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Short communication

Online state-of-health estimation of lithium-ion batteries using Dynamic Bayesian Networks

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HIGHLIGHTS

- A novel SOH estimation method based on Dynamic Bayesian Networks is proposed.
- The SOH can be estimated in an online manner.
- Only terminal voltages during the constant charge process should be measured.
- The estimated SOH can be provided inherently as either a fuzzy or an exact value.

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ABSTRACT

Li-ion batteries are widely used in energy storage systems, electric vehicles, communication systems, etc. The State of Health (SOH) of batteries is of great importance to the safety of these systems. This paper presents a novel online method for the estimation of the SOH of Lithium (Li)-ion batteries based on Dynamic Bayesian Networks (DBNs). The structure of the DBN model is built according to the experience of experts, with the state of charges used as hidden states and the terminal voltages used as observations in the DBN. Parameters of the DBN model are learned based on training data collected through Li-ion battery aging experiments. A forward algorithm is applied for the inference of the DBN model in order to estimate the SOH in real-time. Experimental results show that the proposed method is effective and efficient in estimating the SOH of Li-ion batteries.

1. Introduction

With the advantages of high cell voltage, low mass, low self-discharge and long cycle life, Li-ion batteries are widely used in energy storage systems, electric vehicles (EVs), communication systems, etc. Energy storage is an enabling technology for power system integration, as it can supply more flexibility for peak shaving and load balancing to the grid, providing a backup to intermittent renewable energy. An energy storage system is also the key component of distributed power systems or smart-grids. In energy storage systems, Li-ion batteries can provide mobile and highly flexible storage capacity and can be placed at several different locations of the grid to ensure efficiency. EVs have numerous advantages over internal combustion engine vehicles in terms of operational convenience, cleanliness, and energy efficiency, and Li-ion batteries are used as main power sources for them. In communication systems, Li-ion batteries are used as secondary power sources. The battery states, such as the state of charge (SOC) and the state of health (SOH), are very important to the safety of these systems [1]. The SOC depicts the remaining capacity that can be drawn from a battery, while the SOH is a measure of the battery's ability to store and deliver electrical energy. The SOC reflects the short-term state of a battery, while the SOH depicts the long-term state of a battery. To maintain optimal battery performance and maximize lifespan of a battery unit, a battery management system (BMS) is often used and is of great essence and significance [2,3]. Currently, many SOC estimation methods have been proposed in the literature, and a subset of them have been used in BMS implementations successfully [4,5]. However, there is still much work that needs to be done for the estimation of SOH.

SOH is defined as the ratio of the current maximum capacity of a battery to its nominal capacity as follows:

$$SOH = Q_{c\max}/Q_n \times 100\% \tag{1}$$

where $Q_{c\max}$ denotes the current maximum capacity and Q_n refers to the nominal capacity of the battery.

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So far, the most reliable means to determine SOH is through off-line discharge testing of batteries [6]. However, off-line testing is time-consuming and usually requires specialized equipment.

Alternately, the internal resistance of a battery increases continuously, along with the digression of the maximum capacity, during its aging process [7]. A SOH estimation method based on the internal resistance estimation was proposed in Ref. [8]. There are two important issues to address for this and similar methods. One issue is that the measurement of battery internal resistance is difficult, and the other is that the relationship between the internal resistance and the SOH is ambiguous. Many studies have been performed relating to these two aspects, respectively. The most common method to measure the internal resistance is the AC impedance method. For example, the authors in Refs. [9] and [10] presented a fast estimation algorithm that models the battery and then estimates the internal resistance using the Extended Kalman Filter (EKF). To address the relationship between resistance and SOH, the authors in Ref. [11] redefined SOH as a function of resistances. However, this new SOH prediction concept still needs to gain widespread recognition. Another popular method of SOH estimation is to combine the internal resistance with fuzzy logic [12]. However, the battery internal resistance is not only related to the SOH but also the SOC. In other words, the battery internal resistance will rise with the reduction of SOC. Therefore, there is still much left to be done before the internal resistance can be used to estimate SOH precisely.

