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A Review of Lithium-Ion Battery for Electric Vehicle Applications and Beyond

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Abstract

Among many kinds of batteries, lithium-ion batteries have become the focus of research interest for electric vehicles (EVs), thanks to their numerous benefits. However, there are many limitations of these technologies. This paper reviews recent research and developments of lithium-ion battery used in EVs. Widely used methods of battery sorting are presented. The characteristics and challenges of estimating battery's remaining useful life (RUL) and state-of-charge (SOC) are critically reviewed, along with a discussion of the strategies to solve these issues. A new method of sorting retired lithium-ion batteries and estimating the RUL and SOC of the retired lithium-ion batteries is proposed.

Keywords: Lithium-ion Battery; Optimization; SOC; Algorithm; Second life battery

Nomenclature

Abbreviation

EVs	Electric vehicles
RUL	Remaining useful life

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SOC	State of charge
OCV	Open circuit voltage
CVDs	Cell voltage differences
CDM	Cell difference model
EKF-UKF	Extended Kalman filter--Unscented Kalman Filter
DSTs	Dynamic stress tests
MAPE	Mean absolute percentage error
MLSERRC	Mixed least square estimator ramp rate compliant
LSE	Linear estimate
MA	Moving average
SOH	State of health
HPPC	Hybrid pulse power characteristic
EIS	Electrochemical impedance spectroscopy

1. Introduction

Petrol and diesel fuel vehicles cause a large amount of carbon dioxide emission, which leads to some serious consequences on global warming [1]. To avoid worsening the above problems, recently, the government of the UK, France, Germany, Netherlands and other countries have announced a schedule to stop producing petrol vehicles, most of which are from 2025 to 2040 respectively [2]. In the foreseeable future, EVs will replace petrol vehicles to a large extent. The rechargeable battery is the core component of an EVs, which requires a high performance [3].

Compared with other commonly rechargeable batteries like Ni-Cd, Ni-MH and Lead-acid battery, the lithium-ion battery is featured by high energy and power density, long service life and environmental friendliness and, thus, has been widely applied in consumer electronics [4]. However, in the applications that require lots of power, like EVs and energy storage systems, a large number of batteries need to be packaged in serial and parallel to be a battery pack. This causes problems of costs, stability, consistency and safety. These problems limit the applications of lithium-ion batteries.

Lithium-ion batteries must be operated in a safe and reliable operating area, which is affected by the charge rate, temperature and voltage range. Exceeding these ranges will lead to rapid attenuation of battery performance and even result in safety problems. In addition, to ensure the reliable operation of lithium-ion batteries, it is important to evaluate the lithium-ion battery capacity and predict the RUL over the entire service life. Moreover, cell sorting methods, referring to the selection of qualified cells from raw ones according to quantitative criteria, such as capacity, resistance, open circuit voltage (OCV), are indispensable processes to assure reliability and safety of cells.

The retired batteries from EVs still have 80% of primary energy [5]. The reuse of retired batteries from EVs in the applications, energy storage systems and renewable energy plant, is a proper way to make the best use of retired batteries. The second life batteries can be obtained at a lower cost than brand new batteries, however, the reliability of the reused batteries becomes an important issue. The reason is that these batteries may suffer from failure and degraded performance [6]. All of these researches will be introduced in this paper.

2. Sorting of the lithium-ion batteries

The battery pack consists of large numbers of batteries in serial and parallel. In the process of using these batteries, the battery cells performance (SOC , RUL, OCV) are inconsistent. The inconsistencies performance are caused by the inconsistencies of the battery parameters. It have a great impact on the efficiency and longevity of the battery pack. Take cylindrical $LiFePO_4$ battery as an example, 20% parameters mismatch reduces lifetime by 40% [7]. Compared with the single battery, its service life is greatly reduced. Therefore, optimizing the battery parameters consistency is of great significance to improve the performance of battery pack.

Recently, considerable attention has been paid to study cell-to-cell parameters variations about resistance, OCV and SOC, which are closely pertaining to cell sorting [8]. Battery sorting means that by using some methods, the batteries have the same performance will be put together to improve the consistency of batteries and to reduce the negative impact of initial differences among batteries, so as to improve the use efficiency of the batteries and prolong their service life. This section describes different methods in sorting lithium-ion batteries.

Battery sorting includes single parameter sorting methods, multi-parameter sorting methods, dynamic character sorting methods and model sorting methods. Each method has its own advantages and disadvantages, as summarized in Table I.

Table 1. Advantages and disadvantages of existing battery sorting methods.

