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Life Prediction and Matching Test of Decommissioned Power Battery Based on Energy Storage System

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In this paper, the author researches on the life prediction and matching test of decommissioned power battery based on energy storage system. The practical background of the research on decommissioning batteries was analysed. The research status and development trend of lithium battery prediction at home and abroad are introduced. The research methods of battery quality prediction technology are introduced, especially the utilization and key technology of decommissioned lithium battery in power system. Through the practical application of various prediction techniques, the overall quality of the decommissioned battery (charge state, internal resistance and material deterioration degree, etc.) is finally determined. Thus, the utilization ratio of lithium power battery is further improved.

1. Introduction

In the future, the new energy auto industry focuses on the development of plug - in hybrid electric vehicles, pure electric vehicles and fuel cell vehicles. It is expected that the industrialization of new energy vehicles will be realized in 2020, and the electric vehicles mainly use lithium ion batteries as power sources.

In September 2010, ABB announced the signing of a cooperation agreement with general motors, exploring the possibility of building an economical energy storage system by using Chevrolet Volt's on-board power lithium battery (Soares et al., 2015; Komiyama and Fujii, 2015). In China, China Electric Power Research Institute and the State Grid Electric Power Research Institute and other research institutions for energy storage to carry out a series of studies in the new lithium battery, Byd Co, Amperex Technology Limited, Henan Huanyu Purcell design and manufacturing capacity of energy storage system, but for the retired battery energy storage for electric power system research is still in the demonstration the exploration stage. In the future, electric vehicles will achieve rapid development and popularization (Choi et al., 2016). The cascade utilization of decommissioned batteries is an indispensable part of the healthy and sustainable development of the electric vehicle industry, which can improve the clean development chain of electric vehicles, and has the comprehensive benefits of environment, society and economy. Figure 1 shows the basic map for the decommissioned power battery.

Figure 1: The basic map for the decommissioned power battery

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2. Research method of battery quality prediction technology

The main problems to be solved are the estimation of the state of charge, the estimation of the internal resistance and the estimation of the life span. The residual capacity in order to maximize the decommissioning of lithium battery, the battery itself should consider the performance and external factors should be two aspects, important parameters measuring battery internal resistance, capacity, etc., and according to the battery life attenuation change corresponding relationship with the parameters of the battery, the battery is determined quality.

2.1 Electrochemical impedance spectroscopy (EIS) prediction technique for decommissioned batteries

In recent years, due to the growth of battery industry, many scholars have paid close attention to the state of battery, and developed many battery prediction equipment, and integrated modern control theory, making the prediction equipment more digitalized and automated (Choi et al., 2016).

The electrochemical impedance spectroscopy (EIS) method of EIS is a method of electrochemical measurement with a small amplitude sinusoidal potential (or a current 1 as a disturbing signal. Electrochemical impedance spectroscopy (EIS) is a measurement method in frequency domain. It studies electrode system with wide impedance spectrum obtained from measurement (Smyth et al., 2015).

EIS research method in the prediction of battery technology application in recent years, studies the relationship between different quality battery ohmic resistance and polarization resistance, estimated total battery internal resistance in different stress (temperature, charge and discharge rate) under the influence, to find out the relationship between the internal resistance of battery and battery life. The important electrochemical research method of EIS is introduced into the field of battery prediction. First, the impedance model of lithium battery is deeply analyzed, and the parameter relationship related to the life of lithium battery is found out, which provides a reliable theoretical basis for the life estimation of lithium battery. Secondly, the correct establishment of the model provides a theoretical basis for the prediction of ohmic internal resistance and polarization internal resistance (He et al., 2017).

2.2 Prediction technology of charge state (SOC) of battery

(1) The practical significance of the SOC prediction method. The parameters of Li ion battery all have the characteristics of nonlinearity and time-varying. When the real vehicle is running, the equivalent DC internal resistance, capacity and charge state of the battery will change with the battery life, charge and discharge state and temperature. The on-line estimation of the SOC value of the battery will effectively reduce the overcharge and over discharge of the battery, and the performance of the battery can be fully used. Thus, the reliability of the system is improved, and the maintenance cost in the later period is also greatly reduced.

(2) The integral method to estimate the battery's SOC cannot get good results. The open circuit voltage method is only suitable for off-line prediction of electric vehicles.

(3) Other on-line identification of battery accurate models, such as artificial intelligence, fuzzy control, neural network and other methods to identify the accurate battery models, is to integrate all kinds of factors that affect SOC to the battery model, and improve the accuracy of SOC estimation. At present, most of the results at home and abroad are in the stage of computer simulation results, and there is still a distance from the practical application.

