Diagnostic Analysis and Research on Battery Health Status of Electric Vehicles

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Abstract. With the rapid development of electric vehicles, the attenuation problem of high-specific energy lithium-ion batteries has been paid more and more attention. Its health state is the core parameter of durability management, which is crucial to prolong battery life and improve system reliability. Aiming at the safety and power performance of power battery in the operation of electric vehicles, the kalman filter method was combined with battery charge-discharge curve identification, and the battery health (SOH) diagnosis method based on online testing platform was proposed. The results show that the battery health state can be estimated by the change of internal resistance of the battery model, and the absolute error is not more than 3%, and with the improvement of the model accuracy, the estimation of the battery health state becomes more accurate.

Keywords: Electric vehicle battery, Battery model, Parameter identification, A healthy state.

1. Introduction
In recent years, lithium-ion battery, as a new energy storage device with long life, high specific energy/specific power and environmental protection, has been applied in various fields by large-scale commercialization, especially in the field of electric vehicles. At present, it has replaced the traditional lead-acid battery as the mainstream. With the growth of the lithium battery industry, the battery management system (BMS) also develops rapidly. The basic functions of the battery management system include data acquisition, battery status estimation, charge and discharge management, battery balance and thermal management, etc. The health of the battery is estimated with the recent frequent recalls of laptop computers and electric cars getting more and more attention. Although lithium-ion batteries are generally considered to have a long life, they are also limited by environmental factors and operating conditions. Therefore, it is of great significance to study the battery health state in the commercial field, especially in the application of electric vehicles.

Battery system attenuation mechanism of monomer battery, the randomness of aging, its external characteristic performance also presents diversity, for complex on-board application under the condition of lithium ion battery capacity estimation problem, according to determine whether there is a mathematical expression, the researchers proposed health state estimation method can be summarized as two classes: model driven method and data driven method, the model driven method to establish the battery capacity and cyclic number or to determine the relationship between throughput capacity, the
mathematic expression of the data driven method is not clearly defined, use a large amount of data to construct the approximate relationship between estimated battery capacity [1]. According to the voltage recording data of ev parking time before and after use, the corresponding battery SOC was calculated backward, and the battery capacity was estimated by combining the accumulative capacity throughput value recorded by on-board BMS in the SOC interval. Although the invariance of the mapping relation of battery EMF-SOC is applicable to some lithium-ion batteries, the establishment of this method has strict requirements on the running trajectory of electric vehicles, especially the parking stage, that is, the parking behaviour must exist before and after the vehicle running, and the time length should meet the requirements of acquiring battery EMF.

To sum up, the equivalent circuit model of batteries can accurately and effectively represent the characteristics of batteries. Therefore, this paper intends to use the model method to estimate the health status of batteries based on the equivalent circuit model of lithium-ion batteries. Different models of lithium-ion battery are analysed and the corresponding model parameter identification method is proposed [2]. The proposed model and parameter identification method were used to estimate the health status of lithium-ion batteries and the results were verified by experiments.

2. Lithium-ion battery model

Considering that there are many equivalent circuit models for lithium-ion batteries, three battery models with different accuracy are selected for analysis in this paper, including first-order RC(1-RC) model, second-order RC(2-RC) model and fractional impedance model.

2.1. Lithium-ion battery 1-RC model

The 1-RC equivalent circuit model of lithium ion battery is shown in Figure 1, where: \( V_{ocv} \) is the battery open-circuit voltage, \( V \); \( R_{oc} \) to battery ohm internal resistance, \( \Omega \); \( V_{so} \) is the operating voltage of the battery, \( V \); \( I \) is the operating current of the battery, mA; \( R_{1}, C_{1}, V' \) is respectively the resistance, capacitance and partial voltage of the 1-RC loop. According to the circuit theory, assuming that the current \( I \) is positive when the battery is discharging, the 1-RC equivalent circuit model can be expressed as:

\[
\begin{align*}
\dot{x}' &= A x + B I \\
y &= C x + D I
\end{align*}
\]

Where, \( A = [1/R_{1}], B = [1/C_{1}], C = -1, D = [-R_{oc}], x = [V_{1}], y = [V_{0} - V_{ocv}] \). The recursive least squares (RLS) algorithm can be used for parameter identification.

![Figure 1. 1-RC equivalent circuit model](image)
2.2. Lithium-ion battery 2-RC model
The 2-RC equivalent circuit model of lithium-ion battery is shown in Figure 2, where: \( R_2, C_2, V_2 \) is respectively the resistance, capacitance and partial voltage of the 2-RC circuit. Assuming that the current \( I \) when the battery is discharging is positive, according to the circuit theory, the 2-RC equivalent circuit model can be expressed as:

\[
\begin{align*}
A &= \begin{bmatrix} 1/R_1 & 0 \\ 0 & 1/R_2 \end{bmatrix}, \\
B &= \begin{bmatrix} 1/C_1 \\ 1/C_2 \end{bmatrix}, \\
C &= \begin{bmatrix} -1 & -1 \end{bmatrix}, \\
D &= \begin{bmatrix} -V_{soc} \end{bmatrix}, \\
x &= \begin{bmatrix} V_1 \\ V_2 \end{bmatrix}.
\end{align*}
\]

\[
\begin{align*}
x' &= Axx + BxI, \\
y &= Cxx + DxI.
\end{align*}
\] (2)

