Rapid Detection Technology for Performance and State of Li-ion Power Batteries

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Abstract: Power li-ion batteries are often used in fields such as electric vehicles due to their high energy density, long cycle life, and low self-discharge. To ensure safe, stable, and reliable operation of power li-ion batteries, accurate and effective detection of battery performance is crucial. Conventional detection methods of battery capacity, remaining life, and other battery performance parameters usually require complete charge-discharge cycle data, resulting in long detection times and low efficiency. Therefore, how to achieve rapid detection of battery performance has become a hot research topic with engineering demands. There have been certain research achievements in the rapid detection technology of power li-ion battery performance. This article elaborates on the significance of rapid detection of li-ion power battery performance, summarizes key technologies and technical characteristics related to rapid detection based on current research achievements, and provides reference to the rapid detection of li-ion power battery performance.

1. Introduction

In recent years, under the influence of environmental and resource issues, China has introduced many preferential policies to support the development of the electric vehicle industry. Pure electric vehicles powered by li-ion batteries have become the main direction of development, and in recent years, the recharging and power supply technology of li-ion batteries has gradually matured, becoming a common source of energy for new energy vehicles. In order to ensure the safe, stable, reliable, and efficient operation of power li-ion batteries during the power supply process, it is necessary to perform online detection of the battery's performance status, such as SOC, SOH, and RUL. Current methods are able to detect the performance status of the battery and the detection means had become mature, such as the time-consuming Coulomb counting method, which causes serious energy waste.The Kalman filtering method requires a large amount of training data. The empirical model method requires a large amount of offline experimental data onto different operating conditions to summarize the relevant function model, which has great limitations. The electrochemical model method requires modeling on battery charging and discharging, which requires a large amount of modeling and calculation, and the development of accurate and general health models is still underway. The equivalent circuit model method converts the electrochemical principle of a circuit model, but still has the problem of large modeling and calculation. The data-driven abstract model method establishes a black box model between the input variables and the target, and data-driven methods such as support vector machines and Gaussian process regression have also been used to estimate the health of batteries. The advantage of this method is that it does not require a detailed degradation model of the battery, but it requires a large amount of online calculation and depends on a large amount of data. Moreover, the conventional detection methods of the performance status of li-ion power batteries usually require complete charging and discharging to cycle data, which leads to long detection times, serious energy waste, and low efficiency.

This article discusses the significance of the rapid detection of the performance status of li-ion power batteries of the perspective of extracting health indicators. Based on the research achievements so far, this article summarizes the key technologies and characteristics of rapid detection, providing a reference to the field of rapid detection of the performance status of li-ion power batteries.

The rest of this article is organized as follows. Section 2 discusses the three main methods of extracting characteristic quantities of li-ion batteries. The extraction techniques for battery characteristic quantities are analyzed, and the evaluation methods of the data are discussed. Section 3 discusses the common data analysis methods of li-ion batteries. Finally, a summary is given in Section 4.

2. Extracting characteristic parameters of li-ion batteries

Traditional battery performance estimation methods usually require complete charge-discharge cycle data and the complex internal mechanisms of the battery, making

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it difficult to directly measure the battery's SOC, SOH, and RUL. This approach is slow and energy-intensive to a certain extent. Therefore, it is necessary to find a correlation between health factors and the battery's health status. Currently, the extraction of health indicators for power li-ion batteries is mainly based on charging curves, incremental capacity curves, and electrochemical impedance spectroscopy curves. The following are research results and related technologies for rapid detection, which provide some reference to the rapid detection of the performance status of li-ion power batteries.

2.1Power li-ion battery performance rapid detection technology based on charging curve

The charge and discharge curved is the easiest way to obtain health factors compared to the other two methods, and many studies directly extract health factors from the curve. Guo et al. [1] found a health factor that can characterize the maximum capacity of the battery. The health factor used in this article is estimated by the change in the battery terminal voltage during the battery storage period to estimate the remaining life of the battery. The voltage drop in a short period of time is used as a feature, and it was found through experiments that the worse the health status of the battery, the greater the voltage drop during the same storage time. This greatly shortens the testing time and experimental cost, and a neural network is used to model the data. On this basis, this article proposes a weighted mixed neural network, which improves the accuracy of the results. The average relative error can reach 1%, indicating high accuracy.

