International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: ID # 752

STATE-OF-HEALTH ESTIMATION OF LITHIUM-ION BATTERY BASED ON GREY RELATIONAL ANALYSIS METHOD

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ABSTRACT

Lithium-ion battery state-of-health estimation plays an important role in battery management system in electric vehicles. Here, we report a novel method for battery state-of-health estimation through grey relational analysis with entropy weight method. Firstly, an interpolation method is proposed to obtain the differential voltage curves. Then health performance indicators are extracted from the partial differential voltage curve considering the inflection points. Secondly, the evaluation indexes are proposed by using entropy weight method to evaluate the significance of health performance indicators in the partial differential voltage curve. The evaluation indexes of the fresh cycle battery are defined as reference sequence and others as comparative sequences. Then the proposed method to calculate the grey relational degrees between the reference and comparative sequences and the results are applied to analyze battery health condition. At last, the corresponding experiment indicates that the proposed method can accurate estimation battery health condition.

Keywords: Lithium-ion battery, state of health, differential voltage curve, grey relational analysis method

1. INTRODUCTION

Lithium-ion batteries have been widely regarded as main power sources of many applications for their high energy density, low self-discharge and long lifetime. However, when the battery is degraded to the end-of-life (EOL), which refers to the available capacity takes up 80% of the rated capacity, it is no longer efficient and economical use in the EVs. It is imperative to estimate the state of health (SOH) of batteries for reliable and safety of EVs [1,2]. Currently, the function of SOH prediction plays an important role in battery management system (BMS) based on two main reasons: On the one hand, the SOH can provide essential data for planning and controlling the EVs during operation process and, on other hand, the parameters can pave the way for fault detection and diagnosis for EVs.

Typically, equation circuit model (ECM) is a primary model for battery SOH estimation by identifying the corresponding parameters during the battery-degraded process [3,4]. In [4], genetic algorithm (GA) and recursive least square (RLS) are used to obtain the internal resistance based on standard ECM. Recently, the incremental capacity analysis (ICA) and differential voltage analysis (DVA) methods are proposed to estimate battery SOH. In [5], during the charging phase, the features of battery degradation are extracted from terminal voltage and DV curve. Then a battery degradation model is built based on the features and SVM algorithm. In [6], based on IC curve, feasibility and accuracy of degradation model is established using Gaussian function and Lorentzian function. The battery SOH estimation is achieved by analysis measured capacity.

In this paper, the partial DV curve is regarded as the evaluation indexes to estimate battery SOH by using grey relational analysis (GRA) with entropy weight method (EWM). The EWM is employed to evaluate the significance of evaluation indexes in the partial DV curve. The evaluation indexes of the first cycle battery are set as reference sequence and others as comparative sequences. Then the reference and comparative sequences are employed to calculate the grey relational degrees for SOH estimation.

2. EXPERIMENTAL PLATFORM AND DATA ANALYSIS

The lithium-ion batteries aging experimental data is obtained from a test bench, which consists of an Arbin battery charging/discharging test system, a thermal chamber, and a host computer for data monitoring and storage. The experimental battery is rated capacity of 5Ah, and normal voltage is 3.3V, with upper and lower cut-off voltages of 4.2 V and 2.5 V, respectively. The test schedule contains 5A constant charging/discharging and

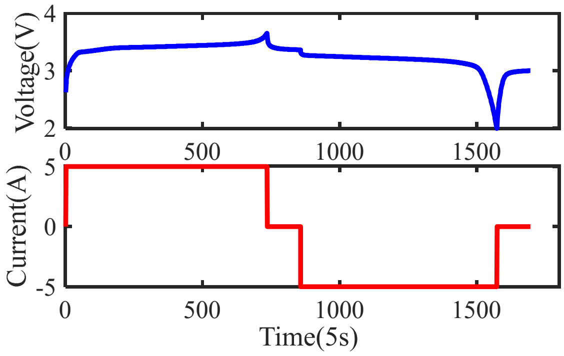

Fig 1 Battery test scheldue

10mins rest. According to the test schedule, the voltage and current profiles are shown in Fig.1 and the battery degraded data is plotted in Fig. 2.

