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Research on Parameter Identification of Lithiumion Batteries Based on Improved SCE Algorithm

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Abstract: Evaluating the charging status of power batteries is very important in battery management systems, and the accuracy and parameter identification of battery models are crucial for it. Using DST and FUDS lithium-ion battery dynamic mode datasets for simulation verification, and comparing with particle swarm optimization algorithm, grey wolf algorithm, and genetic algorithm. The simulation results show that this method has advantages in recognition accuracy, with an average quadratic error of 0.0166V for parameter recognition. Compared with other optimization algorithms, it decreased by 7.8%, 8.3%, and 14.9% respectively.

1.Introduction

Lithium ion batteries are widely used as energy sources for new energy vehicles due to their high energy density, long lifespan, and environmental friendliness. The performance of lithium-ion batteries directly affects the availability of new energy vehicles. In practical applications, battery management systems (BMS) are used to monitor the operating status of batteries, prevent abnormal charging and discharging of power batteries and high temperatures, and avoid safety accidents caused by power batteries. The accurate identification of model parameters can not only reflect the current operating status of power batteries, but also serve as the basis for evaluating the charging status and predicting the state of health (SOH) of BMS (SOC) systems. Building an accurate power battery model is crucial for BMS[1].

2. Theoretical analysis

2.1. Establishment of Equivalent Circuit Model for Battery

This article uses two RC circuits and a second-order RC model with an ohmic resistance to simulate the dynamic characteristics of a battery, as shown in Figure 1. Two RC circuits represent the electrochemical polarization and differential polarization of battery concentration, and Ohmic resistance represents the internal resistance of the battery. Compared with other models, this model has higher modeling accuracy and more convenient and accurate parameter identification[2].

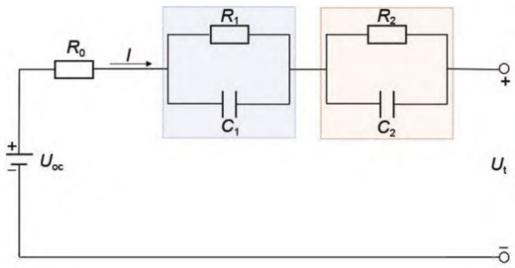

Figure 1. Second order RC equivalent circuit mode.l

In Figure 1, U_{oc} Indicates the open circuit voltage of the battery; U_1 Indicates the terminal voltage of the battery; I represents the charging and discharging current of the battery during operation; R_0 Indicates the ohmic resistance of the battery; R_1 and R_2 Indicates the polarization resistance of the battery; C_1 and C_2 Indicates the polarization capacitance of the battery. By applying Kirchhoff's law, the functional relationship of the circuit can be obtained:

$$\begin{cases} U_{oc} = IR_0 + U_1 + U_2 + U_t \\ I = \dfrac{U_1}{R_1} + C_1 \dfrac{dU_1}{dt} \\ I = \dfrac{U_2}{R_2} + C_2 \dfrac{dU_2}{dt} \end{cases} \tag{1}$$

In the formula, U_1 and U_2 Voltage for two RC circuits; U_{oc} Can be determined by battery SOC; I and U_t The current and voltage during battery operation can be measured by sensors[3].

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2.2. Offline parameter identification method based on experiments

In the equivalent circuit, I and U_t It can be measured by sensors, U_{oc} It is a function about SOC that requires consideration of the remaining R_0、R_1、R_2、C_1、C_2 Identify and determine its value during battery operation. The currently commonly used offline identification method is to conduct composite pulse power performance testing on batteries.

To validate the effectiveness of the proposed SOC evaluation method, laboratory data from the University of Maryland was used in this study. The testing equipment used includes the ARBINBT200 battery testing system, which monitors and records the battery charging and discharging process, as well as a hot chamber that monitors the ambient temperature of the battery. This study takes the test data of INR18650-20R lithium-ion battery pack as an example to confirm the effectiveness of SOC evaluation method. The battery specifications are shown in Table 1[4].

Table1. Battery Specifications.

Battery parameters	specification
types of	LiNMC
Rated capacity/Ah	2
Nominal voltage V	3.7
Charging cut-off voltage V	4.2
Discharge cut-off voltage/V	2.5

During the experiment, a direct current pulse discharge test was conducted on the battery, with the following experimental stages:

(1) Using the direct current direct current charging method to charge the battery, SOC=100%.

(2) Discharge the battery at 0.5c (1A) until the battery SOC decreases by 10%.

(3) After discharge, keep the battery static for 2 hours.

(4) Repeat steps (2) and (3) until the battery SOC=0 or reaches the discharge cut-off voltage, and then complete the experiment.

The experimental results are shown in Figure 2[5].

