

Comprehensive evaluation of cells inconsistency in Lithium-ion battery module

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ABSTRACT

To explore the relevance of battery inconsistency parameters and evaluate the cells inconsistency in Lithium-ion battery module. A comprehensive evaluation method of cells inconsistency in Lithium-ion battery module is proposed. Experimental tests for 8 series battery cells have been carried out to obtain the inconsistency data including internal resistance, voltage, capacity. An inconsistency evaluation model taking internal resistance, voltage and capacity as the inputs is established by using the information entropy-grey relational analysis (GRA). The inconsistency of 8 series lithium-ion cells is comprehensively evaluated by the proposed model under the conditions of accelerated aging experiment at 25 °C and 3C rate. The results show that the proposed method can evaluate the cells inconsistency and identify cells inconsistency feature distribution.

Keywords: Lithium-ion battery, battery inconsistency evaluation, grey relational analysis (GRA), information entropy

1. INTRODUCTION

Battery module is usually composed of hundreds of lithium-ion batteries in series and/or in parallel to provide enough capacity and voltage [1-3]. However, the slight differences during the manufacturing process of the battery lead to the inconsistency of the capacity, internal resistance and voltage. With the increase of cycling times continued to deteriorate, the battery safety and life are seriously affected. At present, many studies have been carried out on battery inconsistency from different dimensions. Baumhoefer et al. [4] tested 48 lithium batteries for cyclic aging, and the result showed that the life of the worst battery was only three quarters of the best battery. Jin et al. [5] used 12 series $LiMn_2O_4$

batteries for accelerated life test, and the inconsistency of battery voltage was statistically analyzed. Zheng et al. [6] proposed a method based on discrete wavelet transform to evaluate the voltage inconsistency of battery module. Ouyang et al. [7] developed a mean difference model to separately evaluate the consistency of battery internal resistance and state-of-charge (SOC).

Many battery inconsistency evaluation researches have been reported. But most of them have described the battery inconsistency from a single feature, such as, only from voltage or SOC, which is difficult to characterize the inconsistency of battery module in multi-dimension. To make up for the above shortage, an inconsistency evaluation model with multi-dimensional features is established by using the information entropy-grey relational analysis (GRA). The rest of the paper is organized as follows. A total of 180 charge and discharge cycle tests for 8 series lithium-ion cells at 25 °C and 3C rate is carried out, and the inconsistency change trend in different cycle life of cells is analyzed in Section 2. Section 3 establishes an inconsistency evaluation model via GRA for 8 series lithium-ion cells to quantitatively evaluate and identify the distribution of cells inconsistency in multi-dimension. Finally, the conclusions are summarized.

2. TEST AND ANALYSIS OF BATTERY INCONSISTENCY VARIATION

2.1 Experimental test

To obtain multi-dimensional inconsistency parameters during charge and discharge stages, 8 lithium-ion cells of 18650 with rated capacity of 3000 mAh and rated voltage of 4.2 V connected in series are evaluated. The charge and discharge test of 8 series cells is carried out at 25 °C and 3C rate. A total of 180 cycle tests are carried out. The charge and discharge capacity

of each cell was measured in every 30 cycles of measuring the internal resistance of each cell in every 10 cycles. The battery test platform and test process are shown in Fig.1.

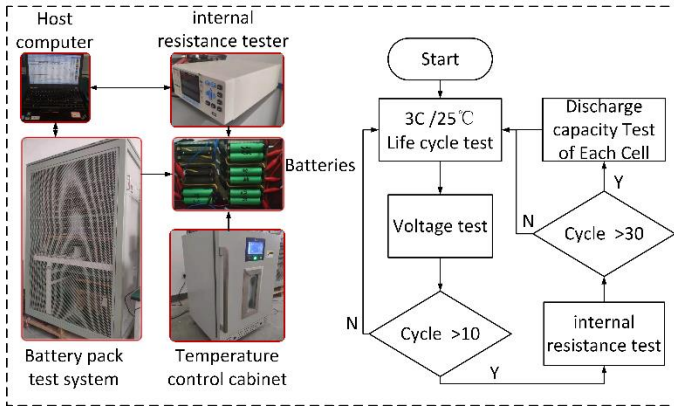


Fig. 1. Battery test platform and test process.

