial u_o}{\partial u_p} \end{bmatrix} \tag{38}$$

The algorithm procedure of estimating SOC based on the established cell model is shown in Fig. 9.

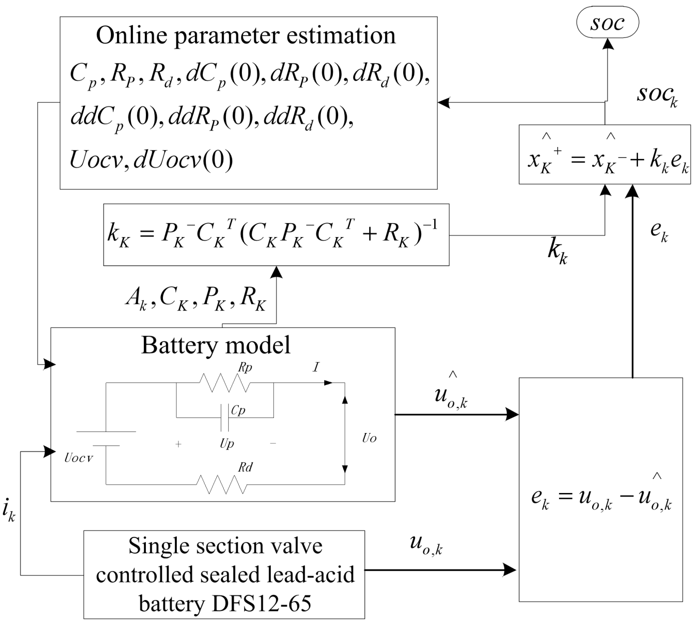


Fig.9 Flowchart of the SOC estimation.

The experimental data, that is to say the acquisition of the battery current and terminal voltage, are mainly obtained from the battery online monitoring system and stored into the database. Through the database storage and call, the experimental data are fed into the established mathematical model of battery in software MATLAB. Then the online parameter identification method and the extended Kalman estimating algorithm are used to predict the remaining capacity SOC values after finite iterations.

V. Algorithm Verification and Results Analysis

In order to demonstrate the effectiveness of the model and the accuracy of estimation algorithm, the charge and discharge experiments are carried out on the valve controlled sealed type colloid lead-acid battery DFS12-65 at environment temperature (25℃). Software MATLAB 7.0 is adopted to carry out the simulation analysis on the collected experimental data. Then the simulation results are compared with the actual results. The following figures show the simulation results under different conditions in order to obtain verification and comparison results. In the simulation process, the initial parameters are set based on the model identification results. Then the data collected from the data acquisition unit of the monitor system are imported into the MATLAB for data processing. MATLAB programming language is adopted to realize the parameters identification of the battery model and extended Kalman algorithm. At the same time in order to clearly compare the on-line identification results of the SOC with the model fitting voltage and the actual voltage, a simulation display interface is designed. The button on the interface can be used to carry out the on-line parameters identification algorithm and the extended Kalman estimation algorithm.

A. Verification of SOC Estimation Results under Constant Current Charge and Discharge Conditions

Generally the battery more works under the constant current charge and discharge, especially when the battery is used as a backup power supply. The charging and discharging experiments results under the constant current working condition are shown in Fig. 10 and Fig. 11. It can be seen from Fig. 10 that under the case of the 0.2C charging current, the voltage waveform can well simulate the real battery voltage after the online parameter identification also including the battery floating charging stage. This can effectively show the battery model and the parameter identification results have very high precision. The voltage simulation results under the 0.25C discharge current with the constant current discharge working conditions and the SOC estimation experiments are shown in Fig. 11. The SOC estimation results shown in Fig. 10 and Fig. 11 represent the extended Kalman estimation method has very high accuracy and is coincided with the estimation results of the ampere hour method.

