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Comparison of methods for obtaining model parameters of lithium ion batteries

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Summary

The parameters of resistor, capacitor and other components in the battery equivalent model can't be measured directly, but can be obtained by calculation, identification and other methods. In order to determine which of these methods is the best way to obtain the parameters of the battery equivalent model, the two most commonly used methods are compared in this paper. By comparing, it is found that the identification method is faster than the direct calculation method, and the calculation amount is small and the precision is high. This laid the foundation for accurate estimation of SOC.

Keywords: lithium battery, battery management, battery model, battery SOC (state of charge)

1 Introduction

SOC of battery is a very important state parameter, which directly affects the control strategy of battery in the application process, thus affecting the battery life and vehicle performance. However, SOC can't be measured directly. The most widely used method is to estimate SOC based on battery model. Some basic parameters in the battery model can't be measured directly, and need to be calculated, curve fitting, identification and other methods to obtain.

In this paper, the two most commonly used methods for obtaining the parameters of battery model are compared: direct calculation method and system identification method. First, the Second order Thevenin equivalent circuit model is established. Then, the DC internal resistance of the battery was tested by HPPC experiment. The parameters of the battery model are obtained by system identification method and curve fitting after direct calculation method respectively. Finally, using Simulink to build a simulation model to simulate the parameters of the battery model obtained by the two different methods mentioned above, and then compare with the true values. Through the analysis of the comparison results, an optimal scheme for obtaining the parameters of battery model with higher fitting degree and convenience is determined, which lays a foundation for the accurate estimation of SOC.

2 Model establishment and parameter acquisition

2.1 Model establishment

This paper chooses the Second-order Thevenin model. The research on the number of RC links in the multi-order model in reference1 shows that with the increase of the order of the model, the computational difficulty is also increasing. Therefore, the second-order Thevenin model, which is the most widely used and has higher accuracy and less computational difficulty, is chosen as the research basis. Its structure is shown in Figure 1.

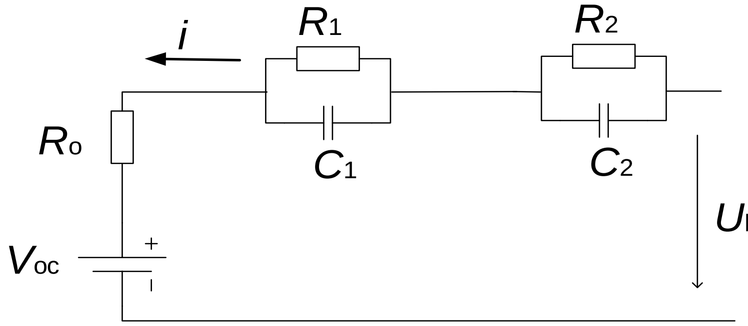

Figure1: Second-order Thevenin model

In the model, the first RC link represents the electrochemical polarization of the battery, the second RC link represents the Concentration polarization of the battery. According to Kirchhoff's law, the output equation and state equation of the Second-order Thevenin model can be obtained, such as formula (1).

$$\begin{cases} U_b = U_{OC} + IR_0 + U_1 + U_2 \\ \dot{U}_1 = -\frac{U_1}{C_1 R_1} + \frac{I_1}{C_1} \\ \dot{U}_2 = -\frac{U_2}{C_2 R_2} + \frac{I_2}{C_2} \end{cases} \tag{1}$$

U_1 and U_2 indicate the polarization voltage of battery.

2.2 HPPC experiment

The battery used in this experiment is 3 LiFePO4 batteries. The basic performance parameters are as shown in Table 1.

Table1: Basic performance parameters of LiFePO4 battery

Battery production number	L060E1604042386
Nominal voltage (V)	3.2
Rated capacity (Ah)	60
Length * Width * Height (mm)	130*36*190
Weight (Kg)	1.9
Upper cut-off voltage (V)	3.6
Lower cut-off voltage (V)	2.8

Because the parameters of each element in the battery model can't be measured directly, the HPPC is used to measure the ohmic internal resistance, polarization internal resistance and polarization capacitance of the battery.

In different SOC states, the battery is tested in the working condition shown in Figure 2. The abscissa is time, the ordinate is relative current, and the charging direction is positive.