Among them, \( A = \begin{bmatrix} 1/R_1 & 0 \\ 0 & 1/R_2 \end{bmatrix} \), \( B = \begin{bmatrix} 1/C_1 \\ 1/C_2 \end{bmatrix} \), \( C = \begin{bmatrix} -1 & -1 \end{bmatrix} \), \( D = \begin{bmatrix} -V_{soc} \end{bmatrix} \), \( x = \begin{bmatrix} V_1 \\ V_2 \end{bmatrix} \).

2.3. Fractional impedance model of lithium-ion battery
The fractional impedance model (FIM) of lithium-ion battery is shown in FIG. 3, where \( R_1-CCPE1 \) is a resistor - constant phase Angle element parallel combination 1, which is used to represent the concentration polarization phenomenon of the battery. \( R_2-ccpe2 \) is a parallel combination of resistance-constant phase Angle elements 2, which is used to characterize the activation polarization of the battery [3]. According to the circuit principle and fractional order definition, the equivalent circuit of fractional impedance model can be expressed as:

\[
\begin{align*}
V_0 &= V_{soc} - V_{soc} - V_1 - V_2 \\
V_{soc} &= R_{soc}I \\
I &= C_1\Delta V_1 + V_1/R_1 + C_2\Delta V_2 + V_2/R_2.
\end{align*}
\] (3)

Where, \( V_1 \) is the internal resistance partial pressure of battery concentration polarization, \( V_2 \); \( \alpha \) is the fractional order of battery concentration polarization; \( V_2 \) is the partial pressure of battery activation...
polarisation, $V$; $\beta$ is the fractional order of battery activation polarization; $\Delta^\alpha$ represents the operation of fractional order is $\alpha$; $\Delta^\beta$ is for operations of fractional order $\beta$.

3. Power battery health status diagnosis

3.1. Charge and discharge test

In this paper, the charging and discharging test of lithium-ion battery is conducted with Aero Virement’s ABC-150 dual-channel, returnable test equipment. Due to its 450V/150A charging and discharging performance, it is often used in the analysis test of electric vehicle charters and batteries. Lithium-ion battery charge and discharge test refers to the test of capacity, internal resistance, open voltage and other characteristics of the battery pack during the charge and discharge process by combining high-power charging and discharging equipment with temperature control box and multi-dimensional vibration table in the laboratory environment [4]. The test object in this paper is the on-board NB-LFP60 lithium iron phosphate battery module. The specific nameplate parameters are shown in Table 1.

| Table 1. Parameters of NB-LFP60 lithium-ion battery |
|--------------------------------------------------|
| Category                        | The parameter value         |
| Individual specifications       | 60 a/V 3.2                  |
| Group norms                     | 1p24s                       |
| Nominal capacity                | 60Ah                        |
| Group voltage                   | 76.8 V                      |
| The body weight                 | 65kg                        |
| Body shape                      | 23 cm * 27 cm * 80 cm       |
| Cycle life                      |                             |
| Charging and discharging        |                             |
| Charging: 18 -75 °C             |
| Discharge: -30 -75 °C           |
| Monomer resistance              | 2 m or less Ω               |

According to QC/T743-2006, if there is no specific test requirement strategy, lithium iron phosphate battery is usually discharged with I3A current at 20°C±5°C. When the battery voltage reaches 2.0V, the battery is stopped and left standing for 1h. Then the battery is charged at 15~25°C with constant current I3A. When the battery voltage reaches 3.65V, the battery is charged at constant voltage. When the charging current drops to 0.1I3a, it stops. It can be seen that the characteristics test of lithium-ion battery is mainly based on the test standards and specific requirements of the test objects, and the deep charging and discharging cycle is conducted in the laboratory environment to obtain process data and characterization parameters, and analyse and evaluate the health status of lithium-ion battery. According to IEEE standard 1188-1996, lithium-ion batteries will be withdrawn from electric vehicles when their capacity is reduced to 80% of the rated value.

3.2. SOH diagnostic test

Under the actual road conditions of electric vehicles, when SOC is less than 20%, the vehicle with deep discharge is easy to run with reduced power or even break down. However, the battery charging and discharging test at both ends of the profit and loss can best reflect its health degree. At the same time, it is difficult to ensure the consistency of test environment in actual road conditions, and it is not easy to install testing instruments. Removing the battery pack from the vehicle for testing may damage the electrical and mechanical properties of the vehicle. Therefore, SOH diagnosis of on-board batteries becomes very difficult [5].

In order to qualitatively analyse the decline of SOH, the CAN communication module is connected to the vehicle control system in this paper, and the upper computer remote control vehicle charging relay is used to separate and close. The battery pack is directly charged and discharged through the DC charging gun, and the BMS information is fed back to the charger to form a control closed loop, so as to realize the SOH information data collection. The specific charge and discharge control topology are shown in Figure 4.