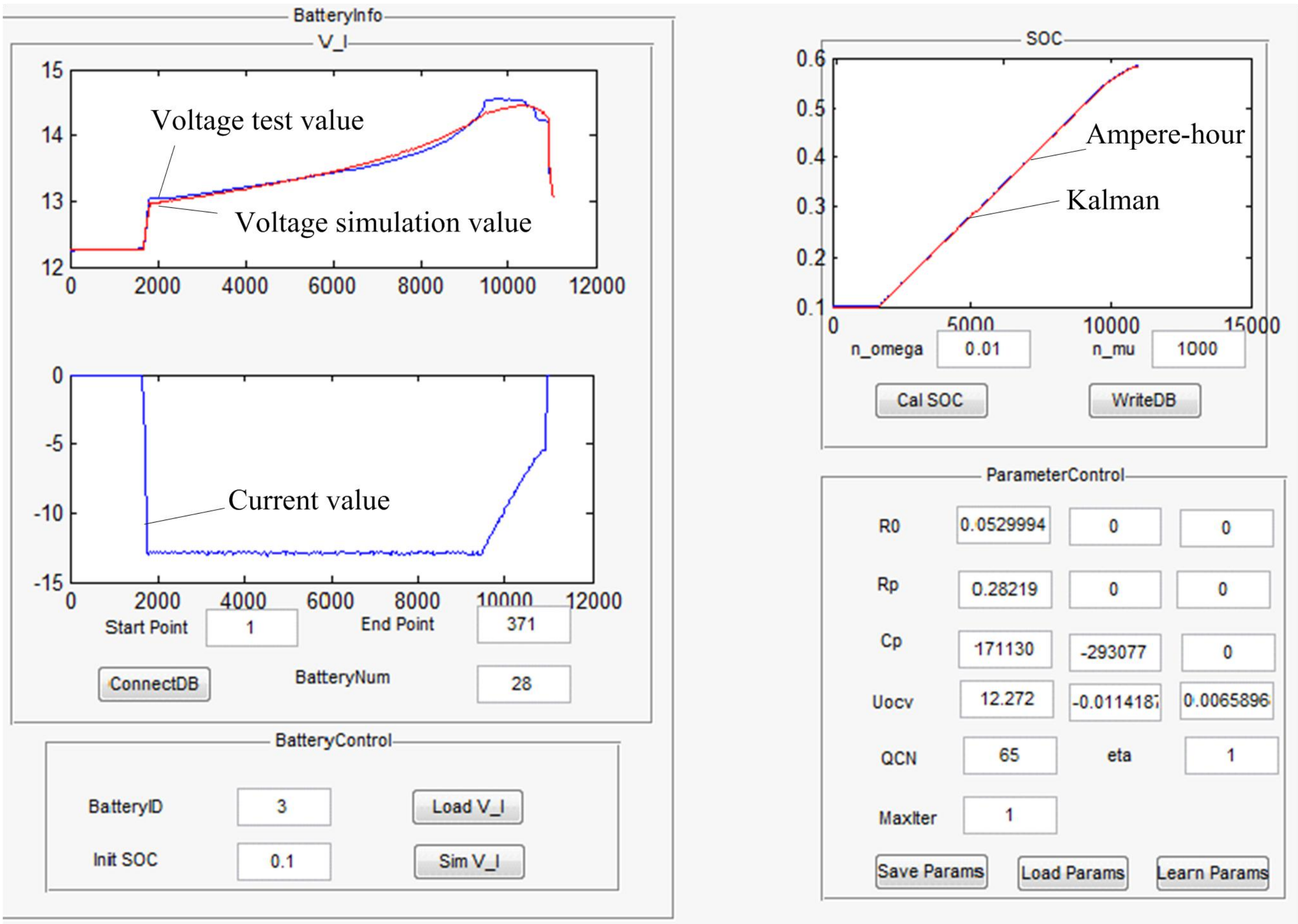


Fig.10 SOC estimation comparison chart of constant current charging.