3. Life prediction model and algorithm

(1) The practical significance of life prediction

After battery decommissioning, the life test of lithium battery is a very complex process, because the environment of lithium battery application is constantly changing, and the temperature and discharge system will all affect the life of lithium battery (Lee et al., 2015). Therefore, it is necessary to analyze and predict the life of lithium battery. Based on this background, establishing cycle life model of lithium-ion battery is of practical significance whether it is further perfected in performance research or reliability life prediction.

(2) Research method of life prediction

At present, there has been a lot of research on battery life prediction abroad. The SONY Corporation of Japan has studied a method of calculating the residual capacity of the battery by using the relationship between the end voltage and the residual capacity of the battery. The deterioration degree of the battery is calculated by the ratio of the battery capacity to the battery nominal capacity. Yuri and Bode Richard J Ki, an advanced charging technology company of Mei Tong, proposed a fast method for measuring the state or electric parameters of battery, such as the current capacity of battery and the maximum charging capacity of battery. A fast prediction method of lithium ion battery capacity is put forward in China. Its special existence is: according to the charge discharge curve characteristics of lithium ion battery capacity, the characteristic data of charge and discharge curves are analyzed, and then the degradation degree of M lithium ion battery is calculated. A Cheng relays Limited by Share Ltd. proposed adaptive neural fuzzy system modeling method of battery deterioration prediction model, comprehensive multi variable for calculation of impact and deterioration, achieve accurate estimation on the degree of deterioration of the battery. Harbin Zi Mu Technology Co., Ltd. also studies the prediction of the degree of degradation of lithium ion batteries. By analyzing the relationship between the open circuit voltage of lithium ion battery and lithium ion battery AC resistance and battery capacity, will build capacity forecast and artificial neural network model is applied to the lithium ion battery, proposes a method for rapid prediction by partial discharge capacity of lithium ion battery. Then the life of the lithium battery is predicted by the prediction of the capacity. Henan Electric Power Research Institute and Central South University also carried out life test related.

The main contents are charge and discharge capacity, rate performance, high and low temperature, and cyclic performance at room temperature. The performance prediction results are statistically analyzed. The first one is matching prediction from the model library. Then we deduce the cause of the function. The second one is modeling from physical meaning and validates it. Through the comparison, the prediction accuracy of the life model is verified, and the standard model library of battery cycle life is established. Figure 2 shows the recycle model of the decommissioned power battery.

Figure 2: The recycle model of the decommissioned power battery

(3) Data processing method involves a lot of data in battery life prediction test.

Data fitting is usually needed to explore the implicit rules of these data. Such as interpolation method, curve fitting method, least square method, genetic programming algorithm and so on. The interpolation method is only related to the direction of the last few points of the discrete data when predicting the direction of the curve. It is not good to respond to the law of the whole change (Aamir and Mekhilef, 2016). The least square method requires the pre determination of the structural form of the equation and then the parameter estimation of the function structure. But in fact, it is difficult to accurately determine the structural form of the equation. Especially when the data volume is large, the relationship between the data is frying and the accuracy of fitting is often less satisfactory (Li et al., 2015). Genetic programming algorithm is a global search optimization algorithm with strong randomness. It usually needs to be improved in advance to improve its convergence performance and make it more suitable for practical applications. Other methods include multivariate scattered data polynomial interpolation, partition based method, Sibson method, Shepard method, Kriging method, thin plate spline, radial basis function method and so on. Due to the power battery SOC, impedance and life data is composed of a large number of Southern floating-point data, the above analysis can choose which combines the least square method and genetic programming algorithm based on the structure of the fitting function using genetic programming algorithm for identification, then the parameters of the fitting function of the minimum two multiplication are identified, such complementary the algorithm of fitting function is the best, the accuracy is optimal in all algorithm. The life prediction of the decommissioned lithium battery can also be used. In this paper, the Matlab and ZSimpWin software are used to establish the data fitting of the electrochemical impedance spectroscopy combined with the least square method based on the genetic algorithm.