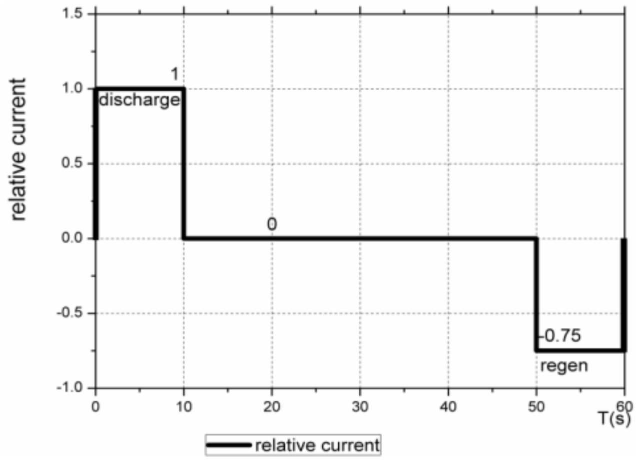

Figure2: HPPC experiment institution

3 Acquisition of model parameters

3.1 Identification of open circuit voltage U_{OC}

There is a certain mapping between the electromotive force and the SOC during the charging and discharging process of the battery. In the HPPC experiment, whenever SOC decreased by 0.1, and rest 1h. So we can take the voltage measured after each static as the open-circuit voltage corresponding to the SOC state, and the mapping relationship is shown in Figure 3.

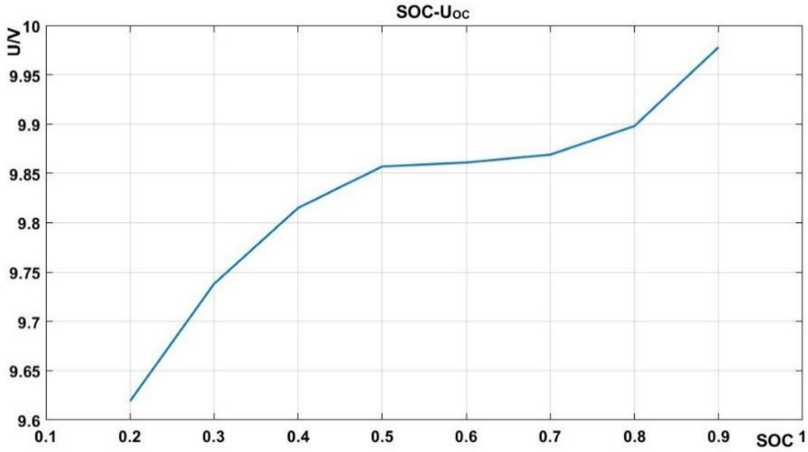

Figure3: The corresponding curve between open circuit voltage and SOC

3.2 Direct calculation method

3.2.1 Direct calculation of ohmic internal resistance R0

Before HPPC pulse current is loaded, the terminal voltage of the battery isV_1, after 1 second, the current is loaded, the terminal voltage of the battery isV_2. HPPC pulse current before unloading, the terminal voltage of the battery isV_3, after 1 second, the current is unloaded, the terminal voltage of the battery isV_4. The ratio of voltage difference $(V_1 - V_2)$ at the moment of current loading and voltage difference $(V_3 - V_4)$ at the moment of unloading to pulse current is taken as ohmic internal resistance. In order to reduce the error, the average value of the two voltage difference is calculated as follows.

$$R_0 = \frac{(V_1 - V_2) + (V_3 - V_4)}{2I} \tag{2}$$

3.2.2 Polarization resistance and polarization capacitance identification

The voltage response at the time from t_2 to t_3 after the discharge of HPPC pulse, can be regarded as the zero-input voltage response of two RC networks, and the voltage response at the end of the battery can be expressed as:

$$U_b(t) = U_{OC} - e^{-t/\tau_1}U_1(0) - e^{-t/\tau_2}U_2(0) \tag{3}$$

Open-circuit voltage U_{OC} and battery terminal voltage are known, so the change of battery polarization voltage can be expressed by subtracting battery terminal voltage $U_b(t)$ from open-circuit voltage. τ_1 and τ_2 can be obtained by curve fitting through Matlab software, and the fitting curve is shown in Figure 4.