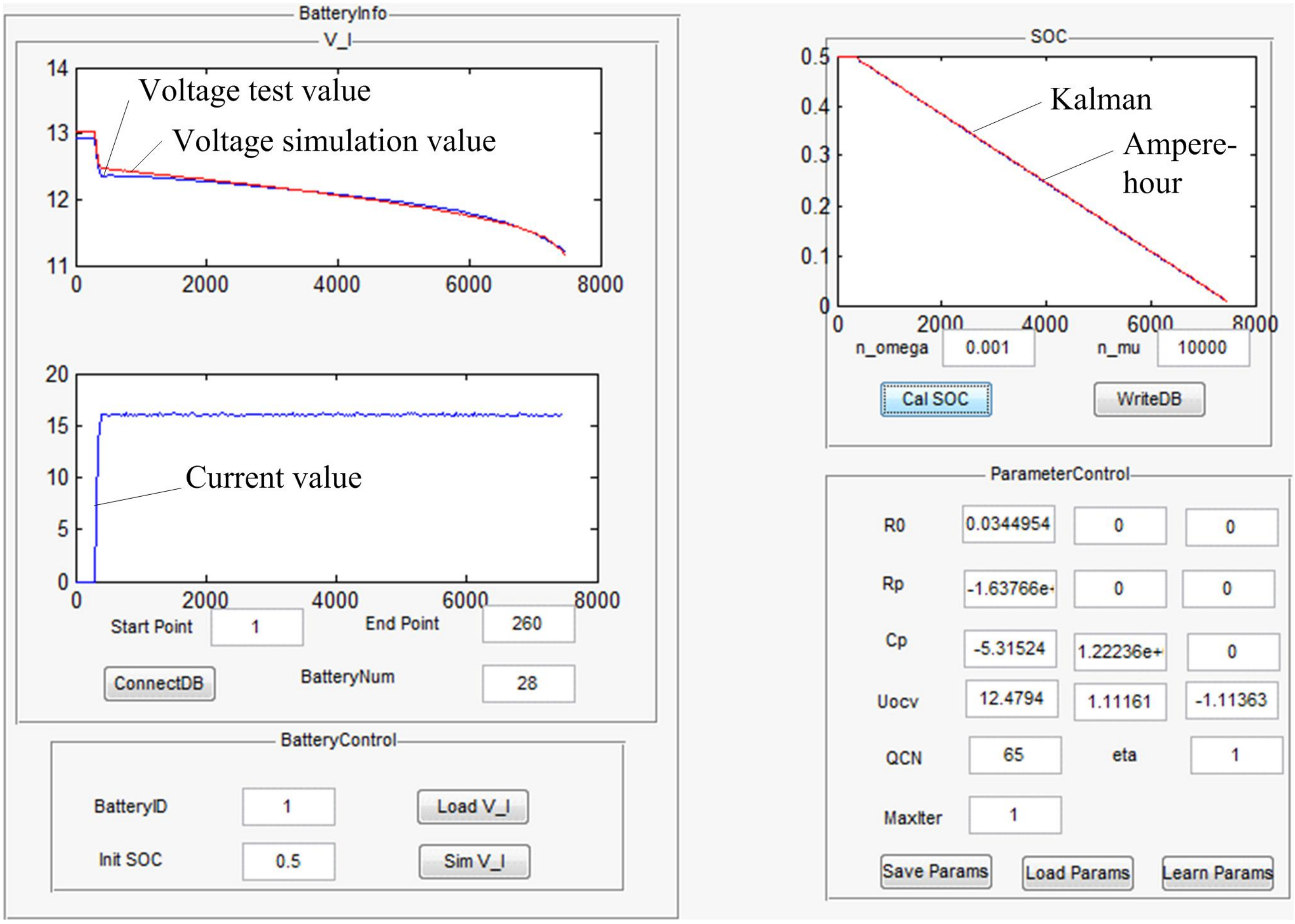


Fig.11 SOC estimation comparison chart of constant current discharging.

B. Verification of SOC Estimation Results under Complex Charge and Discharge Conditions

In this paper, the remaining power prediction in the battery is carried out on the micro-power reservoirs. The working condition of this kind of storage power plant is very complex, so the mathematical model and estimation algorithm must have good prediction accuracy under the complex working conditions. The final estimation results are shown the following figures. It can be seen from Fig. 12 that the Kalman algorithm has good convergence in the case of equal interval pulse discharge and the Kalman algorithm can converge to the theoretical position of SOC especially in the case of large initial error. Also it can have a good correction function on the SOC initial error so that the shortcoming of the ampere-hour integral method not eliminating the initial error and only cumulating error is overcome.

Seen from Fig. 13, under the working conditions of the pulse interval charge and discharge, when the simulation experiments are carried out on the selection of intermediate points, the Kalman algorithm can converge to the theoretical SOC position. It can be seen from Fig. 14-16 that the extended Kalman algorithm can estimate SOC accurately under two complex working conditions: the interval and non-interval charging and discharging.