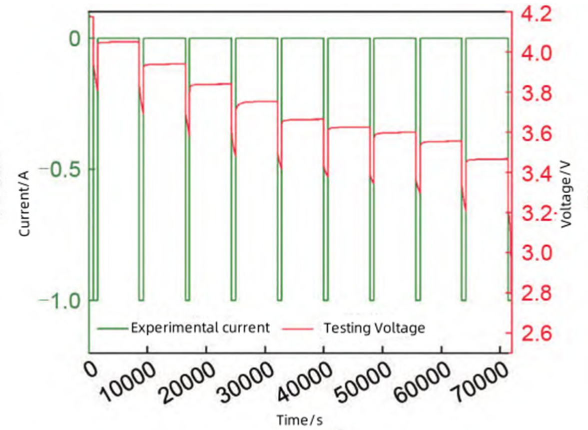

Figure 2. Changes in current and voltage during constant current pulse discharge.

Figure 3 shows the voltage and current variation curve of a lithium-ion battery during a discharge process, with the start and end times of pulse discharge marked as point A and point C, respectively.

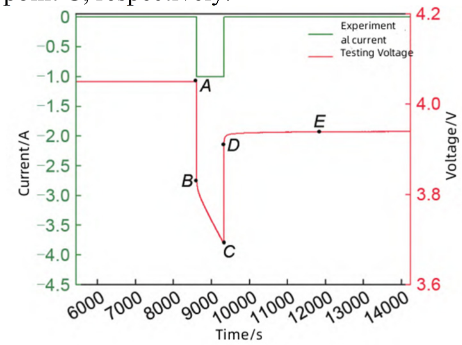

Figure 3. Partial magnification of pulse discharge.

3.Parameter identification algorithm

3.1. Composite Evolutionary Algorithm (CCE)

Step 1: Given q、α、β The initial value. Among them, q represents the number of sub complexes, α represents the number of iterations of the offspring, β represents the number of evolutions of each complex, and each parameter value must satisfy the constraint conditions 2 ≤ q ≤ m, α ≥ 1, and β ≥ 1.

Step2: For each complex A_k Assign weight values according to the probability distribution of triangles $p_i = \{2(m+1-i)/m(m+1)\}$, answer $i = 1,\dots,m$ drop x_1^k The probability value is the highest, which is $p_1 = 2/(m+1)$ .drop x_m^k The probability value is the smallest, which is $p_m = 2/\{m(m+1)\}$.

Step3：Using the probability distribution of triangles to extract from complexes A_k Randomly select q points in the middle $u_i,\dots,u_q$ Form a subcomplex. Then store q vertices and their relative positions in an array $B = \{(u_i, v_i), i = 1,\dots,q\}$ Among them, L v_i It's a point u_i The function value.

Step 4: Evolution of sub complexes composed of q points:

1) Sort arrays B and L so that q vertices are arranged in ascending order of function values. And through the formula $g = [1/(q-1)]\sum_{j=1}^{q-1} u_j$ Calculate the center position of the parent vertex.

2) Calculate new vertices $r = 2g - u_q$, Where r is the vertex U_q The symmetric mapping point for the center position g is U_q Corresponding reflection points.

3) If vertex r is in the feasible solution space H, calculate the function value f_z , And go to 4); Otherwise,

the calculation contains A_k The smallest hypercube $H \in R^n$, Randomly generate a point z in the cube and calculate its function value f_z, make $r = z$, And set $f_r = f_z$.

4) If $f_c < f_q$, Replace with point r U_q, Go to 6); Otherwise, construct a new point c, so that $c = 0.5(q + u_q)$, C is a point U_q Corresponding contraction point. Then calculate f_c.

5) If $f_c < f_q$, Replace with point c U_q, Go to 6); Otherwise, randomly generate a point z in H, calculate f_z, Replace with point z U_q.

6) Repeat 1) to 5) alpha times.

Step 5: Replace the corresponding parent in array B with the generated child. Reorder in ascending order of function values.

Step 6: Repeat steps 2 to 6 β times.

3.2. Identification results of lithium-ion battery parameters

The constant current discharge test dataset is used for parameter identification of lithium-ion battery models. The complete voltage and current curves of the test dataset are shown in Figure 4. The steps of the test are described as follows: first, charge the battery to a voltage of 4.2V using a 1C rate constant current (1C rate refers to the battery taking 1 hour to fully discharge), and then switch to constant voltage charging. Secondly, when the charging current drops to 0.01C, discharge it at a constant rate of C/20 to a voltage of 2.5V. Finally, charge the battery to 4.2V at a constant C/20 rate.

The identification process uses this algorithm for lithium-ion battery parameter identification. When the number of iterations of this algorithm reaches the set objective function value (5000 times), the iteration is terminated. The corresponding SOC values are obtained sequentially U_{oc}、R_0、R_1、C_1、R_2、C_2 Optimal parameters. Substitute the optimal parameters into the equivalent circuit model to obtain the simulated voltage of the model (U_{ISCE}) Test voltage (U_{real}) The comparative data is shown in Figure 5[6].

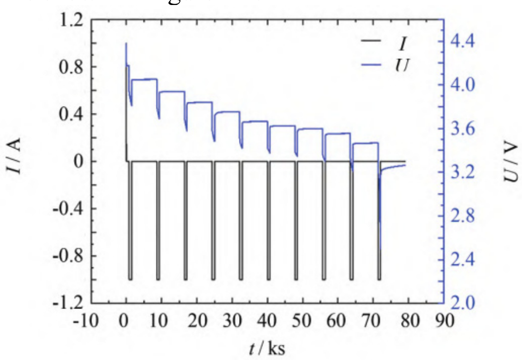

Figure 4. Voltage and current curve of complete operating condition test.