Zhang et al[2-4] believed that multi-parameter sorting can significantly improve the sorting effect. Zhang et al used clustering algorithms to group similar samples of the same category, but clustering algorithms are susceptible to the "curse of dimension". Therefore, literature [2] used factor analysis to reduce data dimensions, and the combination of the two achieved rapid sorting of batteries. This method first obtains the maximum capacity of the battery, then uses the HPPC method to obtain feature quantities, optimizes the feature variables using normalization, and performs clustering analysis on them to complete the recombination of retired batteries. The final results show that the recombination and sorting into single-cell batteries can be compressed to into 30 minutes with good consistency. Duan et al[3] extracted the state voltage and state resistance of retired lithium batteries as their characteristic parameters and used them to achieve rapid battery sorting by discharging the battery once. Huang et al. [4] used three health factors, namely, constant discharge time, DC internal resistance, and constant discharge temperature rise, to estimate retired li-ion batteries complementarily, improving the accuracy of the evaluation and shortening the time. Lai et al. [5] used remaining to charge capacity to quickly estimate the battery pack capacity. The battery pack is briefly charged to obtain the battery charging curve, and the SOC of the battery is obtained by scaling and shifting the charging curves of each cell based on this charging reference curve. Further estimation is used to achieve the goal of quickly estimating battery capacity, and a simulation model of the battery packed is established on the basis of the battery single-cell model. Zheng et al.[6] used to support vector machines to achieve rapid sorting into retired batteries and achieved sorting into a large number of retired batteries of only a small amount of sample data. Then, a fast sorting method of module-level was proposed, greatly improving the sorting efficiency of batteries.

In reference [7], a least squares supported vector regression model with radial basis function kernel was used to establish a State of Health estimation model for batteries. The estimation model only requires extracting some short-term data onto the battery voltage response curve, without relying on equivalent circuit models, and the short sampling method can be completed in only about 4 minutes per sample. To achieve rapid detection of battery performance, it is necessary to find a way to obtain the health characteristics of the battery of the shortest possible time. Reference [8] proposed a new OCV prediction method using multiple correction methods. The proposed method not only improves the time efficiency of OCV measurement of the laboratory, but also has the potential to accurately predict OCV in a short battery idle time of practical applications. In addition, the proposed method does not rely on any prior electrochemical knowledge of the battery. Experimental results have demonstrated the effectiveness of the method of accurately predicting open circuit voltage within a very short relaxation time, highlighting its rapidity.

The article [9] uses the random forest regression algorithm to achieve fast estimation of SOH under constant current charging conditions. This method is different from the previous ICA method, and the constant current charging time method can well replace the incremental capacity peak area. This method does not require preprocessing of data and combines the advantages of the charging voltage curve and the IC curve. The peak of the charging curve is directly matched with the main peak position of the IC curve in the fixed voltage range based on the constant current charging time feature. Accurate and fast SOH estimation is achieved by combining random forest regression.

In summary, methods based on charging curves are generally either constant current charging or constant voltage charging. The above literature has extracted features of short-term charging or discharging curves in their own ways. They have successfully achieved the effects of fast screening and rapid detection.

2.2Rapid detection technology of power li-ion battery performance based on incremental capacity curve

To achieve fast detection of battery performance, researchers have come up with the idea of using localized charge-discharge methods to obtain the battery's health characteristics in the shortest possible time.

Traditional independent component analysis methods limit the current rate to a very low level to extract detailed electrochemical characteristics, as small IC peaks are often drowned out at high current rates. Due to the derivative nature, ICA results may be sensitive to noise and therefore rely heavily on filtering. In addition, these IC curves may vary greatly from different types of batteries, so results obtained for one type may not be applicable to other types.