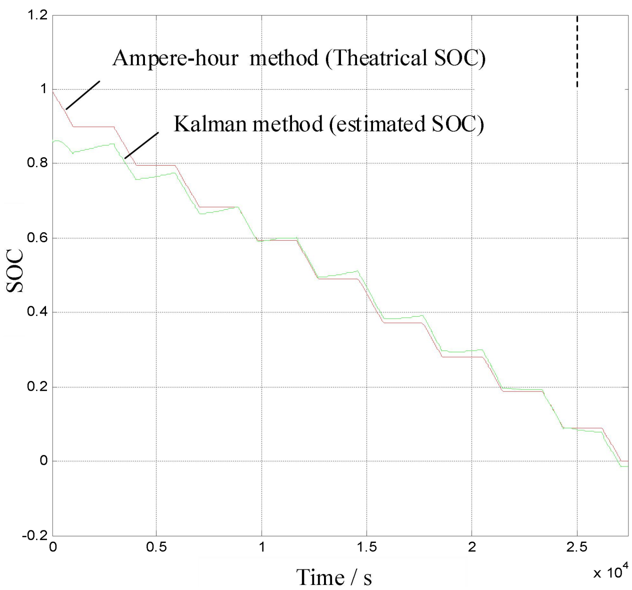


Fig.12 SOC estimation comparison chart of equally spaced pulse current discharging (the initial value has a large deviation).

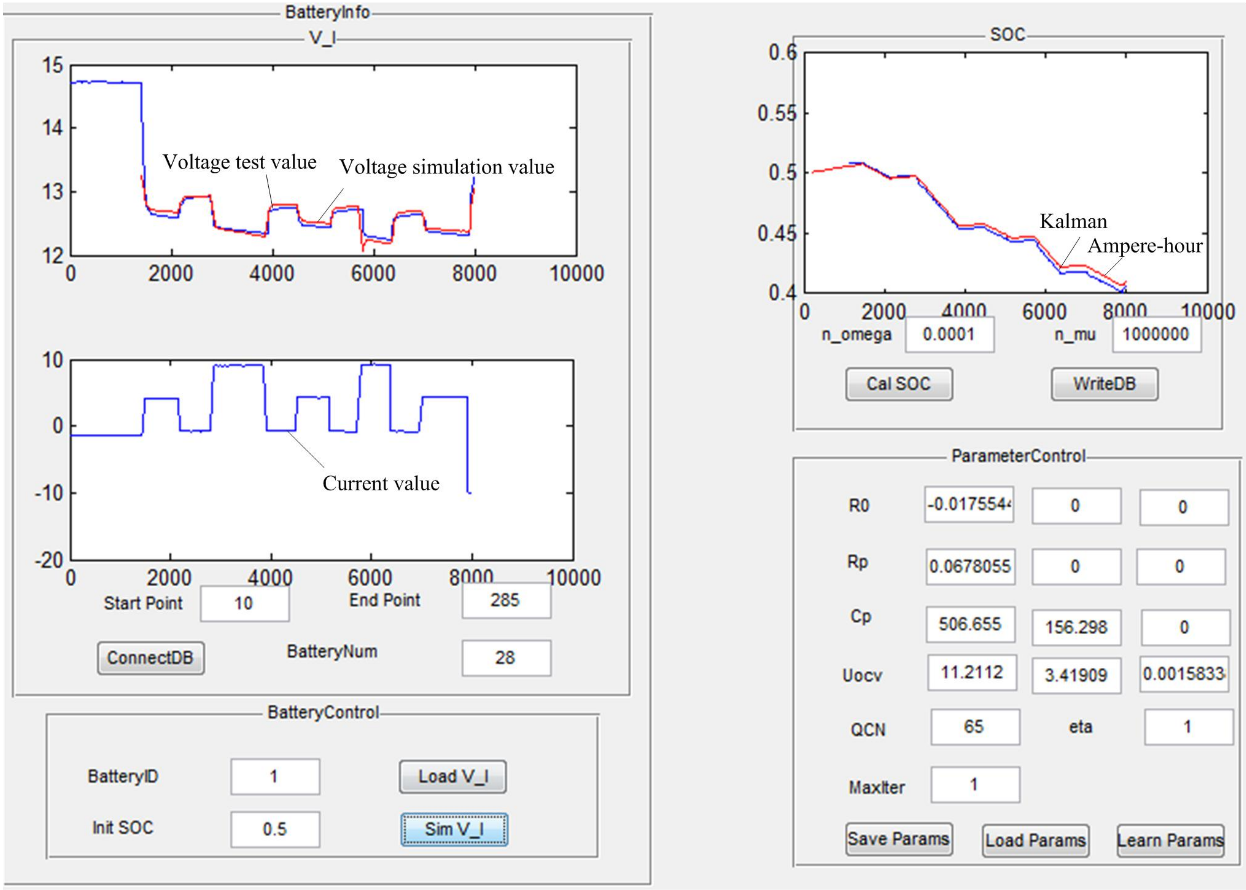


Fig.13 SOC estimation comparison chart of equal interval but not-equal current charging and discharging.