The basic equations of the algorithm are as shown in the following equation (1) (Wang et al., 2016):

$$\hat{f}_H^{\alpha}(x) = \frac{1}{\Gamma(1+\alpha)} \int_{-\infty}^{\infty} \frac{f(t)}{(t-x)^{\alpha}} (dt)^{\alpha} = \frac{1}{\Gamma(1+\alpha)} \int_{-\infty}^{\infty} f(t) g(x-t)(dt)^{\alpha} = f(x) * g(x) \tag{1}$$

The equation is as follows:

$$\partial_j(C_{ijkl}\partial_k u_l + e_{kij}\partial_k\varphi) - \rho\ddot{u}_i = 0 \tag{2}$$

Under the linear theory, that is:

$$\partial_j(e_{ijkl}\partial_k u_l - \eta_{kij}\partial_k\varphi) = 0 \tag{3}$$

The linear equation can be expressed into the following simplified forms:

$$L(\nabla,\omega)f(x,\omega) = 0 \quad L(\nabla,\omega) = T(\nabla) + \omega^2\rho\mathrm{J} \tag{4}$$

In which,

$$T(\nabla) = \begin{Vmatrix} T_{ik}(\nabla) & t_i(\nabla) \\ t_k^T(\nabla) & -\tau(\nabla) \end{Vmatrix},\ \mathrm{J} = \begin{Vmatrix} \delta_{ik} & 0 \\ 0 & 0 \end{Vmatrix},\ f(x,\omega) = \begin{Vmatrix} u_k(x,\omega) \\ \varphi(x,\omega) \end{Vmatrix} \tag{5}$$

Consider delay, the L can be expressed as:

$$L^0 = \begin{Vmatrix} C_{ijkl}^0 & e_{kij}^0 \\ e_{ikl}^{0T} & -\eta_{ik}^0 \end{Vmatrix} \tag{6}$$

These functions can be expressed in the following form:

$$C(\mathrm{x}) = C^0 + C^1(\mathrm{x}),\ e(\mathrm{x}) = e^0 + e^1(\mathrm{x}),\ \eta(\mathrm{x}) = \eta^0 + \eta^1(\mathrm{x}),\ \rho(\mathrm{x}) = \rho_0 + \rho_1(\mathrm{x}) \tag{7}$$

The value with superscript of 1 represents the difference below:

$$C^1 = C - C^0,\ e^1 = e - e^0,\ \eta^1 = \eta - \eta^0,\ \rho_1 = \rho - \rho_0 \tag{8}$$

And local fractional integral of *f(x)* defined by Eq.9.

$$\begin{aligned} {}_aI_b^{(\alpha)} f(t) &= \frac{1}{\Gamma(1+\alpha)}\int_a^b f(t)(dt)^{\alpha} \\ &= \frac{1}{\Gamma(1+\alpha)}\lim_{\Delta t\to 0}\sum_{j=0}^{j=N-1} f(t_{\mathrm{j}})(\Delta t_{\mathrm{j}})^{\alpha} \end{aligned} \tag{9}$$

Its local fractional Hilbert transform, denoted by $f_x^{H,a}(x)$ is defined by

$$\begin{aligned} H_\alpha\{f(t)\} &= \hat{f}_H^{\alpha}(x) \\ &= \frac{1}{\Gamma(1+\alpha)}\int_R \frac{f(t)}{(t-x)^{\alpha}}(dt)^{\alpha} \end{aligned} \tag{10}$$

At home and abroad, the battery testing research has been carried out from three parts of the charge state, internal resistance and life span of the battery, and some research results have been obtained. However, there is a general error between the battery SOC prediction and life prediction and the real value. The error decreases with the increase of battery life. The SOC standard error is mostly between 3% and 5%. Most of the standard error of life prediction is about 10 times. Further research can reduce the error on this basis, and best approach the actual value. If we can achieve this goal, we will greatly improve the battery's actual use performance and improve the battery's use environment. The application of this method in the practical application will bring rich economic benefits to the manufacturers of battery production, and will promote the development of the battery industry.

The external failure type of the battery is demonstrated by the capacity loss in the forms of the second Gaussian function. In order to test the inter failure type that is caused by the cells' resistance, a cell is tested by electrochemical impedance spectroscopy (EIS). The typical EIS spectrum of the chosen cell is tested at the full state of charge and the equivalent circuit is used to fit the spectra in Fig. 3. Different electrochemical reactions usually occur at specific frequency intervals. From Fig. 3, the EIS spectrum can be divided into three stages:

1) The porous and non-uniformity characters on the surface of the electrodes that generate the inductive resistance at a very low frequency;

2) Lithium ion transport and charge transfer at the electrode/electrolyte interface that leads to a semicircle at mi-frequency;

3) The formation of electrolyte impedance and interface film at high frequency. The equivalent circuit is presented to complete the fitting processes.