Generally, the DV curves are obtained from the charging process under constant-current region. The charging capacity and voltage can be calculated as follows,

$$Q = It \tag{1}$$

$$V = f(Q), Q = f^{-1}(V) \tag{2}$$

where t is charging time and I refers to charging current. Based on the Eqs. (1), the DV curve can be expressed as follows,

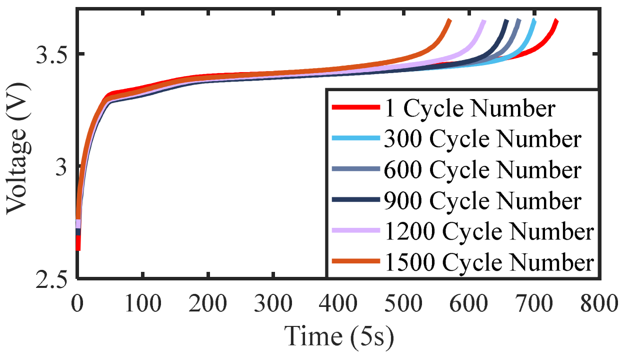

Fig 2 The voltage profiles of degradation battery

$$f' = \frac{dV}{dQ} = \frac{dV}{I \cdot dt} = I \cdot \frac{dV}{dt} \tag{3}$$

To acquire the DV curve with the numerical-derivative method, the Eqs. (3) can be rewritten as follows,

$$\frac{dV_i}{dQ_i} = \frac{f(Q_{i+1}) - f(Q_i)}{\Delta Q} \tag{4}$$

where $Q_i = Q_0 + i \cdot \Delta Q$, $i = 0, 1, 2, 3 \cdots$. Based on the Eq. (4), an interpolation method is applied to obtain the differential voltage (DV) curves through changing the value of the ΔQ . The original DV curves and modified curves are described in Figs. 3 and 4. From Fig. 4, the DV curve keeps moving to the left as the battery degraded. This trend is quite noticeable at capacities range from 4 to 5.3 Ah, hence the partial DV curves are regarded as effective features for battery health indexes.

3. BASIC THEORY OF THE BATTERY HEALTH ESTIMATION

The grey system theory takes advantages of revealing the rules of many things using fewer data and poor information. In the GRA, the basics idea is to find out the closeness of the relationship between system sequences through studying the geometric proximity of the system sequence curves. Generally, the system sequences can be divided into two classifies: comparative sequences and reference sequences. In order to research the degraded condition of battery, the DV curve of the first cycle battery is set as reference sequence and other DV curves are comparative sequences. The closer in shape and shorter in the distance among DV curves between the comparative

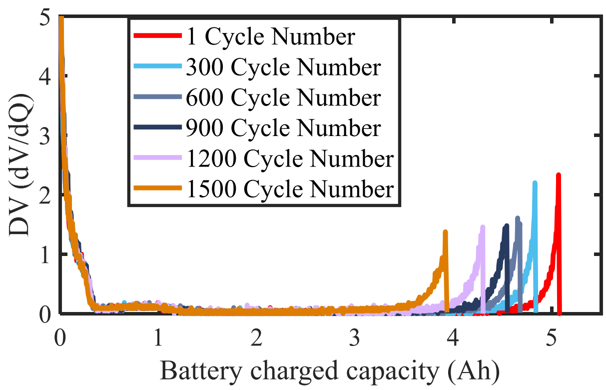

Fig 3 The original DV curves

sequence and reference sequences, the greater the GRG values are. Supposing the batteries' degraded features are expressed as

$$X^* = x_{ij}^* = \begin{bmatrix} x_{11}^* & x_{12}^* & \cdots & x_{1n}^* \\ x_{21}^* & x_{22}^* & \cdots & x_{2n}^* \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1}^* & x_{m1}^* & \cdots & x_{mn}^* \end{bmatrix} \tag{5}$$

where n is the number of indexes and m is the comparative sequence. It's worth noting that the matrix x_{1j}^* is the reference sequence. Then all the system sequences need to be normalized and the features matrix is redefined as follows,

$$r_{ij} = \frac{x_{ij} - \min_i\{x_{ij}\}}{\max_i\{x_{ij}\} - \min_i\{x_{ij}\}} \tag{6}$$