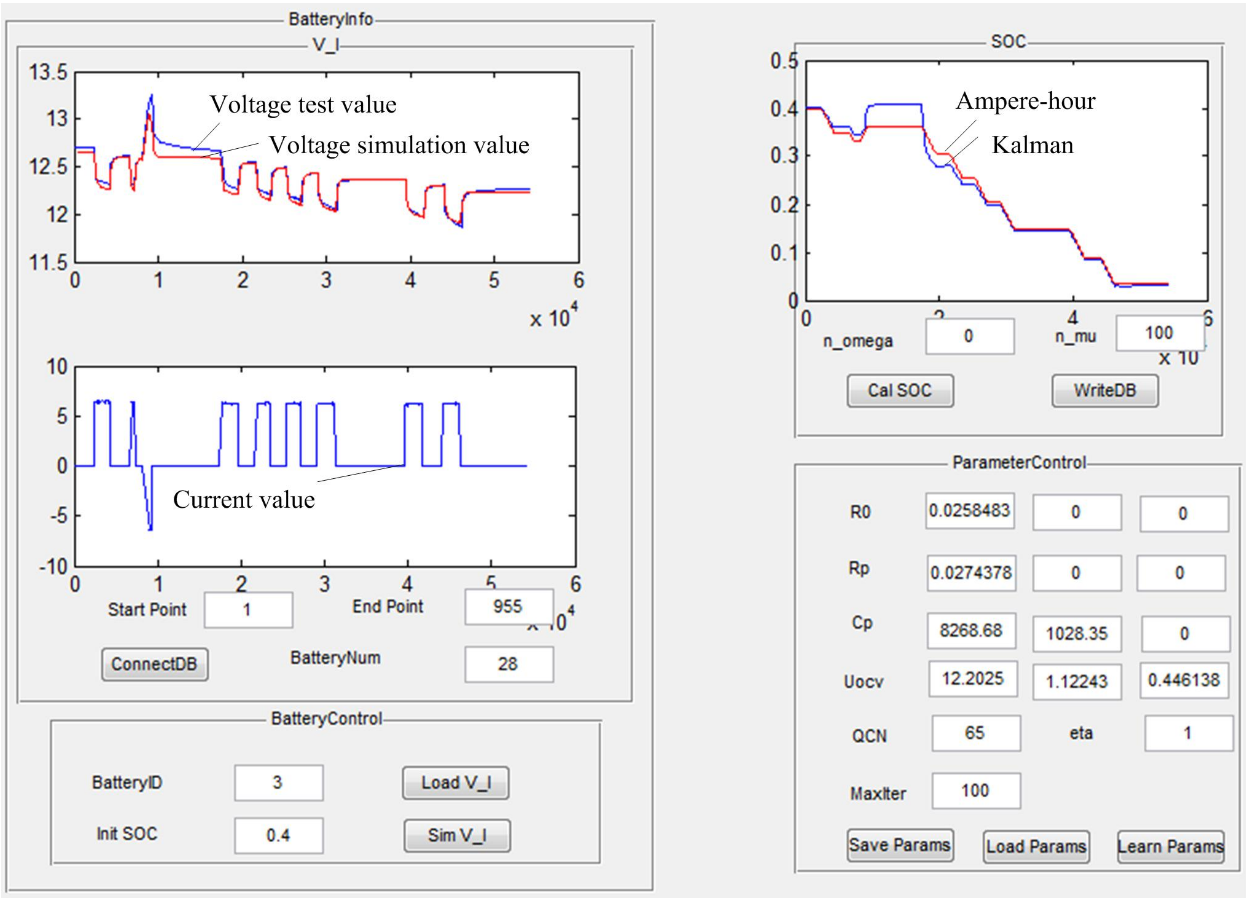


Fig.14 SOC estimation comparison chart of not-equally spaced pulse current discharging.

