Applied Energy 183 (2016) 513–525

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Influence of different open circuit voltage tests on state of charge online estimation for lithium-ion batteries

Fangdan Zheng [a,b], Yinjiao Xing [b], Jiuchun Jiang [a,*], Bingxiang Sun [a], Jonghoon Kim [c], Michael Pecht [b]

[a] National Active Distribution Network Technology Research Center (NANTEC), Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing Jiaotong University, Beijing 100044, China
[b] Center for Advanced Life Cycle Engineering (CALCE), University of Maryland, College Park, MD 20742, USA
[c] Energy Storage Conversion Laboratory (ESCL), Chungnam National University, Yuseong-gu, Daejeon 34134, Republic of Korea

HIGHLIGHTS

- Two common tests for observing battery open circuit voltage performance are compared.
- The temperature dependency of the OCV-SOC relationship is investigated.
- Two estimators are evaluated in terms of accuracy and robustness for estimating battery SOC.
- The incremental OCV test is better to predetermine the OCV-SOCs for SOC online estimation.

ARTICLE INFO

Article history:
Received 15 July 2016
Received in revised form 2 September 2016
Accepted 3 September 2016

Keywords:
Lithium-ion batteries
Battery management system
State of charge estimation
Open circuit voltage
Temperature dependency

ABSTRACT

Battery state of charge (SOC) estimation is a crucial function of battery management systems (BMSs), since accurate estimated SOC is critical to ensure the safety and reliability of electric vehicles. A widely used technique for SOC estimation is based on online inference of battery open circuit voltage (OCV). Low-current OCV and incremental OCV tests are two common methods to observe the OCV-SOC relationship, which is an important element of the SOC estimation technique. In this paper, two OCV tests are run at three different temperatures and based on which, two SOC estimators are compared and evaluated in terms of tracking accuracy, convergence time, and robustness for online estimating battery SOC. The temperature dependency of the OCV-SOC relationship is investigated and its influence on SOC estimation results is discussed. In addition, four dynamic tests are presented, one for estimator parameter identification and the other three for estimator performance evaluation. The comparison results show that estimator 2 (based on the incremental OCV test) has higher tracking accuracy and is more robust against varied loading conditions and different initial values of SOC than estimator 1 (based on the low-current OCV test) with regard to ambient temperature. Therefore, the incremental OCV test is recommended for predetermining the OCV-SOCs for battery SOC online estimation in BMSs.

1. Introduction

The rapid development of electric vehicles (EVs) in the last decade has drawn increasing attention from both industry and academia due to the global energy crisis and demands to reduce greenhouse gases. Different types of batteries, such as lithium, nickel-cadmium, lead-acid, and alkaline, are widely used as the dominant energy source in EVs. In particular, lithium-ion batteries are the most promising and competitive candidates because of their unique features, including their high energy density, long cycle life, high efficiency, and environmental-friendly performance [1–5]. As a critical component inside an EV, a lithium-ion battery should operate stably to guarantee the safety and reliability of the entire electric system. Therefore, a battery management system (BMS) that performs as a connector between the vehicle and the battery is developed to indicate the state of batteries and avoid abuse of batteries. One of the main concerns of BMSs is battery state of charge (SOC) estimation. SOC is a measure of the amount of charge stored in a battery at the present moment and acts as the equivalent of a "fuel gauge" in an electric vehicle. SOC shows how long the battery will sustain before it is recharged. Accurate SOC estimation can relieve users' anxiety about running out of battery power. Moreover, it can ensure that batteries operate

* Corresponding author.
E-mail address: jcjiang@bjtu.edu.cn (J. Jiang).

http://dx.doi.org/10.1016/j.apenergy.2016.09.010
0306-2619/

appropriately within desired limits and thus can prolong a battery's useful life by avoiding over-charging or over-discharging. However, battery SOC cannot be measured directly but must be inferred from observed variables, such as current and voltage. Indeed, many factors can affect the accuracy of SOC estimation results and should be investigated [6]. Therefore, SOC estimation is not only a vital function but also a crucial task of BMS to ensure the safety, efficiency, and longevity of a battery for vehicle life extension.

The following SOC estimation techniques are widely used: the coulomb counting method via the integration of the loading current [7–9]; the data-driven method, which considers a battery as a "black box" and uses machine learning techniques to analyze data [10–12]; and the physical model-based method via equivalent circuit models (ECMs) and electrochemical models [13–21]. In addition, a combination of the above-mentioned methods is used [22–26]. For algorithm implementation in a BMS, a model-based filtering approach is most popular due to its merits: high accuracy, closed-loop, self-corrective ability, and good adaptability. Among battery models, equivalent circuit models (ECMs) are much more practical than electrochemical models since ECMs facilitate estimation schemes with electrical parameters (e.g., charge/discharge current and battery terminal voltage), which are much easier to measure online than electrochemical model parameters (e.g., film resistance and diffusion coefficients). Open circuit voltage (OCV) is a vital element in ECMs because it builds a connection between measured electric parameters and SOC via an OCV-SOC mapping curve. For a certain battery type, its OCV performs as a function of its SOC in nature. The premise of using OCV-SOC is that a battery needs to rest a long time to ensure that its terminal voltage approaches the OCV [6]. However, a long rest time is not practical for EV batteries in the field. Thus filtering techniques based on state-space models are utilized to enhance SOC estimation through combining OCV and coulomb counting [27].