Efficient calculation and real-time computing are the development trends for SOH estimation. Recently, researchers proposed various data-driven methods for battery SOH estimation [13–16]. In Ref. [13], the authors utilized the famous machine learning algorithm, support vector machine, to estimate the SOH by using load collectives as the training and test data. The authors in Ref. [14] first developed an empirical model based on the physical degradation behavior of lithium-ion batteries, with the model parameters initialized by combining sets of training data based on Dempster–Shafer theory. The Bayesian Monte Carlo is then used to predict the remaining useful life based on available data from battery capacity monitoring. In Ref. [15], the authors utilized a probability neural network to estimate the battery SOH, with three significant characteristics as the inputs. The three used characteristics are the length of the constant current charge time, the voltage drop during the alternation of the constant voltage charge and the constant current discharge, and the initial voltage at the constant current charge. Similarly, the authors in Ref. [16] utilized four characteristics, capacity, resistance, length of the constant current charge time and length of the constant voltage charge time, to estimate the SOH. The key to these data-driven methods is two-fold. The first is what kind of characteristics are to be used for SOH estimation. The second is how to combine these characteristics with a proper inference algorithm. In this paper, we also propose a data-driven method for estimating the SOH of Li-ion batteries. The proposed novel method is based on Dynamic Bayesian Networks (DBNs). In this method, consecutive terminal voltages of batteries during constant charge processes are recorded as training data. The training data are first categorized into K different classes according to the SOH of batteries, and K corresponding DBNs are built. The structure of each model is the same and is built according to the experience of experts, while the parameters of the models are different and are learned based on each category of training data. A forward algorithm is then applied to real-time data of batteries for the inference of the DBN models, to estimate the SOH in real-time.

The main contributions of the paper are as follows: Firstly, a novel DBN-based method is proposed to estimate the SOH for Li-ion batteries. Although DBN has been widely used in many application fields, to our knowledge, it has never been used for SOH estimation. Secondly, the proposed method is an online estimation method, and only terminal voltages during the constant charge process should be measured. Thirdly, the final estimated SOH can be provided as either a fuzzy value or an exact value.

The rest of this paper is organized as follows: Section 2 describes, in detail, the battery aging procedures, which provide the data acquired for training DBNs. Section 3 focuses on the proposed DBN-based SOH estimation method. Section 4 shows a forward algorithm that can be used to estimate the SOH in real time. To validate the SOH prediction method presented, an experiment is conducted and the results are presented in Section 5. Finally, Section 6 states the main conclusion of this paper.

2. Life-cycle testing of batteries

In this research, Li–Mn batteries are used for the life-cycle test, which is performed in a laboratory. Detailed electrical characteristics of the batteries are shown in Table 1. Fig. 1 illustrates the experimental equipment used for the life-cycle testing.

As shown in Fig. 1, batteries are discharged by the programmable electronic load IT8513B, manufactured by ITECH Electronics Co. Ltd., and charged by the power supply JC6030A, manufactured by Hangzhou Jingce Electronic Co. Ltd. A multi-meter UT804, manufactured by Uni-Trend Group Limited, connected to a PC is used to measure and store the voltages of the battery. In the meantime, the internal resistance of the battery is measured by a battery HiTester BT3562-01, manufactured by Hioki.

An initial capacity test was first conducted. The test was initiated by discharging the battery to 0% SOC at a current rate of 1 C. The capacity test then continued by charging the battery to 100% SOC, letting it rest for two hours, discharging it back to 0% SOC, and letting it again rest for two hours; this process constituted one capacity measurement. This initial capacity measurement was repeated several times until the two most recent values of capacity converged to be within an acceptable percentage of one another. This initial capacity test serves to recondition the battery [17].

A complete life cycle test is composed of a charge process and a discharge process. First, the battery was fully charged. The charge process usually consists of two parts: the constant current (CC) subinterval and the constant voltage (CV) subinterval, as shown in Fig. 2. A current of 2.4 A (0.4 C) was used to charge the battery during the CC subinterval until the battery reached its cutoff voltage (4.2 V). Then, the voltage was held constant at 4.2 V during the CV subinterval until the current fell to 100 mA. In the process of charging, the voltages of the battery were measured and stored every 10 s. Secondly, the battery is rested to restore stability. Next, a constant current of 6 A (1 C) was used to discharge the battery, and the cutoff voltage was set to 2.75 V. During the discharge process, the currents and time stamps were recorded to calculate the current maximum capacity, Q_{cmax}, of the battery. During the life-cycle testing, the batteries are placed in a constant temperature chamber at 25 °C.

Table 1
Electrical characteristics of the batteries.

Typ. voltage	3.7 V
Nominal capacity	6000 mAh, 1 C discharge
Maximum charge current	1 C
Maximum discharge current	1 C
Minimum discharge voltage	2.75 V
Maximum charge voltage	4.2 V
Discharge temperature	−20 °C to 60 °C
Initial internal impedance	≤20 mΩ
Self-discharge current	≤200 μA
Cycle life (minimum)	800 cycles