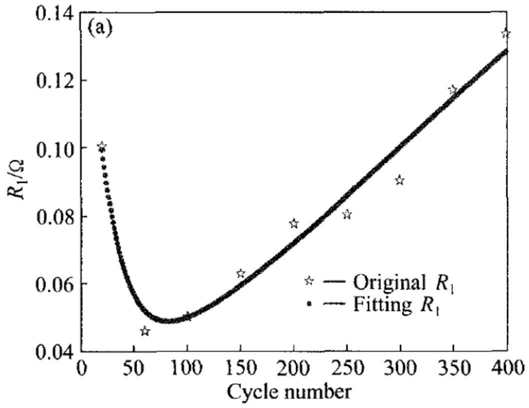

Figure 3: Typical EIS of tested cell

It is comprised of an inductor L and an intercept Rl at a high frequency, a capacitor C paralleled with a resister RZ and so-called constant phase element CPE at a mid-low frequency. It is found from Table 2 that the best fitting results with the lowest error (up to 10%) can be obtained for the battery charging/discharging after 20 cycles. The fitting values are effectively shown the changes as expected. According to Fig. 4, the resistances of R1 and RZ decrease at early cycles, then increase gradually with the increase of the cycles and abruptly deteriorate when the battery life is retired. The value of Rl decreases with cycling for the stable electrode/electrolyte interface film (SEI film) is formed in the first stage, and the electrolyte is sufficient for lithium ion transportation.

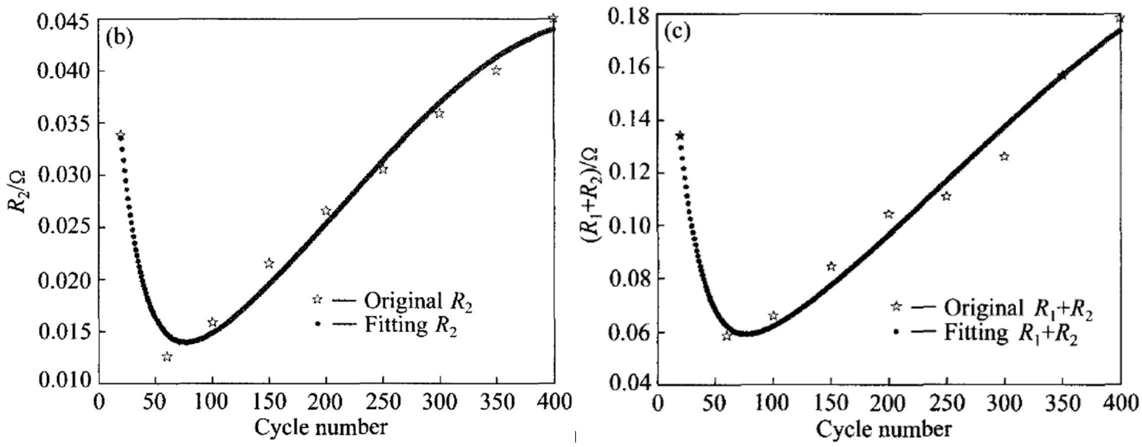

Figure 4: Curves of original resistance

The value of the RZ also reduces with cycling for the intact structure of the electrodes is beneficial to the lithium ion transportation at the electrolyte/electrode a certain degree of degradation, the value of Rl rises because of the electrolyte consumption. The value of RZ also increases. This is because the electrode of the cell undergoes sever polarization reaction, and the damaged SEI film during lithium ions insertion and extraction is continually repaired. From the function above, it can be seen that the accuracy of the model depends on the quantity of the test data. The resistance change meets the second Gaussian function. Comparing with Eq. (1), it is interesting to found that the cell has the same function expression between the capacity degradation and the resistance change (vs cycle number). This shows the battery performance depends on the capacity loss and the increase of resistance. Before 80 cycles, the capacity of the cell rises and the resistance deduces. After that, the capacity of the cell reduces and the resistance rises. Therefore, it is significant to build a model from both the internal and external factors of the cell in order to test the validity of the prediction models.

4. Conclusion

The purpose of this paper is to research on the life prediction and matching test of decommissioned power battery based on energy storage system. The interpolation method is only related to the direction of the last few points of the discrete data when predicting the direction of the curve. It is not good to respond to the law of the whole change. The least square method requires the pre-determination of the structural form of the equation and then the parameter estimation of the function structure. But in fact, it is difficult to accurately determine the structural form of the equation. The experimental results show that this method can effectively improve the overall performance of the system.

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