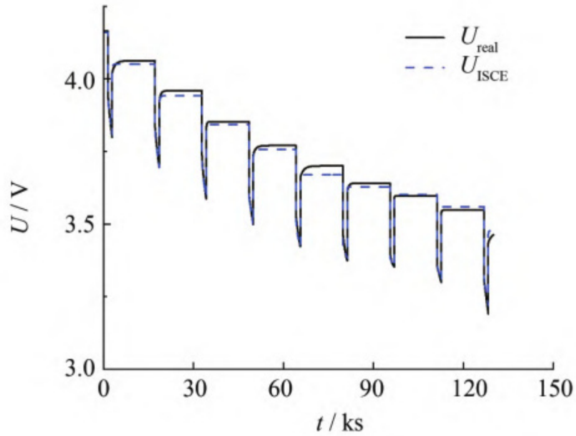

Figure 5. Improved SCE algorithm simulation voltage and test voltage.

Due to the fact that lithium-ion batteries generally cannot be fully charged and discharged during use, and lower SOC values can result in inaccurate open circuit voltages, SOC values ranging from 0.1 to 0.9 were selected to identify parameter results, as shown in Table 2

Table 2. Identification Results of Lithium ion Battery Model Parameters.

SOC	U/V	R_1/0	C_2/F	C_1/F	R_2/0	R_0/0
0.1	3.4671	0.0043	100.0000	7.6487	0.006.6	0.245
0.2	3.5550	0.0092	69.7499	6.5228	0.0058	0.240
0.3	3.5997	0.0072	57.2662	6.1381	0.0067	0.235
0.4	3.6260	0.0043	59.407.0	6.1143	0.0047	0.235
0.5	3.6647	0.0034	43.4993	6.1143	0.006.0	0.235
0.6	3.753.5	0.0212	41.0336	10.0000	0.0101	0.235
0.7	3.8399	0.0052	57.1821	4.7875	0.0047	0.240
0.8	3.939.8	0.0228	36.8641	0.8275	0.0059	0.220
0.9	4.0500	0.0174	31.5260	0.7727	0.0051	0.220

4. Experimental results and analysis

4.1. Experimental setup

Choose a ternary lithium battery (INR18650-20) for experimental verification, with a nominal capacity of 2000mA · h; The standard voltage is 3.60V; The discharge termination voltage is 2.75V; Charging termination voltage 4.2V.

4.2. Evaluation indicators

Select root mean square error (E_{RMS}), maximum error $(E_{\max})$ And cumulative error (E_{acc}) As a model evaluation indicator, i.e

$$\begin{cases} E_{RMS} = \sqrt{\dfrac{1}{N}\sum_{k=1}^{n}\left[Y_k - y_k\right]^2} \\ E_{\max} = \left|Y_k - y_k\right| \\ E_{acc} = \sum_{k=1}^{n}\left|Y_k - y_k\right| \end{cases} \tag{2}$$

In the formula: E_{RMS} It is used to measure the degree of deviation between real values and simulated values; N represents the length of the data; K represents the current time; Y_k Representing the simulated terminal voltage of the model; y_k Indicate the true voltage value of the battery testing terminal; $E_{\max}$ Can reflect the stability of real and simulated values; E_{acc} Can more accurately reflect the actual error size of sample points and avoid mutual cancellation of errors[7].

4.3. Result Analysis

According to the data in Table 3, the average ERMS of this algorithm is 0.0166V, which is 7.8%, 8.3%, and 14.9% lower than the other three algorithms, respectively. Similarly, the average cumulative error of this algorithm is 68.2670V, which is 10.7%, 14.4%, and 23.03% lower than the other three algorithms, respectively. The above data indicates that this algorithm can effectively improve the accuracy of parameter identification and obtain more accurate equivalent circuit models[8].

Table 3. Comparison of Accuracy of Multiple Algorithms on the Test Set.

data set	algorithm	evaluating indicator		
		E_{acc}	E_{RMS}	$E_{\max}$
FUDS	PSO	112.840	0.0249	0.361
	GWO	114.070	0.0241	0.345
	GA	121.745	0.0252	0.350
	This algorithm	97.890	0.0220	0.346
Constant current discharge	PS0	63.862	0.0119	0.250
	GWO	66.495	0.0124	0.265
	GA	95.420	0.0175	0.277
	This algorithm	33.267	0.0063	0.225
DST	PSO	77.155	0.0217	0.952
	GWO	93.210	0.0225	0.955
	GA	110.240	0.0247	0.930
	This algorithm	73.645		0.413

5. Summary

The results showed that the ERMS algorithm decreased by an average of 10.3%, and the cumulative error decreased by an average of 16.04%. In summary, this algorithm can accurately determine the parameters of lithium-ion batteries, ensuring the safe and reliable operation of electric vehicle battery management systems.

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