2.2 Analysis of battery inconsistency change trend

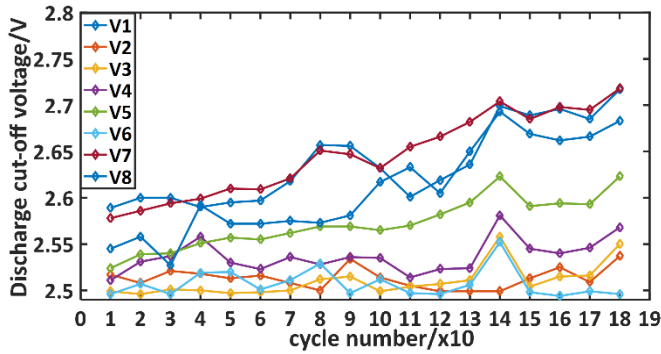


Fig. 2. Change trend of voltage inconsistency.

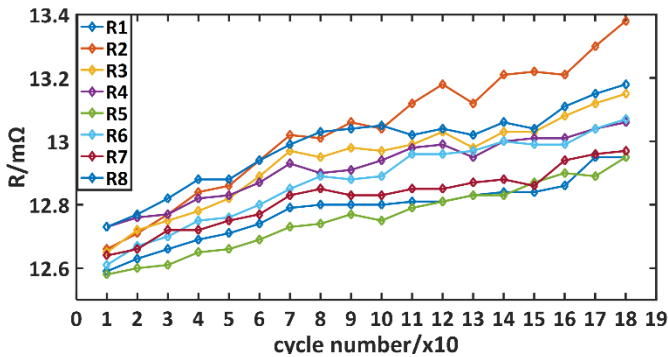


Fig. 3. Change trend of internal resistance inconsistency.

The change trend of the battery inconsistency of the cut-off voltage and the internal resistance during the test progress are shown in Fig.2 and Fig.3, respectively. Except that the cell reaches the discharge cut-off voltage first, the discharge capacity of other batteries is not fully

utilized. The internal resistance shows a collective upward trend during the test progress. After 180 charge and discharge test cycles, the voltage range increases from 0.075 V to 0.236 V, and the internal resistance range of the cells increases from 0.13 mΩ to 0.39 mΩ. The inconsistency of voltage and internal resistance increases by about 3 times. On the one hand, there are differences in internal resistance of cells during the test progress lead to drop inconsistent of the voltage, resulting in an increase in voltage inconsistency between the cells. Moreover, the increase in the power consumption of the internal resistance causes the temperature inconsistency in cells. The increase in temperature inconsistency may aggravate the inconsistency of voltage.

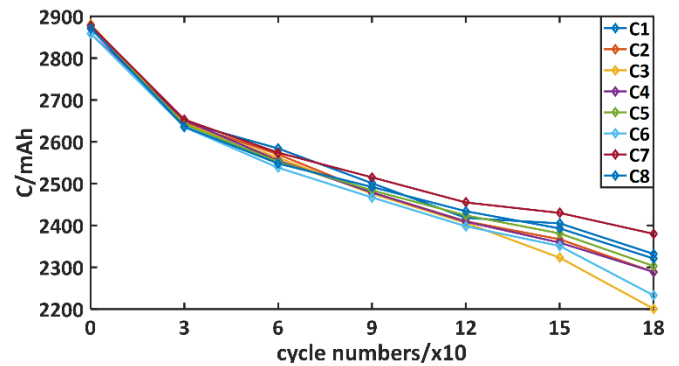


Fig. 4. Change trend of discharge capacity inconsistency.

With the increase of cycle times, the discharge capacity of each cell shows a rapid decline trend in Fig.4. Due to the influence of the cumulative effect of inconsistency, the capacity range increases from the 22 mAh to 107 mAh after 150 charge and discharge test cycles. The available capacity of the 8 batteries in series is lower than 80% of the rated capacity. However, the minimum charging capacity of all cells is 2428 mAh.