Table 1 shows a common processing method of SOC online estimation for a BMS is shown in Table 1. Firstly, the relationship between OCV and SOC is predetermined by an offline OCV-SOC test. The corresponding mapping data is then stored in a BMS as a lookup table or a mathematical function. Secondly, a battery ECM is selected to model the battery dynamic behavior with parameter identification. Lastly, filtering approaches are implemented to enhance model-based SOC online estimation [28]. Efforts have been made to improve the SOC estimation accuracy and the efficiency of a BMS from different aspects. For example, OCV-SOC functions instead of a lookup table have been proposed to describe the relationship between SOC and OCV and thus to save the memory space in a BMS [29–34]. Studies have been conducted on the model selection to pursue a model that can provide high estimation accuracy and also ensure the computational efficiency of a BMS. A first-order resistance-capacitor (RC) model using a parallel RC network to describe the dynamic relaxation effects of the battery is recommended as a model that balances SOC estimation accuracy with model complexity [35]. In addition, different filtering algorithms have been used for online estimation. For instance, the studies in Refs. [6,26,33,36–38] adopted extended Kalman filter, robust extended Kalman filter, and unscented Kalman filter to estimate the SOC. Instead of the Kalman family, the studies in Refs. [39–42] used particle filter, unscented particle filter and dual particle filter to do SOC estimation. Luenberger observer [43] and support vector machine method [44] were also utilized for battery SOC estimation. The performance of different filtering algorithms is compared in terms of tracking accuracy, convergence behavior, and computation time [28].

Several existing issues are seldom addressed in the literature. Firstly, as the basis for SOC online estimation, OCV-SOC tests have not been comprehensively evaluated yet. There are two OCV tests

Table 1
Common processing of SOC online estimation for BMS.

Step 1	OCV-SOC mapping 1. OCV-SOC test 2. Determine OCV-SOC relationship a. OCV-SOC lookup table b. OCV-SOC functions
Step 2	Battery modeling 1. Select a battery equivalent circuit model 2. Model parameter identification
Step 3	Algorithm implementation a. Kalman filter family b. Particle filter

for OCV-SOC mapping commonly used in both industry and academia: the low-current OCV test and the incremental OCV test. One OCV-SOC mapping result differs from another and thus has a different influence on SOC online estimation. It will be helpful to compare two OCV tests and their influence on SOC online estimation results in order to give a suggestion to manufacturers regarding offline predetermined OCV-SOC relationship. Secondly, the temperature dependence of the two OCV-SOC mapping results is rarely investigated. For an existing BMS, an OCV–SOC relationship constructed at a certain temperature (e.g., room temperature) is widely employed [22]. A large error may occur in inferring SOC when the battery is operating at varied temperatures instead of at room temperature, which is typical in the field. Lastly, most SOC online estimation models are validated using a single loading profile and show high estimation accuracy in existing studies [6,23,26,45,46]. But these estimators would perform poorly if they were applied in other working conditions (i.e., using different loading profiles). Therefore, it makes sense to verify the robustness of the SOC estimation approach against varied loading profiles.

This paper innovatively investigates the influence of different OCV tests on online SOC estimation and the temperature dependency of battery OCV characteristic. The main contributions of this paper are as follows: (1) to present a general understanding and a comparison of two OCV-SOC mapping techniques; (2) to investigate the temperature dependency of OCV-SOC curves via two OCV tests, and (3) to show the influence of two OCV tests on SOC online estimation and thus to give a suggestion for predetermining offline the OCV-SOC relationship for practical BMS application.

The remainder of this paper is arranged into five sections. The experiments conducted for this study are introduced in Section 2. Two OCV-SOC mapping results at various temperatures which reflect the temperature dependency of OCV curves is presented in Section 3. Section 4 illustrates the implementation of the SOC online estimation algorithm. Section 5 shows the influence of two OCV tests on the SOC estimation results. A comparison is given using statistics, and the robustness is verified with regard to various experimental cases. Section 6 concludes with a summary of the main findings of this paper.

2. Experiments

As shown in Fig. 1, the experimental platform consisted of the test samples, a thermal chamber, an Arbin BT2000 battery test system, and a PC with Arbin software to give test system orders (e.g. charging, discharging) and monitor data information. The test samples were the 18,650 $LiNiMnCoO_2$/Graphite lithium-ion cells. Their basic specifications are given in Table 2. Three separate test schedules were conducted on the battery test bench at low temperature (0 °C), room temperature (25 °C), and high temperature (45 °C), respectively. Test samples were placed inside the chamber so that their ambient temperature was controlled. All the test data were measured and recorded in 1 s intervals.