![Figure 4. SOH test topology for electric vehicles](image)

### 4. State diagnosis algorithm

With the rapid development of lithium-ion battery in various fields, the research on battery monomer has been increasingly perfect and mature. In recent years, with more and more attention paid to battery safety, RUL prediction and SOH diagnosis technology have become the hot spots in battery field at home and abroad. At present, the commonly used methods for predicting battery life can be divided into two categories: empirical model and parametric model [6].

#### 4.1. Empirical Model

The empirical model directly predicts the parameters that best reflect the aging of lithium batteries by using a large amount of data, aging mechanism or a combination of the two: capacity attenuation and internal resistance increase. The model based on the Arrhenius equation is the most common empirical model, which is the relationship between the rate constant of chemical reaction and temperature. The experiment describes the variation law of capacity or internal resistance with cycle or time through charge and discharge cycle or storage under specific conditions, and then fits this law into the equation to obtain parameters:

\[
Q_{\text{loss}} = A e^{E_a/RT} t^\varepsilon
\]  

(4)

Where, \(Q_{\text{loss}}\) is the predicted value, which can be area energy ratio impedance (ASI) or attenuation power; \(A\) is a constant; \(E_a\) is the activation energy; \(R\) is the gas constant; \(T\) is the temperature in Fahrenheit; \(t\) is time. Since the cycle is not always fixed, some scholars use Ah as the abscissa instead of time or cycle number.
4.2. Parametric model

Based on the existing battery model, the parameter model can be identified through the optimal state estimation techniques, such as least squares, Kalman filtering and other algorithms, and the current battery health state can be predicted by the change of corresponding parameters. The typical Kalman filtering idea can be represented by the following internal resistance state estimation function:

\[ R_{k+1} = R_k + r_k \]  \hspace{1cm} (5)

\[ y_k = OCV(Z_k) - R_k i_k + e_k \]  \hspace{1cm} (6)

Where: \( R_k \) is the internal resistance of the battery; \( r_k \) represents the change of internal resistance caused by noise; \( y_k \) is the estimated voltage of the battery; \( i_k \) is the working current; \( Z_k \) is the battery SOC, which is used to contact the SOC-OCV relationship. \( e_k \) represents the error of the battery model. It can be seen that the above two methods are more suitable for laboratory and other occasions. The empirical model relies on the fixed cycle mode, while the prediction of the parameter model relies on the accurate SOC-OCV relation. Both of these methods cannot be satisfied under the vehicle working condition, so it is difficult to be applied in practice [7].

5. Experimental simulation

5.1. Verification of non-destructive analysis method for battery aging mode

FIG. 5A shows the fitting results of the proposed improved non-destructive quantitative analysis method for the four OCV-SOC curves of the whole battery in different aging stages, and the fitting curves have a high degree of coincidence with the measured curves. All the curves in FIG. 5A have been converted to the SOC scale of the brand-new battery, which is cycled in the charging and discharging mode of 1CCc-CV charging & 1C constant discharge at the ambient temperature of 25°C. In the aging process, one-time energy test is conducted every 100 cycles. The performance test includes 0.05c constant current charge and discharge test with a small multiplier. It is generally considered that the average voltage curve of constant current charge and discharge with a small multiplier is the OCV curve of the whole battery. In FIG. 5b, the measured OCV curve and the fitted OCV curve were differentiated respectively to obtain the capacity increment curve, which had a high degree of coincidence in IC peak position, peak height and peak width.

Fig.5c and 5d show the voltage error and SOC error between the fitted curve and the measured curve respectively. The maximum voltage error and maximum SOC error are ±15mV and ±2%, respectively, and the square root mean error of voltage and SOC are 4mV and 0.7% respectively. The above results show that the improved method can fit the OCV-SOC curve of different aging stages of the battery life cycle well, and the accuracy can be guaranteed in the non-destructive quantitative analysis of the battery aging mode. Figure 6 is the evolution curve of LLI, LAMNE and LAMPE with cycle times obtained by fitting the oCV-SOC curve of the full battery, including the analysis results of the two sample batteries.
5.2. Battery health state estimation and analysis based on fractional impedance model

The LSGA method was used to identify the internal resistance parameters of FIM, and the obtained ohmic internal resistance of the battery was fitted linearly with the battery health state. The results are shown in FIG. 7.

**Figure 5.** Fitting curve of full battery

**Figure 6.** Results of non-destructive quantitative analysis of battery aging mode
6. Conclusions
For electric car battery module under complicated condition and individual health status is difficult to accurate diagnosis of the status quo, in full review existing monomer diagnostic technology, on the basis of collection of wavelets transform and statistical theory, this paper puts forward a new type of power battery module health diagnosis methods, this method can not only provide the current module's state of health, but also to a judgment module within single cells. At present, the algorithm has been installed in BMS, which has positive significance for improving the stability and safety of the battery system and reducing the maintenance cost.

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