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An improved PNGV modeling and SOC estimation for lithium iron phosphate batteries

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Abstract. Because lithium iron phosphate battery has many advantages, it has been used more and more widely in the field of electric vehicle. The lithium iron phosphate battery, presents the improved PNGV model, and the batteries charge discharge characteristics and pulse charge discharge experiments, identification of parameters of the battery model by interpolation and least square fitting method, to achieve a more accurate modeling of lithium iron phosphate battery, and the extended Calman filter algorithm (EKF) is completed state nuclear power battery (SOC) estimate.

1. Introduction

The energy crisis is on the horizon, and calls for global pollution reduction, environmental improvement and sustainable development are on the rise. Faced with this situation, the automobile industry has thrown its eyes back to electric vehicles again, and developed electric vehicles as the future direction of the development of the automotive industry. Olivine type lithium iron phosphate (LiFe - PO4) material is in recent years the talent shows itself as cathode materials for lithium ion batteries, research paper [1] shows its outstanding performance in complete and cycle performance makes it in the car in the field of power battery plays a more and more important to share, study on using technology of phosphoric acid the lithium iron battery has become the hot spot.

Lithium iron phosphate (LiFePO4) batteries and other lithiumion batteries characteristics are different, especially the voltage and DC internal resistance characteristics. The body reads as follows:

(1) The open circuit voltage and the SOC of the battery are nonlinear, so it is difficult to estimate the charge state (SOC) of the battery by reverse interpolation.

(2) The DC internal resistance will increase sharply at low temperature, resulting in the deterioration of the low temperature performance of the battery.

Battery SOC estimation is one of the key technologies in the lithium iron phosphate battery management system (BMS) for electric vehicles. The accuracy of battery modeling directly influences the accuracy of SOC estimation.

The SOC estimation algorithms include current integration method, discharge test method, open circuit voltage method, load voltage method and electrochemical impedance spectroscopy. Method, resistance method, linear model method, neural network method and Calman algorithm [2 - 3], these methods have their advantages and disadvantages and the scope of the use of electric vehicles currently in use, often using the current integration method and the open circuit voltage method or by their combination derived algorithm for SOC estimation. The algorithm is simple, easy to implement and small in memory, but it is prone to accumulate errors.

Therefore, this paper adopts the improved PNGV model for LiFePO4 cell modeling, then the static characteristics of battery and constant current charge discharge characteristics and pulse charge

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discharge characteristics based on least square fitting was used to identify the model parameters; finally, the PNGV model of lithium iron phosphate battery was improved based on the extended Calman filter is used to estimate the battery SOC.

2. Model of Lithium Iron Phosphate Battery

According to the balancing of the single cell and the balancing energy flow, the balancing strategy can be divided into the following categories:

Battery management system is still the most widely used battery in the equivalent circuit model [4-5], its battery based on the principle of electric network theory to describe the battery working characteristics, clear physical meaning, can be expressed by analytic mathematical model, applicable to a variety of cell modeling.

According to the nature of the elements in the circuit, it can be divided into 2 kinds: linear equivalent circuit model and nonlinear equivalent circuit model. The PNGV model is a nonlinear equivalent circuit model [6] whose model parameters vary with voltage, temperature, or SOC, as shown in figure 1. Among them, the resistance R0 describes the change of the battery internal resistance, and the ideal voltage source E and capacitor C0 describe the change of open circuit voltage and capacity, and the shunt RC link describes the polarization voltage of the battery.

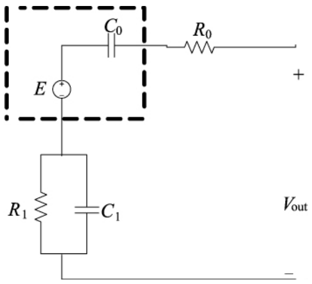

Figure 1. PNGV Model for Lithium Iron Phosphate Battery

PNGV model is selected based on the following:

(1) The internal resistance parameter of PNGV model has definite physical meaning, which is in good agreement with the DC internal resistance of the battery.

(2) The PNGV model is suitable for modeling the monomer and module of lithium iron phosphate battery, and the modeling accuracy is higher when the electric vehicle is running in the city.

3. An improved PNGV Model and Parameter Identification

3.1 An improved PNGV model for lithium iron phosphate batteries

Taking into account the lithium iron phosphate battery and lithium ion battery the existence of difference, based on the original model of PNGV, the lithium iron phosphate battery, PNGV model is used to improve the structure shown in figure 2.