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{7}$$

The grey relational coefficient can be calculated as follows,

$$\gamma(x_{1j}, x_{i,j}) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{ij} + \zeta\Delta_{\max}} \tag{8}$$

$$for \quad i = 2,3,4\cdots m;\, j = 1,2,3\cdots n.$$

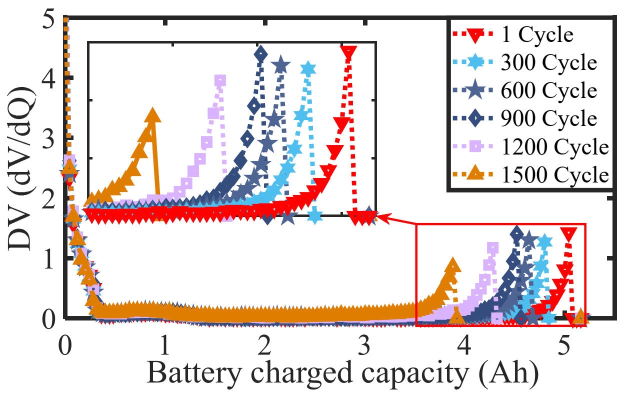

Fig 4 Interpolation method modified DV curves

$$\Delta_{ij} = \left|x_{1j} - x_{ij}\right|,$$
$$\Delta_{\min} = \min\{\Delta_{i,j}, i = 2,3\cdots m;\, j = 1,2\cdots n\}, \tag{9}$$
$$\Delta_{\max} = \max\{\Delta_{i,j}, i = 2,3\cdots m;\, j = 1,2\cdots n\}$$

where ζ is the distinguishing coefficient and the range from 0 to 1, which is used to control the range of grey relational coefficient. The grey relational degree can be obtained by the weighted relational grade,

$$r_{i-1}^W = \sum_{j=1}^{n} w_j \gamma(x_{1j}, x_{i,j}) \tag{10}$$

where w_j is the weights factors for the corresponding index, and $w_j \in (0,1)$. Here, the weighted relational grade is adopted to decide the weights of comparative sequences and taking the advantages of entropy weight method to choose the proper weights. The weights calculation processes contain two steps in initial procedure: (1) Collect individual evaluation indexes and construct a set of decision matrices; (2) Normalization. Here, the Eqs. (7) is used as the standardization of indexes for entropy weight method. And the residual calculation steps as follows

Step 1: Calculation of the index's entropy

$$H_j = -\frac{\sum_{i=1}^{m} f_{ij} \ln f_{ij}}{\ln m} \tag{11}$$

$$f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \tag{12}$$

Step 2: Calculation of the index's entropy weight

$$w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}, \sum_{j=1}^{n} w_j = 1 \tag{13}$$

According to the health performance indicators (HPIs) of partial DV curves, the EWM is employed to evaluate the significance of evaluation indexes in the partial DV curve. Then the GRA method is applied to predict the degraded degree for different cycles' battery.