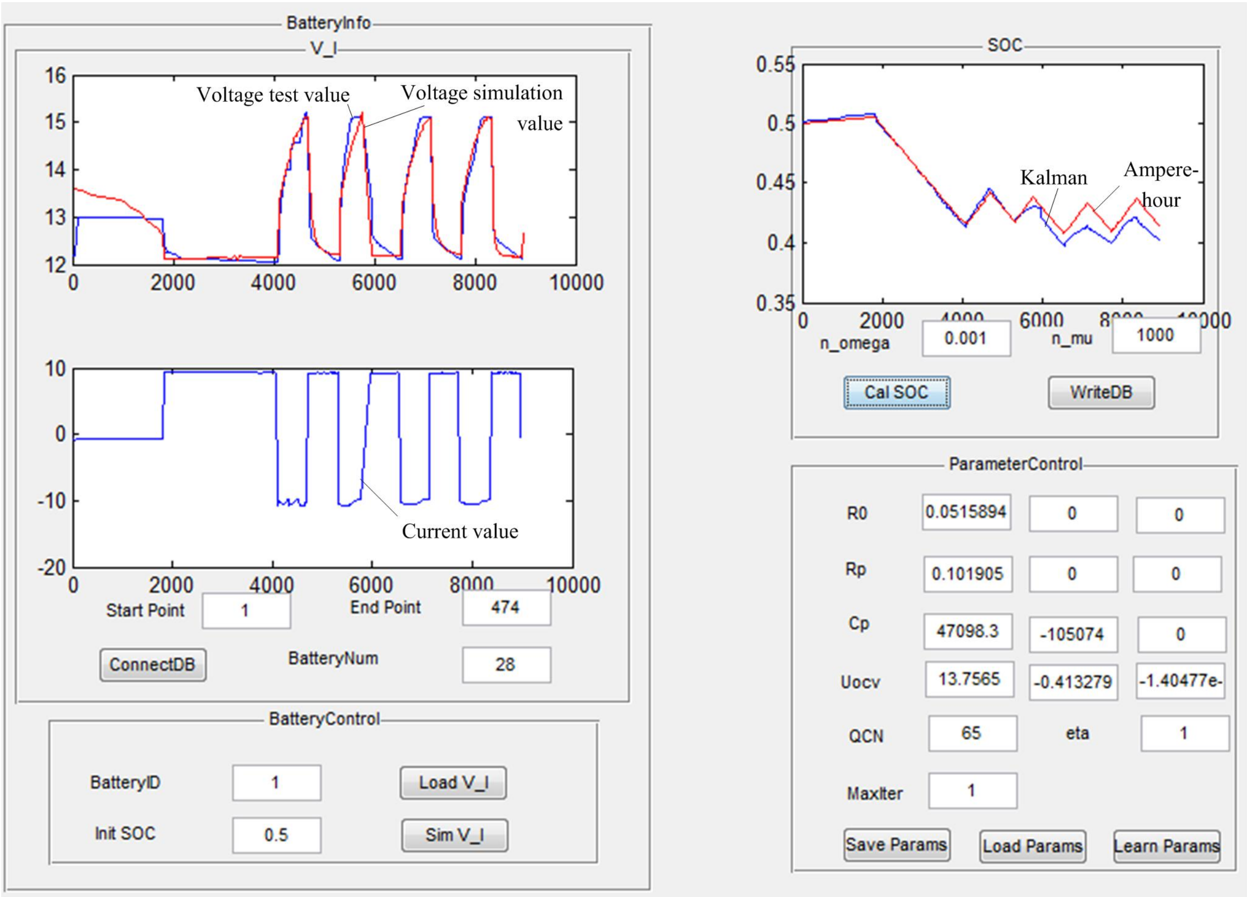


Fig.15 SOC estimation comparison chart of equal interval continuous current charging and discharging.