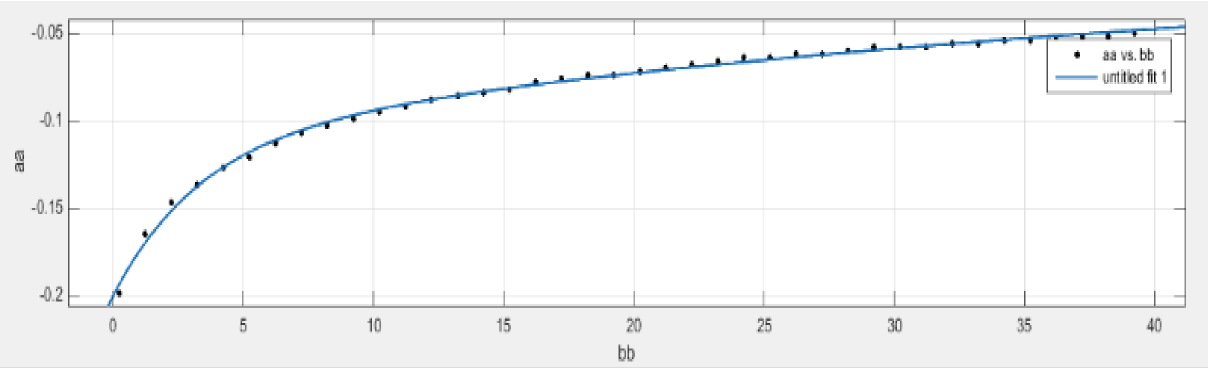

Figure4: Zero state response curve fitting

Substitute τ_1 and τ_2 from zero input response into Eq. (3), and then calculate a R_1 and R_2 by curve fitting. The fitting curve is shown in Figure5. As a result of $\tau_1 = R_1C_1$, $\tau_2 = R_2C_2$. So, C_1 and C_2 can be obtained. The model parameters of different charge states can be obtained by using this method to make repeated HPPC experiments on different SOC points.

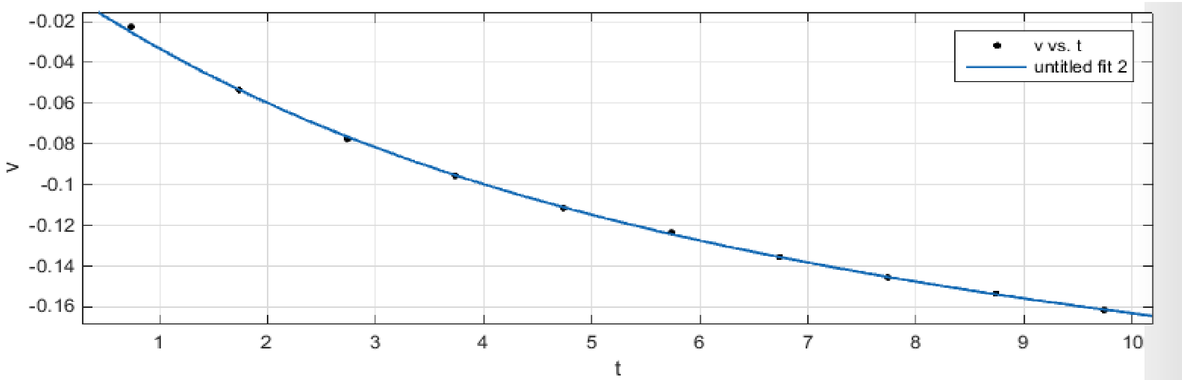

Figure5: Zero input response curve fitting

3.3 System identification method

The Least Squares method can be used in dynamic systems, static systems. The estimation results obtained by this method have good statistical properties. In this paper, the LS (Least Squares), RLS (Recursive Least Squares) and RELS (Recursive Extended Least Squares) are used to identify the model parameters. The relationship between the model parameters and the difference equation can be obtained by bilinear transformation of the (1) equation. The difference equation of the second order Thevenin model is as follows.

$$U(k) + \alpha U(k-1) + \beta U(k-2) = \gamma I(k) + \xi I(k-1) + \eta I(k-2) \tag{4}$$

3.3.1 Least Square method (LS)

LS is a zero deflection and consistent minimum variance estimation for white noise; for colored noise, the parameter estimation is biased but convergent; for high-order systems, it is superior to other algorithms, and the precision of one-time completion algorithm is higher. The solution of Least Square estimates method as follows.

$$\hat{\theta}_{LS} = (\Phi^T \Phi)^{-1} \Phi^T Y \tag{5}$$

3.3.2 Recursive Least Squares (RLS)

The characteristics of RLS are similar to those of LS, and the computational complexity of RLS is less than that of LS. It is suitable for on-line identification. The solution of RLS estimates method as follows.