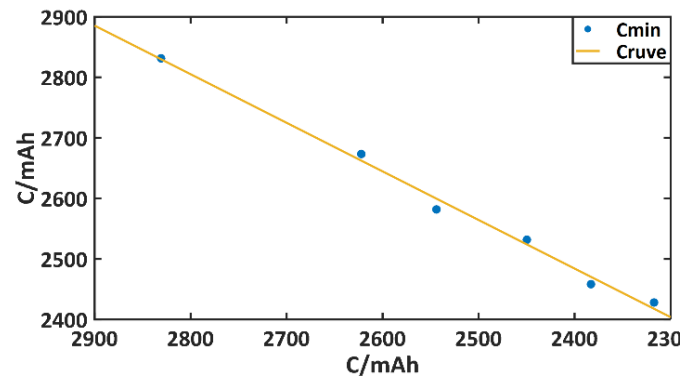


Fig. 5. Fitting curve of the capacity.

Accordingly, the discharge capacity of the batteries in series and the cell with minimum charging capacity are fitted and analyzed. The fitting curve is shown in Fig.5, and the fitting equation is shown in Equation (1):

$$C = 0.8026C_{\min} + 557.8 \quad (1)$$

where C is the discharge capacity of 8 cells in series, and C_{\min} is the capacity of the cell with the minimum charging capacity of all cells.

Due to the influence of uncertain factors, such as charge and discharge efficiency, the discharge capacity of the 8 cells in series is determined by the cell with the minimum capacity. Therefore, to maximize the capacity utilization of battery module, it is necessary to comprehensively evaluate inconsistency of cells and timely identify the outlier cells.

3. BATTERY INCONSISTENCY EVALUATION BASED ON INFORMATION ENTROPY-GRA

The statistical average of the self-information $I(x_i)$ of each random event represents the overall information of the system:

$$\begin{cases} I(x_i) = 1 / \log p(x_i) \\ E_p I(x_i) = C \sum_{i=1}^n p(x_i) \cdot I(x_i) = -C \sum_{i=1}^n p(x_i) \cdot \log p(x_i) \end{cases} \quad (2)$$

Then the information entropy of the system can be defined as:

$$H(x) = -C \sum_{i=1}^n p(x_i) \cdot \log p(x_i) \quad (3)$$

where K is a constant, and $p(x_i)$ is the probability of occurrence of x .

It can be seen from the derivation formula of information entropy that the higher degree of chaos of the system makes the entropy value be larger, and vice versa. The GRA is used as a quantitative description and the comparison of the development trend for several data sequence curves has been implemented.

Here 8 lithium-ion batteries of 18650 with the rate capacity of 3000 mAh in series are taken as the evaluation object. The experiment data, such as the terminal voltage when battery module discharge is cut off, internal resistance and discharge capacity of each cell are taken as the evaluation indicators.

Firstly, by calculating the average value of the evaluation indicators of each cell in different cycle life during the test process, the original comparison matrix of the evaluation indicators and the reference matrix are constructed. To eliminate the influence of the unit, the original comparison matrix and the reference matrix are

normalized to obtain a normalized matrix. The results are shown by Equation (4).

$$\begin{cases} X = (x_{ij})_{n \times k} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \\ X_{0j} = [x_{01} \quad \cdots \quad x_{0k}] \end{cases} \quad (4)$$

where n represents the number of cells; k represents the number of evaluation indicators; x_{ij} represents the j -th evaluation indicators value of the i -th cell; and x_{0j} represents the reference value of the j -th evaluation indicators.

Normalized matrix is used to calculate the information entropy of the inconsistency evaluation indicators with different cycle life states. The entropy is used to determine the weight of each evaluation indicator in battery inconsistency evaluation process.

$$\begin{cases} p_{ij} = x_{ij} / \sum_{i=1}^n x_{ij} \\ e_j = -(1 / \ln n) \sum_{i=1}^n p_{ij} \ln p_{ij}, j = 1, 2, \cdots, k \\ w_j = \frac{1 - e_j}{k - \sum_{j=1}^k (1 - e_j)}, j = 1, 2, \cdots, k \\ W = [w_1 \quad \cdots \quad w_k] \end{cases} \quad (5)$$

where k is the number of evaluation indicators; e_j is the information entropy of the j -th evaluation indicators, and its value range is $[0,1]$; Note that when $p_{ij}=0$, $p_{ij} \ln p_{ij}=0$; w_j is the weight of the j -th evaluation indicators.