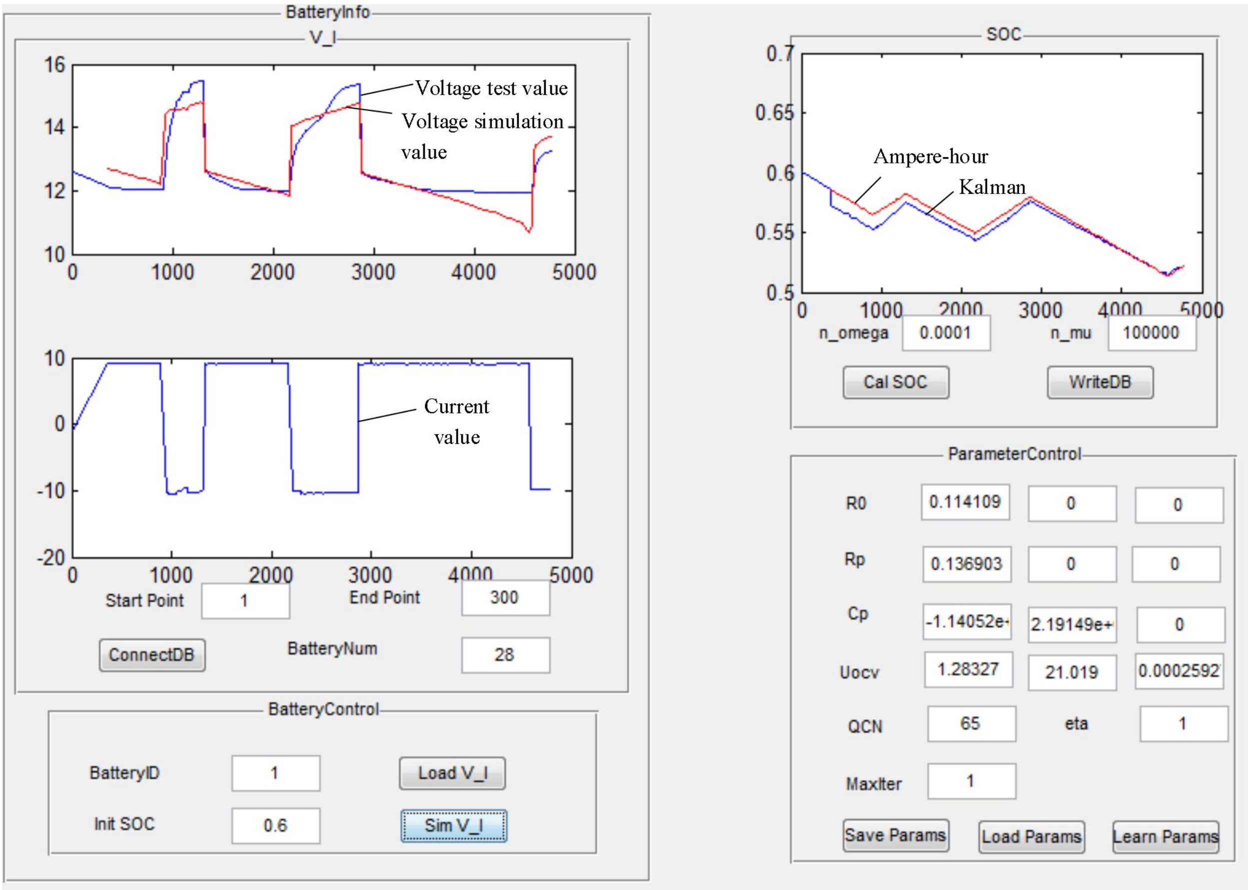


Fig.16 SOC estimation comparison chart of not-equal interval continuous current charging and discharging.

VI. Conclusion

By using the battery equivalent circuit based on the classical Thevenin model, the model parameter identification procedure and the online identification method are discussed in details. The established battery model and the electrical equations are combed with to establish the state space equation. Then the state space equations are nonlinearized and the extended Kalman theory is used to realize the estimation of the battery SOC. It can be seen from the simulation results that the extended Kalman estimation method and online parameter identification algorithm can well predict the battery remaining power and have the good convergence. Especially when the deviation of the initial value is large, the convergence of the Kalman algorithm can be closed to the theoretical SOC and correct the error of the initial SOC. On the other hand, it can overcome the cumulative error of the ampere hour integral method and eliminate the shortcoming of the initial error.

References

[1] X. G. Xu, S. Yang, and Y. F. Li, "A Method of SOC-estimate Based on Forecast of Open-circuit Voltage," *Electronic Design Engineering,* vol. 19, no. 14, pp. 127–129, 2011.

[2] C. John, and V. Baskar, "Estimating the State of Charge of a Battery," *IEEE Transactions on Control Systems Technology*,vol. 13, no. 3, pp. 465–470, 2005.

[3] T. O. Ting, K. L. Man, C. U. Lei, and C. Lu, "State-of-charge for Battery Management System via Kalman Filter," *Engineering Letters*, vol. 22, no. 2, pp. 75–82, 2014.