$$\begin{cases} \hat{\theta}_{N+1} = \hat{\theta}_N + G_{N+1}\left[y_{N+1} - \varphi_{N+1}^T \hat{\theta}_N\right] \\ G_{N+1} = \frac{P_N \varphi_{N+1}}{1+\varphi_{N+1}^T P_N \varphi_{N+1}} \\ P_{N+1} = P_N - G_{N+1}\varphi_{N+1}^T P_N \end{cases} \tag{6}$$

3.3.3 Recursive Extended Least Squares(RELS)

The Extended Least Squares method is widely used in practical engineering because of its high estimation accuracy, uniform unbiasedness and simple algorithm. The RELS algorithm is consistent with RLS. It is only the dimension of parameter vector θ and data vector φ_k that extends m dimensions. The solution is as follows.

$$\begin{cases} \hat{\theta}_{k+1} = \hat{\theta}_k + G_{k+1}\left[y_{k+1} - \hat{\varphi}_{k+1}^T \hat{\theta}_k\right] \\ G_{k+1} = \frac{P_k \hat{\varphi}_{k+1}}{1+\hat{\varphi}_{k+1}^T P_k \hat{\varphi}_{k+1}} \\ P_{k+1} = [I - G_{k+1}\hat{\varphi}_{k+1}^T] P_k \end{cases} \tag{7}$$

3.4 Comparisons and Analysis of the results of calculation and identification

3.4.1 Ohmic internal resistance R0

The following figure shows the results of Ohmic internal resistance R0 obtained by three methods of system identification and the results of Ohmic internal resistance R0 obtained by curve fitting after direct calculation (Curve Z).

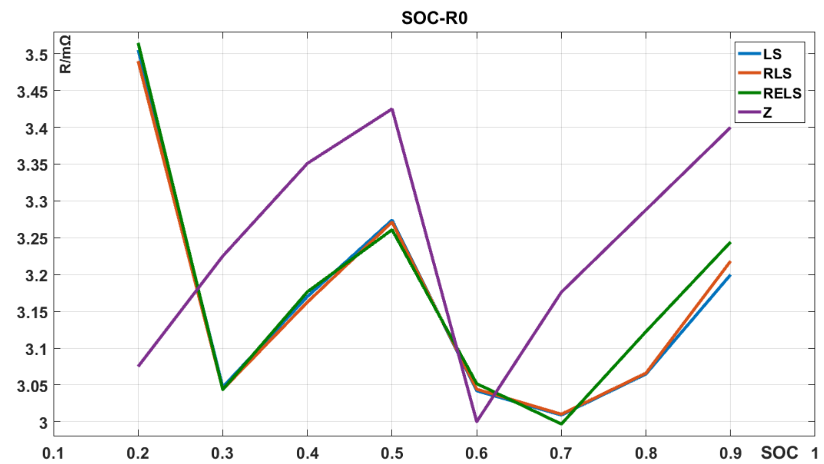

Figure6: R0 Identification results

It can be seen from the graph that the curves of R0 varying with SOC obtained by three different system identification methods almost coincide, and only after SOC is greater than 0.7 will there be a slight difference. However, the value of R0 obtained by direct calculation (Curve Z) is different from that obtained by system identification method, but the trend of R0 varying with SOC is similar to that obtained by system identification method.

3.4.2 Polarization Internal Resistance R1 and R2

The following Figure7 and Figure8 shows the results of Polarization internal resistance R1 and R2 obtained by three methods of system identification and the results of Polarization internal resistance R1 and R2 obtained by curve fitting after direct calculation (Curve Z).