Methods		Advantages	Disadvantages
Single parameter	Internal resistance	Simple	Low accuracy, open loop，easily affected by the temperature
	Open circuit voltage(OCV)	Simple	Low accuracy, sensitive to the voltage sensor precision
	Multi-point spectral impedance	Accurate, reflect the battery internal information	Reflect the battery characteristics in a particular state
Multi-parameters	Capacity+OCV+internal resistance Voltage charging time ratio+Self-discharge rate	Generic,accurate	Time-consuming,complex
	OCV+ Short circuit current+internal Resistance+maximum power point	Generic,accurate, comprehensive	Difficult to obtain data,complex
Dynamic sorting	Pulse charging and discharging voltage curve under different	Generic, reflect the dynamic information of the battery	Not comprehensive enough
	Capacity curves at different temperatures	Simple, generic, easy to get data	Sensitive to the collecting data
Model sorting	Thevenin model	Reflect the battery dynamic Characteristics, simple model	Large amount of computation, complex model
	PNGV model	Higher accuracy than Thevenin model	Too many parameters, complex mode

According to the aforementioned methods, it can be concluded that there are lots of sorting methods can solve the problem of inconsistencies of batteries and some progress has been made. However, these methods still have many drawbacks, such as low accuracy, time-consuming, sensitive to the collect data, poor applicability and so on.

3. State of charge estimation

Due to electrode potential and material limitations, the voltage and capacity of each battery cell cannot fully meet the requirements of the voltage level of EVs [9]. Therefore, thousands of battery cells have to be connected in series and parallels. However, inconsistencies of battery pack parameters and uncertain operating conditions may cause significant differences in batteries' capacity. In addition, a reliable estimation of the rest of the driving range of EV depends on the accuracy of the SOC data, This section introduces some strategies of SOC estimation.

Reference [10] proposed a mean plus difference model (M+D model) by testing the battery voltage in a small battery pack. The cell voltage differences (CVDs) between the cell and the "mean cell" are studied by a low-frequency cell difference model (CDM). This model considers differences in SOC and internal resistance. The model can be used to estimate OCV difference. With the help of this method, current measurement techniques can be used to accurately estimate the SOC inconsistencies of lithium-ion batteries during EV operating.

The above method get the result by calculating the relationship between SOC and OCV. Other parameters are ignored. The inconsistent situations in other SOC rates need to be evaluated.

A parametric modeling method is proposed [11] by using developing model-based SOC estimation approach. Based on the analysis of the mapping relationship between battery parameters and SOC, a three-dimensional response surface open-circuit voltage model is proposed to correct the SOC estimation. Fig. 1 shows the schematic

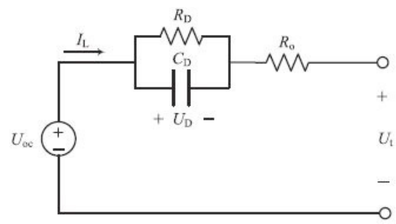

Fig. 1. The schematic diagram of the lumped battery circuit model.

diagram of the battery model. The model is too simple to describe the equivalent circuit model accurately.

In addition, this paper[11] proposed a model-based two-scale unit SOC estimator. It uses micro and macro time scales methods to estimate SOC for selected and unselected cells, respectively. The results show that the maximum estimated errors of the battery voltage and the SOC are less than 30 mV and 1% respectively for the uncertain diving cycle and the battery pack.

Compared to the M+D model method, this method conducted a more detailed study impact of the battery's parameters on SOC in a micro and macro time scale. The battery parameter model is more accurate. But this method is not applicable to the batteries has been deeply discharged, the OCV analytical equations should be redesigned to improve the calibration performance of this method.

In this section, many different methods for estimating the battery's SOC have been discussed, such as Mean-plus-Difference Model, three-dimensional response surface open circuit voltage model. These methods show the ways to estimate SOC, but it has some drawbacks. The equivalent circuit model [11] cannot describe the battery effectively. Some parameters are ignored such as temperature, remaining used of life, constant of charge rate. Besides, the robustness of SOC estimation algorithms cannot deal with unexpected situations.

4. Rul of second used battery

In the EV industry, the batteries must be retired when they drop to 80% of the primary capacity. But these retired batteries still have lots of available capacity and long RUL [12]. It is predicted that by 2028, the retired battery will reach to 120 Gwh [13]. With the increasing number of retired power batteries from EVs, how to deal with retired battery is a significant challenge. One of the best ways to solve this problem is to reuse retired power batteries in other applications such as energy storage systems, mobile battery charging station, frequency response service. To make the best use of the retired power battery, the characteristics of the retired lithium-ion battery need to be studied.

In order to study the aging effect of energy storage system, a mixed least square estimator ramp rate compliant (MLSERRC) algorithm is developed [14]. This algorithm considered a linear estimate based on a parabolic estimate (LSE) instead of a linear estimate complemented with the ramp rate compliance. The result of MLSERRC algorithm is better than using LSE-based least squares estimation and moving average (MA) filtering algorithms. The MLSERRC algorithm also helps to reduce the size of the battery energy storage system and the required to provide smoothing of output power.

This strategy saves the cost of energy storage system. However, the power profiles obtained from this study use brand new batteries as second life batteries. Because there are lots of differences between brand new batteries and retired batteries, there may be very different results compared to using second life battery. Therefore, to analyze the performance of retired batteries and their aging behaviour, more tests need to be carried out on second life battery.

To evaluate the performance and degradation behaviour of the retired lithium-ion battery [15], this paper uses retired EV batteries in two applications: residential demand response management services and power smoothing application. The experiment is divided into two groups: one group is the experiment on the single battery cell, another group is on battery packs. All of these batteries have different state-of-health (SOH) before the experiment. Detailed tests include capacity, hybrid pulse power characteristic (HPPC), OCV, electrochemical impedance spectroscopy (EIS) measurements and impedance parametric tests.