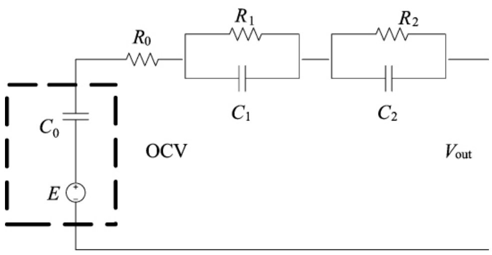

Figure 2. An improved PNGV model for lithium iron phosphate batteries

Increase the links of the parallel RC model, can more accurately describe the cell polarization characteristics, and the parameters of R0, R1, C1, R2 and C2 are not fixed, but related to the environmental temperature, battery charge and discharge, SOC etc..

3.2 Parameter Identification of improved PNGV model

Selection of lithium iron phosphate battery (rated voltage 3.2V, rated capacity of 2.3A - H) as the experimental object, the pulse charge discharge experiment 7, 3C discharge, duration of 20s, and then to the static 60s;3C charging, duration 20s, static 60s, figure 3 shows constant current charge discharge current curve.

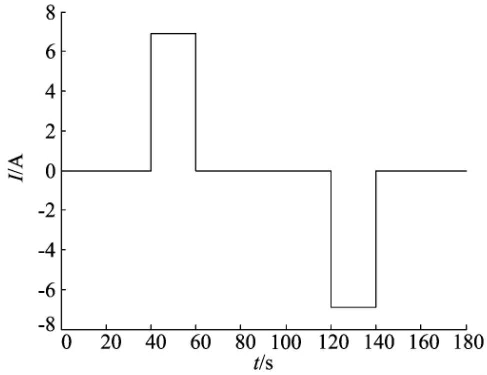

Figure 3. Constant Current Charge Discharge current Curve

In the pulse discharge process, the battery end voltage is shown in Figure 4, and the curves of each section are analyzed as follows:

(1) The vertical drop of voltage is due to the internal resistance of the battery.

(2) The slowly decreasing part of voltage is the zero state response of 2 RC parallel circuits.

(3) The slowly rising part of the voltage at the end of the discharge can be regarded as the zero input response of the 2 RC parallel circuits.

(4) The voltage before the discharge time of the battery is higher than the voltage at the end of the discharge. The reason is that the discharge of the battery reduces part of the capacity and leads to the change of the open circuit voltage.

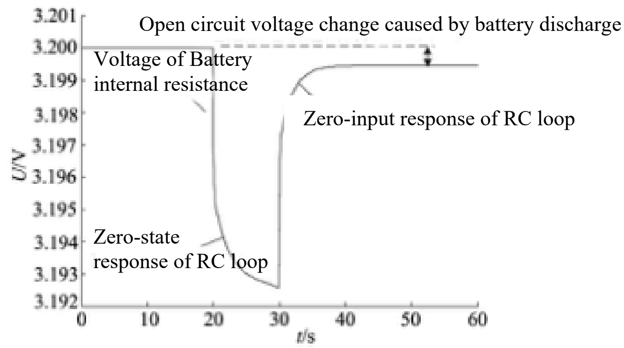

Figure 4. Output voltage response curve of battery

Based on the above analysis, the concrete calculation process is as follows:

$$R_0 = \frac{\Delta U}{I}, \quad C_0 = \frac{\Delta Q}{\Delta U_{OCV}}$$

Among them, ΔU is the vertical drop partial pressure drop; I is the discharge current value; ΔQ is the capacity change before and after the pulse discharge; equal to the change value of SOC times the rated capacity; ΔU_{OCV} is the change of OCV before and after the pulse discharge.

The zero input response of the double RC parallel link can be written:

$$U = U_{C1} + U_{C2} = U_{O1}\exp(-t/\tau 1) + U_{O2}\exp(-t/\tau 2) \quad (1)$$

Among them, U_{O1}、U_{O2} are the initial voltages of C_1、C_2, and $\tau = RC$ is time constant. The U_{O1} 、U_{O2} 、τ_1、τ_2 are regarded as the undetermined coefficient, and the least squares method is used to identify the coefficients[8].

The zero input response of the double RC parallel link can be written:

$$U = U_{C1} + U_{C2} = I_{R1}\exp(-t/\tau 1) + I_{R2}\exp(-t/\tau 2) \quad (2)$$

The τ_1 and τ_2 will be replaced, using the pressure drop on the RC link, the R1 and R2 are regarded as undetermined coefficients, and the least squares fit can be used to find R1, R2, and then desire C1 and C2.