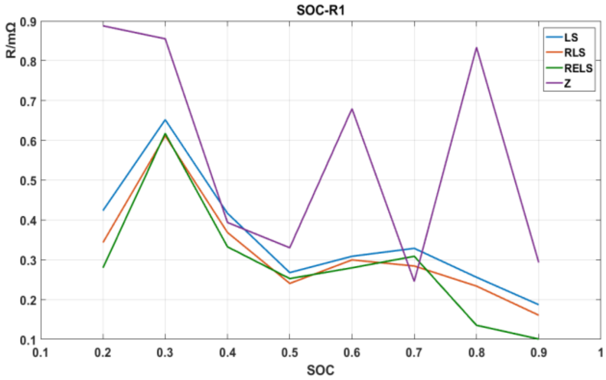

Figure7: R_1 Identification results

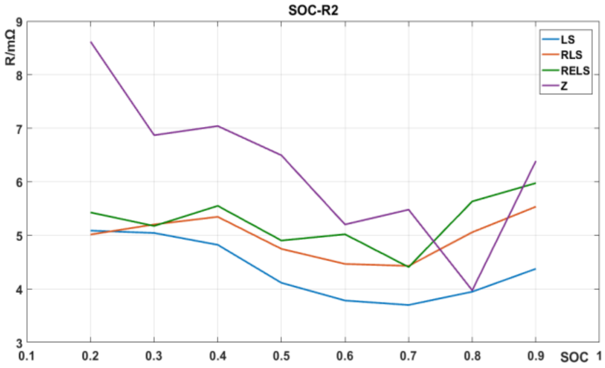

Figure8: R_2 Identification results

As shown in Figure 7, the values of polarization internal resistance R1 obtained by three different system identification methods are similar, and the trend of variation is similar. In contrast, the values of R1 obtained by curve fitting after direct calculation are quite different from those obtained by system identification method. However, when SOC is between 0.3 and 0.7, the variation trend of R1 obtained by direct calculation and system identification is the same.

Figure 8 shows the polarization resistance R2 curves obtained by different methods. It can be seen from the figure that the R2dou calculated by SOC directly before 0.7 is larger than that obtained by system identification.

3.4.3 Polarization capacitors C1 and C2

The following Figure9 and Figure10 shows the results of Polarization capacitance C1 and C2 obtained by three methods of system identification and the results of Polarization capacitance C1 and C2 obtained by curve fitting after direct calculation (Curve Z).

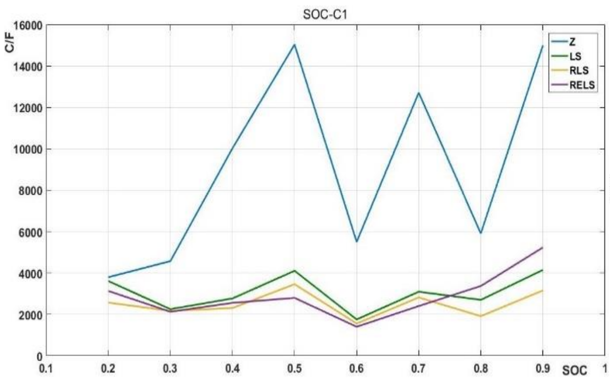

Figure9: C_1 Identification results

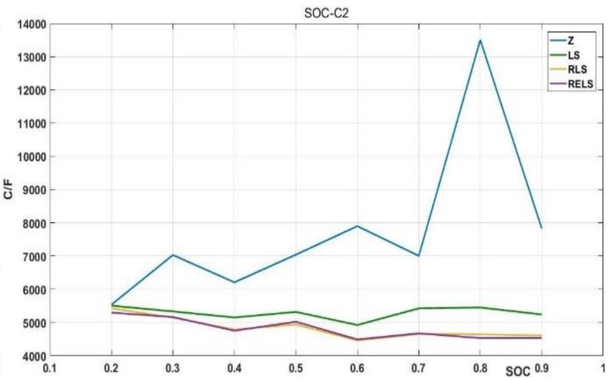

Figure10: C_2 Identification results

It can be seen from the figure that the polarization capacitance obtained by three different system identification methods has little difference. The value of polarization capacitance obtained by curve fitting after direct calculation is relatively large, but the results obtained by several different methods are similar in the changing trend.

4 Simulation and verification of identification results

According to the discrete state output equation of the second-order Thevenin model, the simulation of the model is built in MATLAB / Simulink. The battery model parameters obtained by the two methods described above are simulated and compared with the real values. The Simulink simulation program is shown in Figure 11.