4. RESULTS AND DISCUSSION

To validate the method of SOH estimation above mention, in this section, six datasets are extracted from battery aging experiment interval at 300 cycles. The degraded features are extracted from partial DV curve from 4 to 5.3Ah. The HPIs of the partial DV curves are plotted in Fig. 5. From the Fig. 5, the partial DV curve of the fresh battery is on the far right. In this study, the fresh battery is regarded as reference sequence. With more and more cycles of the battery, the DV curves constantly move to the left and those sequences are comparative sequences. For the battery health estimation, ten indexes are chosen from the HPIs of each cycle and the indexes are weighted by using entropy weight method. The weights of different indexes are presented in Fig. 6. The purpose of weighs is to make a greater weight on the unobvious indicator, the salient features to give a small weight so that all the indexes are

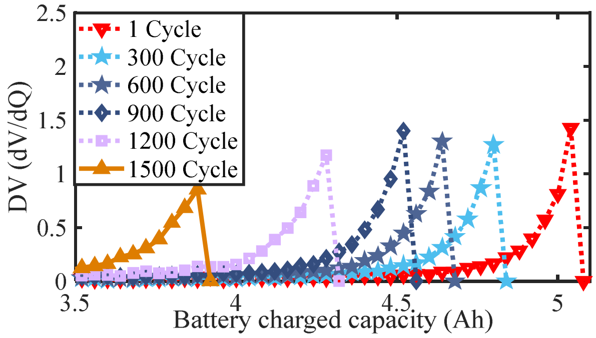

Fig 5 The health performance indicators (HPIs) of partial DV curves

meaningful. From the Fig. 6, the smaller weight is corresponding to the most remarkable feature.

Based on the entropy weight for battery health indicators, the GRA is applied to predict the battery SOH.

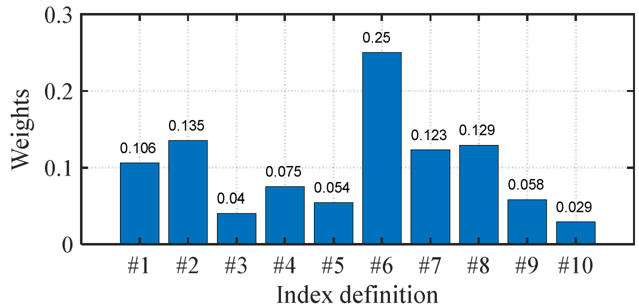

Fig 6 The values of entropy weight method

The SOH of battery should be defined as follows,

$$SOH = \frac{C_{avi}}{C_{rated}} \tag{14}$$

where C_{rated} is rated capacity of battery and C_{avi} is the current available capacity of battery. In Fig. 7, the reference SOH is calculated according to Eq. (14). The maximum error is 1.5% between the reference and estimation SOH. With the battery aging, SOH estimation error is getting smaller and smaller. The experimental validation indicates that the novel method can accurately estimate the battery health status.

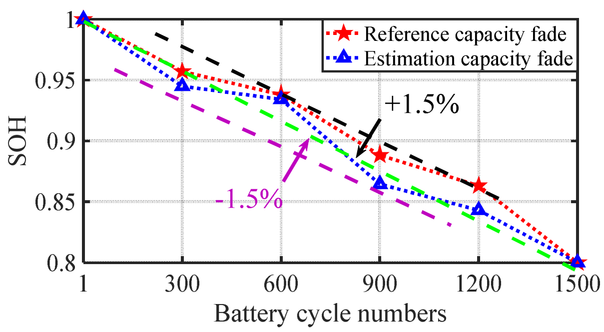

Fig 7 The battery SOH estimation and error analysis

5. CONCLUSION

In this work, the health status of lithium-ion battery has been investigated. For achieving accurate and convenient estimation, the main works can be summarized. (1) In considering that battery degradation is a correlation with the differential voltage (DV) curve, the partial DV curves for battery SOH estimation is proposed at first. (2) Given that the partial DV curve, a novel method is applied to estimate battery SOH based on the health performance indicators (HPIs) that are extracted from the partial DV curve. (3) The grey relational analysis (GRA) with entropy weight method (EWM) is employed to identify the differences between evaluation indexes and the EWM is applied to evaluate the significance of each evaluation index. Future works will focus on testing under different operating conditions and implement the method within an actual BMS.

ACKNOWLEDGEMENT

This work was supported by the State Key Program of National Natural Science Foundation of China [grant number U1564206].

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