Since only the battery terminal voltage (total voltage) data, there is no separate separation of the two resistance link voltage, therefore, the calculation (1) and (2) will be adjusted to:

$$U = U_o + U_{O1}\exp(-t/\tau 1) + U_{O2}\exp(-t/\tau 2) \quad (3)$$

$$U = U_o' - \frac{1}{C_O}\int Idt - IR_1\exp(-t/\tau 1) - IR_2\exp(-t/\tau 2) \quad (4)$$

Among them, U_O and U_O' are voltage rise curve and voltage start point of voltage slow down curve respectively.

The voltage source E is the open circuit voltage detected before the discharge test. According to the model structure, the formula of breaking voltage and frequency is derived:

$$U(s) = E - R_0 I(s) - \frac{R_1}{R_1C_1s+1}I(s) - \frac{R_2}{R_2C_2s+1}I(s) \quad (5)$$

The simulation model [9] of lithium iron phosphate battery can be easily constructed by substituting parameter identification results. The same pulse current is applied to the battery model to simulate the charging and discharging. The output voltage of the battery is shown in figure 5.

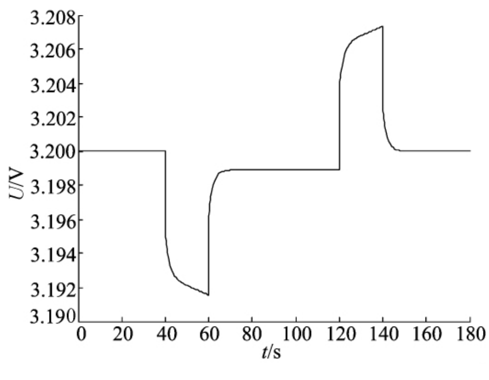

Figure 5. Output dynamics of a battery under pulse charging and discharging

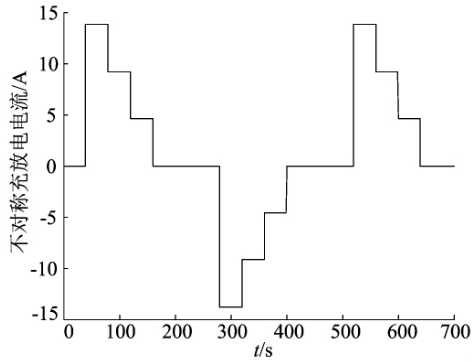

Figure 6. Charge and Discharge Current of Battery Step

Then the asymmetric step charge and discharge simulation experiment is carried out. The result shows that the output voltage of the battery is shown in figure 7 as shown in figure 6. The analysis and calculation results show that the lithium iron phosphate battery model based on the improved PNGV model has higher modeling accuracy.

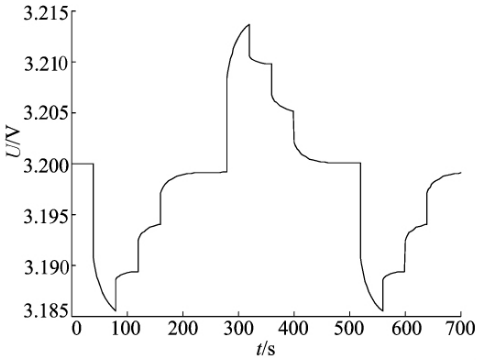

Figure 7. Output Dynamics of Battery step charging and discharging Current

4. SOC estimation of lithium iron phosphate battery

For the model of LiFePO4 cell based on PNGV model, the discrete space state equation and output equation are written as follows:

$$\begin{pmatrix} S_{k+1} \\ U_{k+1}^{R_1C_1} \\ U_{k+1}^{R_2C_2} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_1) & 0 \\ 0 & 0 & \exp(-\Delta t/\tau_1) \end{pmatrix} \times \begin{pmatrix} S_k \\ U_k^{R_1C_1} \\ U_k^{R_2C_2} \end{pmatrix} + \begin{pmatrix} -\dfrac{\eta \Delta t}{Q} \\ R_1\left(1-\exp(-\Delta t/\tau_1)\right) \\ R_2\left(1-\exp(-\Delta t/\tau_2)\right) \end{pmatrix} + \omega_k \tag{6}$$

$$U_k = OCV\left(S_k\right) - i_k R_0 - U_k^{R_1C_1} - U_k^{R_2C_2} + \upsilon_k \tag{7}$$

Among them, η is the Coulomb coefficient; i_k and U_k are the current at the sampling point k and the operating voltage of the battery; the Q is the nominal capacity of the cell; the Δt is the sampling period; the ω_k and υ_k are uncorrelated system noises. The relation between the open circuit voltage OCV and the SOC is expressed by OCV (Sk), and the least square method is used to get the result according to the experimental data. The result is shown in figure 8. In order to prevent the experimental data from being too small and affect the accuracy of SOC estimation, a battery collection consisting of 3 sections of lithium iron phosphate batteries in series is used here to collect data, so the nominal voltage of the battery is 9.6V.

