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A new state-of-health estimation method for lithium-ion batteries through the intrinsic relationship between ohmic internal resistance and capacity

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ABSTRACT

For secure and reliable operation of lithium-ion batteries in electric vehicles, diagnosis of the battery degradation is essential. This can be achieved by monitoring the increase of the internal resistance of the battery cells over the whole lifetime of the battery. In this paper, a method to estimate state of health (SoH) is presented through the established linear relationship between ohmic internal resistance and capacity fade. Firstly, the Thevenin model and the recursive least squares (RLS) algorithm are applied to simulate battery dynamic characteristics and identify model parameters, respectively. Secondly, based on the established linear relationship between ohmic internal resistance and capacity fade, both ohmic internal resistances at the start and the end of the battery's lifetime are estimated by only two random discharge cycles at different aging stages. Finally, an online SoH estimator is formulated and applied to estimate the SoH of a battery's remaining cycles. In addition, a series of experiments were carried out based on dynamic loading to verify the proposed method. The SoH estimates indicate that the evaluated maximum SoH errors are within ± 4%. The proposed SoH estimation method is consistent with the measurement data of the battery and shows good results with very low computational effort.

1. Introduction

To address the challenges associated with increasing world energy consumption and climate change, electric vehicles (EVs) can play a key role. The development of suitable power batteries in EVs is essential, and focuses on the lithium-ion battery due to its excellent power characteristics [1]. Being the main power source of EVs, it is important to manage the battery to extend its lifespan, improve its reliability, and lower its cost. In order to guarantee the realization of these functions, a battery management system (BMS) is necessary [2]. As the main part of the energy system, the BMS plays a crucial role for states estimation, battery monitoring, cell balancing, thermal management, and others [1,3,4]. One of the core functions of state estimation is real-time SoH estimation [3]. SoH estimation is very important for guaranteeing the system's performance and reliable operation, and it significantly affects the overall vehicle performance and life cycle [5].

Conventionally, SoH is a parameter, which indirectly represents the age condition of the battery cell and the remaining lifespan [6–8]. It mainly reflects in two aspects: capacity fade and power fade [6,9,10]. Hence, the SoH can be estimated using the capacity or the impedance of the battery.

A wide variety of SoH estimation methods [9,11] have previously been summarized, each one has its own advantages and disadvantages. The SoH estimations mainly include three categories [8]: (1) direct measurement method; (2) model-based method; (3) data-driven method.

(1) *Direct measurement method:* From the perspective of capacity, the present maximum available capacity can be obtained using the open-circuit voltage (OCV) method and the Coulomb-counting method. From the perspective of impedance, the impedance of the battery can also be measured with specialized equipment [12,13]. The OCV method can determine the battery capacity using the relationship between OCV and state of charge (SoC). And the variation of OCV model is small over the battery lifetime. Thus, the accuracy of the method for aged batteries is almost as high as those new battery [1]. However, the method requires a long rest-time to measure OCV accurately until the battery reaches a steady state [14]. The Coulomb-counting method can determine battery capacity by integrating the battery discharge current, but this is time consuming [8] and an accumulated error and sensor noise represent significant problems. Electrochemical impedance spectroscopy

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(EIS) can determine the impedance using impedance spectroscopy analysis [9]. Resistance test equipment and the Joule effect can also determine the internal resistance [9]. In summary, a direct measurement method usually has less computational complexity and is possible to implement in a BMS. The drawbacks are that it has a low accuracy, and usually requires special equipment and is not suited for situ estimation [1,9].

(2) *Model-based method:* The main idea of the model-based SoH estimation is to connect the measured battery signals (voltage, current, and temperature) with the battery SoH employing a battery model [1]. Adaptive models are developed to describe the dynamic characteristics of the lithium-ion battery, including electrical and electrochemical models. Adaptive techniques known from control theory are employed with these adaptive models. For instance, in Ref. [6], the SoH and SoC are estimated by the Extended Kalman filter (EKF), but the SoH is updated offline and the time scale of the SoH is based on model accuracy. In Ref. [15], the least squares technique is used to estimate SoH. However, the present methodology should be validated at different C-rates and temperatures for a more realistic performance. In Ref. [16], the particle filter (PF) is employed to estimate both the capacity and SoC, but the accuracy is limited because of the simplified battery model. These methods are online and closed-loop [8], and their performance has been validated with different experiments. However, the accuracy and robustness of the model decides the accuracy of the method.