[4] D. Dennis, and A. Suleiman, "A Critical Review of Using the Peukert Equation for Determining the Remaining Capacity of Lead-acid and Llithium-ion Batteries," *Journal of Power Sources*, vol. 155, no. 2, pp. 395–400, 2006.

[5] A. K. Leros, and V. C. Moussas, "Performance Analysis of an Adaptive Algorithm for DOA Estimation," *IAENG International Journal of Computer Science*, vol. 38, no. 3, pp. 309–313, 2011.

[6] M. F. Tsai, Y. Y. Peng, C. S. Tseng, and N. S. Li, "Modeling and Estimation of State of Charge for Lithium-Ion Batteries Using ANFIS Architecture," *IEEE International Symposium on Industrial Electronics*, pp. 863–868, 2012.

[7] K. X. Wei, and Q. Y. Chen, "Electric Vehicle Battery SOC Estimation Based on Multiple-model Adaptive Kalman Filter," *Proceedings of the Csee*, vol. 32, no. 31, pp. 19–26, 2012.

[8] D. D. Li, Z. C. Wang, and X. X. Guo, "Estimation of SOC of Ni-MH Batteries Based on Fuzzy Adaptive Kalman Filtering for HEV," *Chinese Journal of Power technology*,vol. 35, no. 2, pp. 192–194, 2011.

[9] J. C. Á. Antón, P. J. G. Nieto, F. J. D. C. Juez, F. S. Lasheras, M. G. Vega, and M. N. R. Gutiérrez, "Battery State-of-Charge Estimator Using the MARS Technique," *IEEE Transactions on Power Electronics*, vol. 28, no. 8, pp. 3798–3805, 2013.

[10] M. Shahriari, and M. Farrokhi, "Online State-of-Health Estimation of VRLA Batteries Using State of Charge," *IEEE Transactions on Industrial Electronics*, vol. 60, no. 1, pp. 191–202, 2013.

[11] G. L. Plett, "Extended Kalman Filtering for Battery Management Systems of LiPB-based HEV Battery Packs," *Journal of Power Sources*, vol. 134, no. 2, pp. 262–276, 2004.

[12] G. L. Plett, "Extended Kalman Filtering for Battery Management Systems of LiPB-based HEV Battery Packs," *Journal of Power Sources*, vol. 134, no. 2, pp. 277–292, 2004.

[13] G. L. Plett, "Extended Kalman Filtering for Battery Management Systems of LiPB-based HEV Battery Packs," *Journal of Power Sources*, vol. 134, no. 2, pp. 252–261, 2004.

[14] R. Xiong, H. He, F. Sun, and K. Zhao, "Evaluation on State of Charge Estimation of Batteries With Adaptive Extended Kalman Filter By Experiment Approach," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 1, pp. 108–117, 2013.

[15] Z. Chen, Y. Fu, and C. C. Mi, "State of Charge Estimation of Lithium-Ion Batteries in Electric Drive Vehicles Using Extended Kalman Filtering," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 3, pp. 1020–1030, 2013.

[16] H. G. Wang, and G. X. Yao, "A New SOC Estimation Algorithm Study," *Chinese Journal of Power Sources*, vol. 36, no. 6, pp. 834–836, 2012.

[17] M. Charkhgard, and M. Farrokhi, "State-of-Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 12, pp. 4178–4187, 2010.

[18] W. H. Cui, J. S. Wang, and Y. Y. Chen, "Design and Performance Testing of Lead-acid Battery Experimental Platform in Energy Storage Power Station, *IAENG International Journal of Computer Science*, vol. 44, no. 4, pp. 471–481, 2017.

Wen-Hua Cui is with the School of International Finance and Banking, University of Science and Technology Liaoning, Anshan, 114051, PR China; National Financial Security and System Equipment Engineering Research Center, University of Science and Technology Liaoning. (e-mail: cwh@ustl.edu.cn).

Jie-Sheng Wang received his B. Sc. And M. Sc. degrees in control science from University of Science and Technology Liaoning, China in 1999 and 2002, respectively, and his Ph. D. degree in control science from Dalian University of Technology, China in 2006. He is currently a professor and Master's Supervisor in School of School of International Finance and Banking, University of Science and Technology Liaoning. His main research interest is modeling of complex industry process, intelligent control and Computer integrated manufacturing.

Yuan-Yuan Chen is a postgraduate student in the School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051, PR China (e-mail: chenyuanyuan@mail.iee.ac.cn).