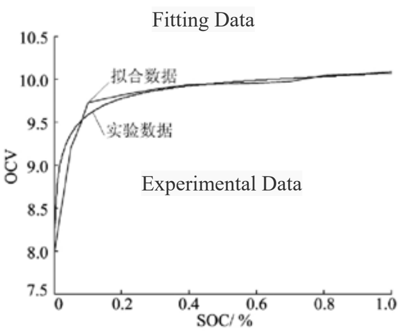

Figure 8. OCV Dynamics under SOC change

When EFK is used to estimate SOC, the state equation and space equation have the following form:

$$x_{k+1} = f\left(x_k, u_k\right) + \omega_k \tag{8}$$

$$y_k = g\left(x_k, u_k\right) + \upsilon_k \tag{9}$$

For battery models:

$$x_k = \left(S_k, U_k^{R_1C_1}, U_k^{R_2C_2}\right)^T \tag{10}$$

$$A_k = \left.\frac{\partial f}{\partial x}\right|_{x=\dot{x}_k^{\,+}} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \exp(-\Delta t/\tau_1) & 0 \\ 0 & 0 & \exp(-\Delta t/\tau_2) \end{pmatrix} \tag{11}$$

$$C_k = \left.\frac{\partial f}{\partial x}\right|_{x=\dot{x}_k^{\,-}} = \left(\left.\frac{dOCV(s)}{ds}\right|_{s=s_k^{\,-}}, -1, -1\right) \tag{12}$$

$$g\left(\dot{x}_k, u_k\right) = OCV\left(S_k\right) - i_k R_0 - U_k^{R_1C_1} - U_k^{R_2C_2} \tag{13}$$

Among them, $S_k^{\,-}$ is the sampling time point k on the left side of the SOC estimate, due to the actual situation of the battery limit, set the initial SOC value is 0.96, according to the Calman filter cycle recursive algorithm [10] to realize the estimation of SOC, as shown in figure 9. In the 360s period, the SOC is reduced from 0.96 to 0.88. Figure 10 shows the application of extended battery end voltage Calman filtering algorithm estimates compared with the measured values, the calculation results show that the extended Calman filter algorithm is applied to the improved PNGV model SOC estimation has high estimation precision technology.

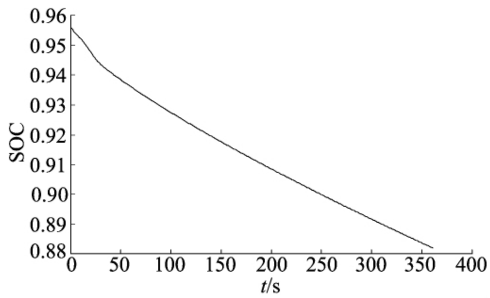

Figure 9. SOC Changes in the Battery under Discharge conditions

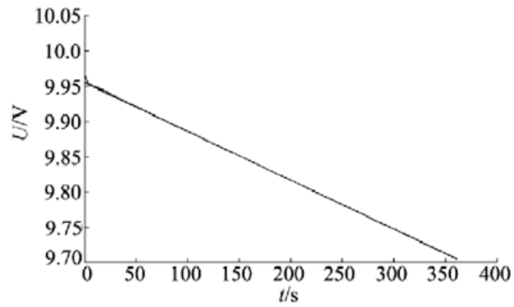

Figure 10. Estimation of the battery terminal voltage when the discharge value is compared with measured value

5. Conclusion

According to the differences in the characteristics of electric vehicle model of lithium iron phosphate battery, with the improved PNGV model for battery modeling and parameter identification, the pulse current charge discharge experiments and asymmetric step current charge discharge experiments showed that the improved PNGV model of lithium iron phosphate battery model has advantages of high precision based on modeling technology. Considering that the extended Calman filter algorithm can be implemented on single chip microcomputer or DSP, it is estimated that SOC has high accuracy and can conveniently estimate the battery lifetime Kalman filtering (EKF) algorithm to achieve accurate estimation of lithium iron phosphate battery SOC improvement based on PNGV model. The current estimate of SOC or in a smaller range (0.96 ~ 0.88), and achieve accurate estimation will be the next focus of the work in a wide range, is established with the current, temperature, change of variable parameter mode SOC and EKF algorithm in consideration of system noise interference.

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