From the experiments, the result shown that the retired batteries are more prone to aging than brand new batteries. All batteries with large direct current internal resistance (> 175% relatively) are difficult to use in circumstances where strict requirements are needed. In addition, the retired batteries that were reused in second life applications before reaching the "aged knee" [16] (i.e. before the dominant mechanism of aging was changed) showed very good performance. Otherwise, these batteries cannot be used because of their rapid decline performance of capacity.

This paper aims to find the relationship between aging and performance of retired batteries. The experiments obtained some progress, but they did not locate the main factors that affect the battery aging rate. Besides, the battery pack is made up of 3 batteries in series. The number of batteries, battery string parallel state and temperature are ignored, these factors have lots of affect on battery performance. Furthermore, they did not propose the aging performance model about the retired battery.

As is shown in this section, predicting battery performance and battery life, battery model and estimate algorithm are the main research points about retired batteries. The research on these aspects has achieved certain acheivements. Some models and algorithms are created. However, these studies have some shortcomings: experimental results were obtained by a small number of batteries; the prediction of the of the retired battery was only conducted by simulations without actual retired battery experiments; the of parameter selection is not accurate enough; comparative experiments between the aged and brand new batteries are not enough.

5. Discussion

5.1. Assessment of sorting methods

From measurement to statistical estimation, there are many different kinds of empirical methods to classify batteries, each of them has pros and cons characteristics. The multi-parameter sorting methods use some measured parameters value at a special time to sort the battery, but the value will change with the use of the battery. Therefore, this method is of no use. In contrast, dynamic parameter sorting methods do not have this problem. However, some dynamic parameter sorting methods can only analyze a phenomenon at the same time. It is difficult to consider a variety of different situations together. For example, self organizing map method can get a good result in its special condition, but it can not perform well in other batteries (different material, capacity). Methods like electrochemical models and equivalent circuit models perform well but can not be used directly in the serial parallel model.

5.2 Assessment of estimate SOC and RUL methods

Each proposed method seeks to improve accurate estimate SOC and RUL in different ways, but each method has its own drawbacks. Many studies have used accelerated life tests to solve the problem of aging batteries, which leads to some errors data in test. Many algorithms are used to calculate the battery's SOC and RUL, it is useful to some extents. But these algorithms need to be based on a lot of historical data. The robustness of the algorithms is not good, they can not effectively calculate the battery SOC and RUL in some unexpected situations. Moreover, the lower battery using time as well as the complex interaction between each variable were not considered in these methods.

The estimate of battery SOC and RUL requires an easily flexible method. Thus, an ideal method should perform quickly with a few and easily obtainable variables and it needs able to adapt to a variety of situations.

5.3 Proposed methods

From section IV, we know that few studies are about the retired battery but its future application prospects are very broad. Therefore, in order to find out the characteristics of retired batteries and clear the obstacles for its application, a method is proposed in this section.

This strategy aims to sort the retired battery and predict the SOC and RUL of the retired battery.

For sorting the retired battery. There are lots of parameters that affect battery consistency include the battery capacity, open circuit voltage, electrochemical impedance spectroscopy, ohmic resistance, charge-discharge efficiency, self-discharge rate, these parameters will be chosen as the first sorting series. Because each parameter has a special impact on battery consistency performance. Firstly, the relationship among these parameters and their shares on the effect of battery performance will be studied by experiments and quantitative assessment method. Secondly, principal component analysis algorithm will be used to determine the main parameters that affect the battery consistency. Finally, using data fitting method to establish the parameter comprehensive model. With this model, batteries with consistent performance will be sorted out.

For estimate RUL, at the first stage, parameters about the number of battery cycles, open circuit voltage, internal resistance, capacity and temperature will be included. A set of experiments will be done to figure out the impact of each parameter on the retired batteries. Principal components analysis used to analyze the affect of these factors on RUL. Find the principal component factors and fit out the correlation function. Then, using Matlab building a model about this function. Lastly, the comparison between simulation experiments and real data will be done to proof the correct of this method.

For estimate SOC, at the beginning, get SOC data about aging batteries with different degrees and other data about OCV, cycle time. The electrochemical model contains polarization resistance and polarization capacitance will be figure out and it can reflect the detail of the battery equivalent circuit. Secondly, using principal components analysis to identify the main influencing factors like battery's aging degree, OCV, cycle time. Thirdly, EKF-UKF and MLSERRC algorithms will be used to improve the accuracy of estimate SOC. Lastly, the simulation will be done to verify the effect of this method.

6. Conclusion

This paper summarizes the key research issues in the lithium-ion battery, including estimation of battery capacity, sorting of battery, remaining use life of the battery, battery circuit model and SOC algorithms. The advantages and disadvantages of these methods are discussed. New method and model for sorting retired battery and estimate SOC and RUL of the retired battery are put forward. Which improve the consistency of retired batteries, decrease the degradation of the retired battery, prolong the battery cycle life. In the future, experiments will to be done to prove the effectiveness of this method.

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