The evaluation process of cells inconsistency is improved on the basis of the GRA. The concept of deviation coefficient ζ_{ij} is introduced, and its physical meaning is the deviation coefficient between the evaluation indicators and reference indicators value. The higher deviation coefficient value reveals a worse consistency of the evaluation indicators. The gray correlation model is as follows:

$$\zeta_{ij} = \pm 1 - \frac{\min_i \min_j |X_{0j}^* - X_{ij}^*| + \rho \max_i \max_j |X_{0j}^* - X_{ij}^*|}{|X_{0j}^* - X_{ij}^*| + \rho \max_i \max_j |X_{0j}^* - X_{ij}^*|} \quad (6)$$

where ρ is the resolution coefficient, and ρ is usually 0.5; ζ_{ij} is the deviation coefficient.

Finally, the coupling relationship of the multi-dimensional inconsistency parameters of the 8 cells in series at different cycle life states is obtained.

$$\begin{cases} R_i = w_1 \times \xi_C + w_2 \times \xi_R + w_3 \times \xi_V \\ R = E \times W \end{cases} \quad (7)$$

where R_i is the deviation of the consistency of the evaluated cell from the reference cell; R is deviation matrix, W is weight matrix; E is deviation coefficient matrix.

The proposed evaluation method is verified with the test data including internal resistance, voltage and capacity. The evaluation results of 8 cells inconsistency variation are shown in Table 1.

Table 1 Consistency deviation of 8 cells in series.

	Initial state	60 cycle	120 cycle	180 cycle
Cell ₁	0.1449	0.4046	0.3194	0.5405
Cell ₂	0.1755	-0.2146	-0.5037	-0.5012
Cell ₃	0.0362	-0.2728	-0.4071	-0.3864
Cell ₄	-0.2205	-0.2027	-0.3205	-0.1546
Cell ₅	-0.2290	0.1305	0.3253	0.2126
Cell ₆	-0.1629	-0.2476	-0.3356	-0.4132
Cell ₇	0.1825	0.4341	0.5633	0.5736
Cell ₈	0.0104	-0.2039	0.2209	0.1415
Range	0.4115	0.7069	1.0671	1.0748
ε_z	0.1634	0.2806	0.3883	0.4002

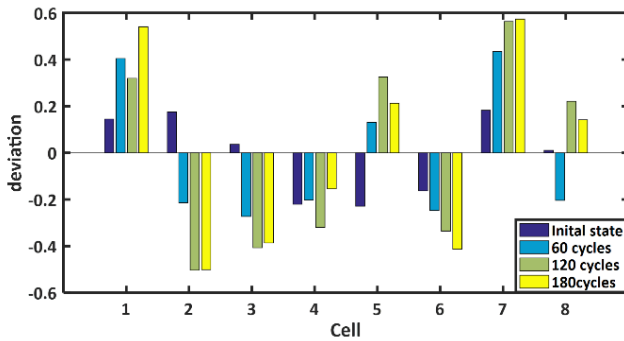


Fig. 6. Column diagram of consistency deviation

The distribution characteristics of 8 cells inconsistency are shown in Fig.6. In initial state, most of the battery consistency deviation is between $\pm 10\%$ - 20% . With the accelerated aging test, the consistency of the battery module significantly worsened, and the distribution interval increased to 10% - 60% , and the standard deviation increased from about 16% to about 40% . According to Fig.6, abnormal batteries with large deviations can be identified, and the batteries can be replaced or the information can be transmitted to the battery management system (BMS) to provide an effective basis for the BMS to make decisions about battery module balancing or other management approaches.

4. CONCLUSION

The charge and discharge tests for 8 series lithium-ion cells at 25°C and 3C rate are carried out, and the multi-dimensional inconsistency variation in different cycle of cells is analyzed. An inconsistency evaluation model taking internal resistance, voltage, capacity as the inputs and consistency deviation as the outputs is established by using the information entropy-grey relational analysis (GRA) to evaluate the inconsistency of 8 series lithium-ion cells. The results showed that the proposed method realized quantitative evaluation on multi-dimensional inconsistency of cells and identified cells inconsistency feature distribution.

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