Capacity increment analysis is currently a widely used method, which is recognized as a mature SOH estimation method. It is based on the peaks and positions of the IC curve to infer the battery performance, which has been shown to be highly correlated with battery capacity. However, it still has significant limitations. Firstly, it requires a complete IC curve to find the position of the peak, and secondly, the peak of the IC curve is easily affected by noise, which requires a high-quality filtering algorithm. Finally, to obtain a complete aging characteristic of the IC curve, it is necessary to sample over a large voltage range, which is very time-consuming. It is unrealistic to apply a complete discharge capacity test of an industrial environment. Therefore, a method that can adjust the whole based of the local information is needed.

Mohamed Ahmeid et al. [10] used incremental capacity analysis, equivalent circuit modeling, and Coulomb counting methods to evaluate the total capacity of retired battery modules based on local discharge curves. ICA is used to describe the aging characteristics of batteries by conducting constant current discharge of the battery and plotting the difference in battery capacity relative to its terminal voltage on an IC curve. Then, information such as peak voltage and peak area on the IC curve is observed and the electrochemical information is extracted to predict the degradation characteristics of the battery. Using terminal voltage and discharge current as features, the IC curve is plotted with constant current discharge. The PDC technique was introduced to the basis of the electrochemical information extracted from these IC peaks, and the concepts of regional voltage and regional capacity were introduced to predict the degradation characteristics of the battery. The values of voltage and peak area can also be used to estimate the state of health of the battery, greatly reducing testing time.

Incremental Capacity Analysis is an algorithm used to process aging li-ion batteries. In reference [11], the concepts of region capacity and region voltage were introduced. Unlike traditional methods, ICA curves were obtained using differential calculation. This approach is less sensitive to noise and filtering algorithms, and a linear fitting relationship between region capacity and State of Health was established to achieve fast SOH estimation. However, there are still some limitations, such as requiring the complete ICA curve to obtain the maximum peak value and the importance of selecting suitable interval voltages. In reference [12], short-term battery health and long-term battery remaining life were studied. The ICA and Gaussian Process Regression was combined, and a dual-Gaussian regression model was used to predict the battery health status.

In conclusion, traditional IC curves require constant current charging data and are susceptible to contamination by noise. They typically require the use of a filtering algorithm and can only observe the desired peak value at low current levels, as high currents can obscure the peak values and their locations in the IC curve. Therefore, the method's generalizability is poor. However, through improvements and enhancements by current scholars, the problem of small IC peaks being submerged at high current rates has been overcome. The challenge to future research is to find the appropriate voltage range and eliminate the influence of noise.

2.3Rapid detection technology of power li-ion battery performance based on electrochemical impedance spectroscopy curve

Luo et al. [13-14] combined electrochemical impedance spectroscopy and equivalent circuit models to achieve rapid estimation of battery state of charge and state of health, reducing testing time of less than 20 minutes. However, this approach still has some limitations, as it can lead to inconsistent impedance spectra obtained under the same parameter settings and external conditions. Building on this work, reference [14] proposed a method based on short-term pulse discharge, which solves the inconsistency problem encountered in reference [13].

Reference [15] addresses these issues by using stepwise waves to identify six health indicators for li-ion batteries and implementing fast capacity estimation of Gaussian regression. This method extracts low-frequency EIS identified in real time with the controlled charging process of injected step waves. The newly proposed three health factors include short-term fluctuations in battery capacity information and the ability to describe long-term smooth capacity decay trends. Due to the large amount of data modeling work, to avoid modeling, reference [16] proposes a model-free, convolutional neural network-based approach for estimating the health status of high-power li-ion batteries based on impedance spectrum measurement data sets. Through a 6-fold cross-validation and comparison with a neural network method based on an equivalent circuit model, it is found that both models have robustness to factors that affect battery impedance measurement of the SOC range of 20% to 100%. This indicates that this method is also effective when training data is limited.

Due to the susceptibility to current, voltage, temperature, and other information on fluctuations, a rapid state of health estimation method for li-ion batteries based on impedance calculation was proposed in reference [17]. From the perspective of electrochemical impedance spectroscopy, a set of impedance features called "health factors" were selected to represent the aging state of the battery based on the relationship between EIS and charging state, as well as the relationship between EIS and degraded capacity obtained from experimental studies. Then, an improved fast

Fourier transformed using the conversion relationship between real and complex signals was proposed to achieve online rapid EIS acquisition. Furthermore, an SOH evaluation model was constructed through extreme learning machine to establish the relationship between health factors and battery aging capacity.