(3) *Data-driven method:* The battery is considered a “black box” to estimate battery SoH without battery model in these methods. For instance, in Refs. [17,18], artificial neural network (ANN) is applied to estimate SoH. The support vector machine (SVM) is used for SoH estimation in Refs. [19,20]. Besides, DVA (Differential Voltage Analysis) [21] and ICA (Incremental Capacity Analysis) [2] are also developed to estimate SoH. The framework of such methods consists of off-line training and online SoH estimation [18]. In this process, the feature extraction of battery degradation is also necessary. What’s more, a precise battery model is not necessary for these data-driven methods, but these methods require a large database for different working conditions during the lifetime. And the DVA and ICA method require a constant and low current to discharge the battery in order to acquire the accurate DV curves or IC curves. In addition, these methods often require high computing power and they may not be suitable for BMS, which only contains some microcontrollers or low-cost systems [22]. Furthermore, the battery parameters may change with the aging process in practical applications.

The values of battery capacity usually are nonlinear, time varying, and uncertain. Thus, it is still difficult to estimate the capacity of a battery precisely. Lithium-ion battery degradation occurs mainly because the active substances, lithium ions and electrolyte, solidify gradually in the SEI. As a result, they cannot continue to participate in the battery electrode reaction. While the concentration of lithium ions is closely linked to the capacity and the conductive properties of the battery, a loss of lithium ions will lead to the decline in capacity and the rise in impedance [23]. In addition, stressing the lithium-ion battery by overcharging, exposure to extreme temperatures, or aging changes also the carbon-based anodes irreversibly. The aging effect of the anodes may be mostly attributed to changes at the SEI [9]. This electrochemical mechanism increases the impedance and reduces the capacity at the same time, and they follow approximately the same trend together [10].

As previously shown, SoH estimation should be made by both: capacity and resistance estimation. However, the resistance is relatively simple and fast to determine. The current algorithms to identify the resistance are precise enough when they use the equivalent circuit model. And Haifeng et al. [24] proposed a new definition of SoH based on ohmic internal resistance. Hence, it is a good choice to estimate SoH via ohmic internal resistance.

In order to estimate the SoH based on the intrinsic relationship between ohmic internal resistance and capacity [25], the ohmic internal resistance of both a new battery (R_{new}) and end-of-life battery (R_{eol}) are important [1,24]. However, due to the irreversible aging process, it is difficult to acquire R_{new} when the battery has been used for some time. Also R_{eol} cannot be measured easily either until the battery is at the end of lifetime.

To solve this problem, a new method is proposed to estimate SoH by using the correlation between ohmic internal resistance and capacity. Thevenin model is suitable for modeling the relaxation effect and the dynamic behavior of lithium-ion batteries. A recursive least squares algorithm with a forgetting factor is used to realize accurate identification of the model parameters [1,6,9]. Based on the correlation between the ohmic internal resistance and capacity, a linking equation to calculate the R_{new} and R_{eol} can be built. Finally, the values for R_{new} and R_{eol} can be estimated via two discharge tests, and the SoH estimation method is developed. Different from other SoH estimation methods based on internal resistance, the linear relationship between the battery impedance increase and the battery capacity loss is built and applied through only two online resistance tests and off-line capacity tests. This method does not require complex matrix operations, special battery tests, and too much previous knowledge of the operation performance of the battery. In addition, a series of battery aging experiments at different temperatures are carried out to demonstrate the validity and precision of the proposed online estimation method.

The remainder of this paper is organized as follows: Section 2 reports our experimental settings and aging experiments of batteries. Section 3 develops the framework of our estimation method, and Section 4 elaborates and discuss the results of the propose method. Section 5 concludes the paper.

2. Experimental

The proposed method is designed for online SoH estimation. Therefore, recorded data of the dynamic load of electric vehicles are required through the whole lifecycle.

2.1. Test bench

The battery test bench is shown in Fig. 1. It consists of an ITECH electronic load IT8511+, an ITECH IT6523D as a charger, a set of batteries (which may reside either inside or outside an environmental chamber), a suite of sensors (voltage, current, and temperature), some custom switching circuitry, a data acquisition system (DAQ) and a computer for control and analysis. In addition, a battery monitoring software PV8500 is used to control the IT8511+ load.

The IT8511+ can discharge a battery/battery pack according to the program with a maximum discharge current of 30 A and the maximum

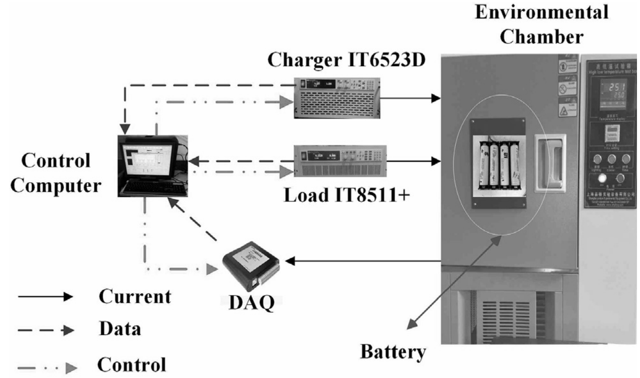

Fig. 1. The architecture of battery test bench.