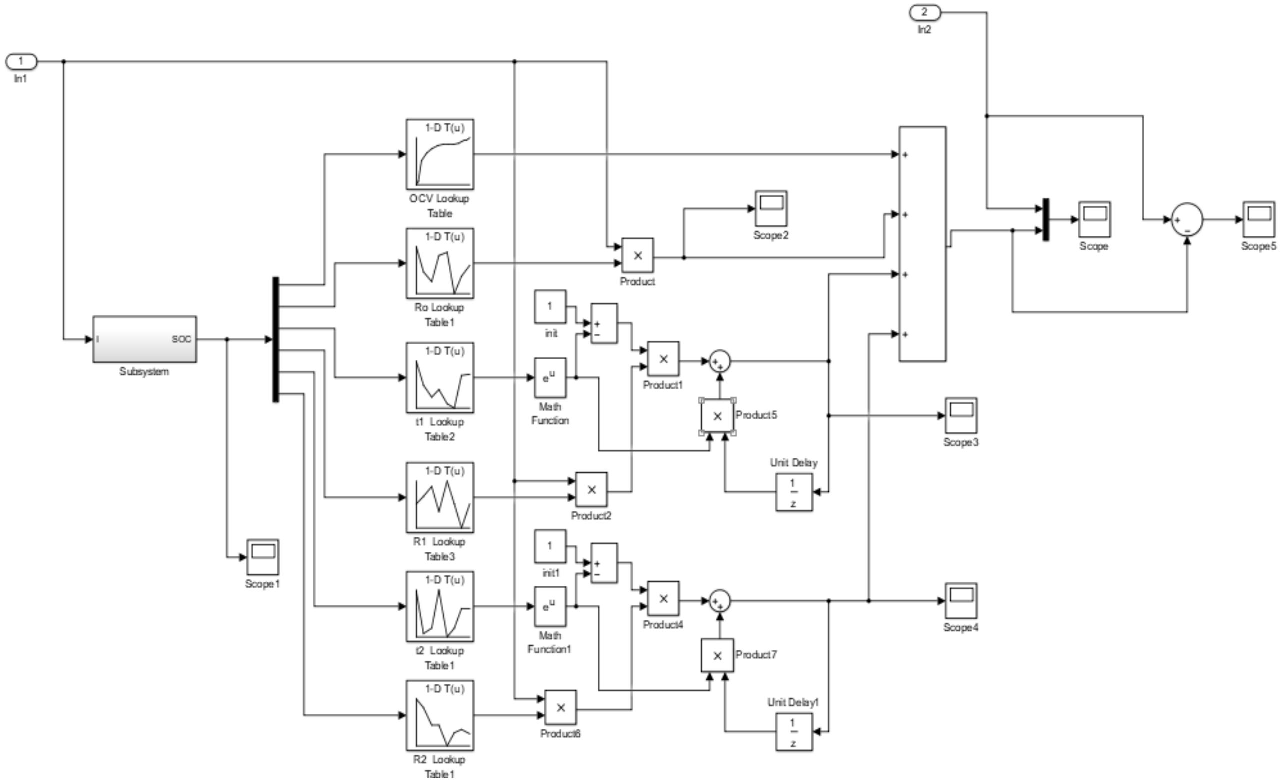

Figure11: Simulink structure diagram of equivalent model

4.1 Simulation and verification using Simulink

The HPPC experiment has been introduced in 1.2 section, and the model is verified by data in the discharge process. Figure 12 shows the voltage waveform of HPPC working condition.