In summary, impedance spectroscopy technology has demonstrated its ability in health state estimation due to its ability to provide information on different aging mechanisms. It has been widely applied to the field of rapid estimation of the health status of dynamic li-ion batteries.

3.Analysis of Existing Estimation Methods

Once these feature quantities are identified, data analysis and modeling techniques are needed to establish the mapping relationship between the feature quantities and the performance status of the battery, thereby achieving rapid prediction of the battery performance status.

Data-driven approaches are widely used for rapid battery performance detection as they can avoid analyzing the complex mechanisms of batteries. Currently, commonly used data-driven methods include neural networks, support vector machines, Gaussian process regression, etc. Although neural networks can handle nonlinear data and have great advantages in solving complex system modeling problems, their principles are very complex and training is time-consuming. Support vector machines and Gaussian process regression already have toolboxes and are fast to run and train. Therefore, they are more suitable for the rapid detection of li-ion batteries.

Reference [7] uses the least squares support vector machine regression method with a radial basis function kernel to construct an SOH estimation model. By only extracting some short-term data from the battery voltage response curve, it can be analyzed to effectively perform rapid on-site measurements. Reference [15] identifies low-frequency electrochemical impedance spectra online through a stepwise wave, combined with Gaussian process regression, extracts six health indicators, and achieves rapid capacity estimation of li-ion batteries.

However, data-driven methods require a large amount of battery data and computational burden. In order to avoid these drawbacks, a model-free SOH calculation method that combines Coulomb counting and differential voltage analysis was proposed in reference [18], which achieved rapid detection during constant current discharge stage. This method avoids battery modeling and huge computational burden. In response to the problem of a single model and low generality in existing research under different working conditions, reference [19] proposed a hybrid data-driven model based on advanced machine learning techniques. Firstly, the initial data was despised using wavelet transform, and then important feature quantities were selected using random forests. Secondly, multi-time scale sliding window data was constructed using approximate entropy theory, which solved the problem of determining the size of the sliding window in traditional methods. The proposed data-driven method was used to model the degradation of li-ion batteries, and experimental results showed that the method is universal and achieves rapid capacity prediction.

In summary, data-driven methods have been widely used in battery performance state research due to their not requiring complex battery mechanics analysis. However, compared with other estimation methods, their computational burden is relatively high.

4.Conclusions

Based on the current achievements in rapid testing technology for li-ion battery performance, methods based on charge and discharge curves are the most common. This is because charge and discharge curves are the easiest to obtain compared to the other two methods, and many studies directly extract health factors from these curves. However, methods based on charge curves require high integrity and regularity of the curve, so it is also challenging to obtain short-term health indicators during charging activities. The method based on IC curves requires constant current charging data and is rarely used directly with non-constant current protocols, so its universality is poor. The current solution is to smooth the online charging curve and eliminate the influence of voltage and current sampling noise on the differentiation process. Therefore, the method based on IC curves is usually used together with filtering algorithms. For the method based on EIS curves, the current online acquisition method mainly applies square waves and multiple sine wave composite signals to li-ion batteries, and obtains impedance through fast Fourier transforms, wavelet transforms, and s-transforms. However, due to the non-linear characteristics of batteries, these waveforms cannot effectively be equivalent to sine waves at each frequency, so custom excitation sources are required and the sampling frequency requirement for the entire EIS is high.

Currently, the majority of research on rapid detection technology for li-ion batteries is focused on quickly predicting battery health status, followed by research on quickly predicting battery capacity. There are relatively few studies on quickly detecting SOC and battery remaining life, and most current studies are based on offline state detection of battery performance, with poor generalization of battery health factors. The online extraction of health factors for li-ion batteries is still constrained by many factors, and there is still a certain distance from application in engineering. Improving the online rapid prediction technology for li-ion batteries and increasing the generalization of battery models are directions for future efforts.

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