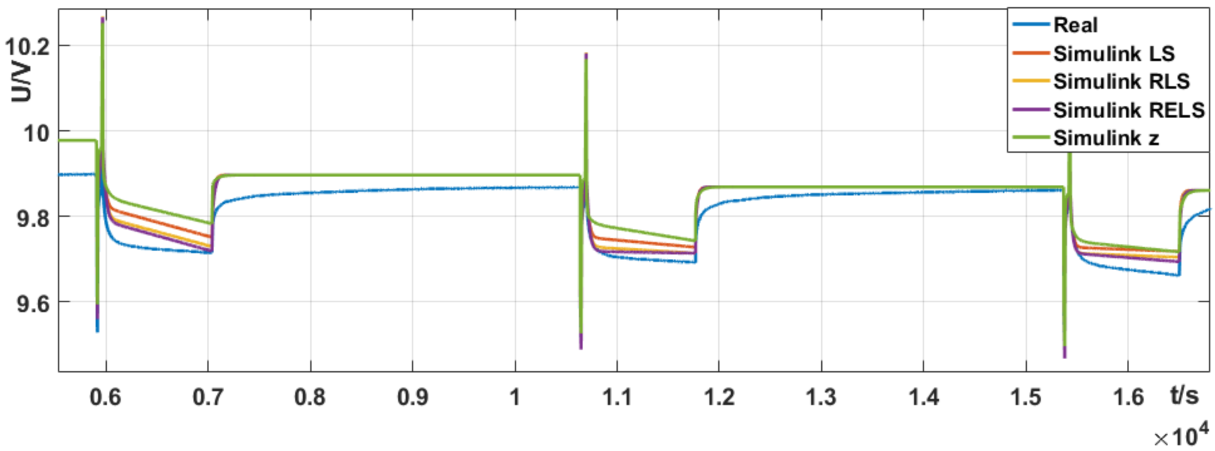

Figure12: HPPC working condition voltage

From the simulation results, it can be seen that in the static process, the simulation results of model parameters obtained by different methods are not very different, and the difference between simulation results and real values is not large; in the dynamic process, the simulation results of model parameters obtained by different methods are quite different, and the difference between simulation results and real values is also large. It can be seen from the figure that the simulation results of the model parameters obtained by curve fitting after direct calculation deviate most from the real values. Then is LS, RLS, RELS.

4.2 Error analysis

4.2.1 Comparison of absolute errors

In order to more intuitively see the deviation between the real value and the simulation results of model parameters obtained by different methods, the absolute error curves are compared in the following figure.

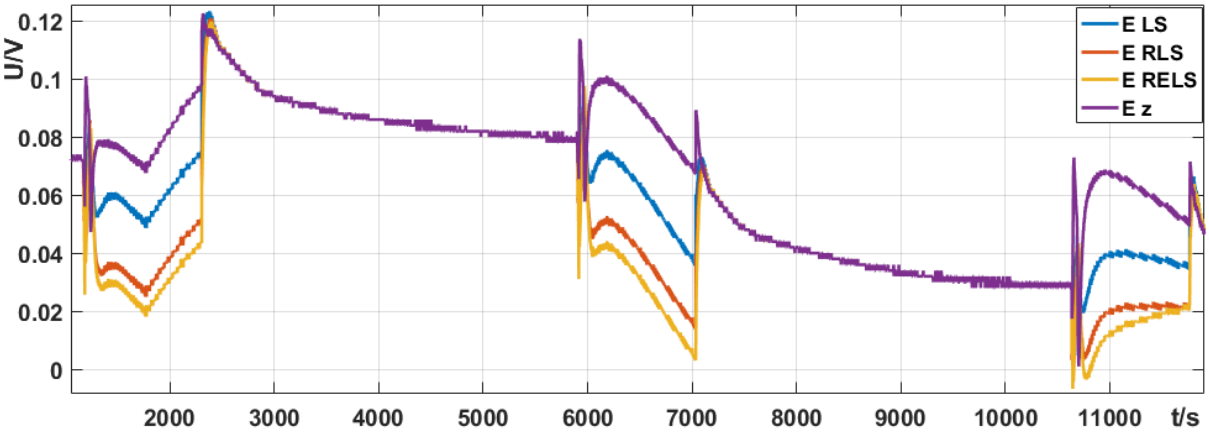

Figure13: Comparison chart of absolute error

By comparing the error curves of the simulation results of the model parameters obtained by different methods, it is found that the absolute error of the curve fitting after direct calculation is much larger than that of the system identification method. Furthermore, the absolute error of the RELS method is the smallest among the three identification methods.

4.2.2 Comparison of root-mean-square errors

In order to compare the accuracy of different parameter acquisition methods, the root mean square error of simulation results of model parameters acquired by different methods is compared. The root mean square error results are shown in Table 2. The comparison result is close to the absolute error. The accuracy of RELS is the highest, followed by RLS and LS.

Table2: Root mean square error

LS	RLS	RELS	Z
0.303582	0.303279	0.302876	0.305255

5 Conclusion

This paper is based on the Second-order Thevenin equivalent circuit model, the basic parameters of battery model are obtained by system identification method and direct post-calculation curve fitting method. Then the simulation model of battery circuit is established by Simulink in MATLAB software. The model parameters obtained by the two methods are verified by HPPC working condition simulation. The simulation results are compared with the real data, it is found that the method of system identification is superior to the method of curve fitting after direct calculation. The method of system identification is faster and more accurate. In addition, three different identification methods of LS, RLS and RELS are compared. LS is more computational than RLS and RELS, and both RLS and RELS are implemented based on recursive method. The amount of computation is relatively small, and the precision of RELS is higher.

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