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A novel state of health estimation method of Li-ion battery using group method of data handling

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HIGHLIGHTS

- SoH estimation is treated and solved as a control theory issue.
- Philosophy of human health diagnosis is used as an analogy.
- Differential geometric is utilized to analyze battery terminal voltage curve.
- Group method of data handling is employed to estimate SoH.
- The method is applied to different types of battery showing universality.

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ABSTRACT

In this paper, the control theory is applied to assist the estimation of state of health (SoH) which is a key parameter to battery management. Battery can be treated as a system, and the internal state, e.g. SoH, can be observed through certain system output data. Based on the philosophy of human health and athletic ability estimation, variables from a specific process, which is a constant current charge sub-process, are obtained to depict battery SoH. These variables are selected according to the differential geometric analysis of battery terminal voltage curves. Moreover, the relationship between the differential geometric properties and battery SoH is modelled by the group method of data handling (GMDH) polynomial neural network. Thus, battery SoH can be estimated by GMDH with inputs of voltage curve properties. Experiments have been conducted on different types of Li-ion battery, and the results show that the proposed method is valid for SoH estimation.

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1. Introduction

Battery, especially lithium-ion battery, has been widely used in many renewable energy systems as an energy storage equipment because of its high energy density, stability and long service life [1–3]. However, battery would have a different performance when the health state changed. Furthermore, it will be unstable and risky when the battery is in a poor health state. Accordingly, a large amount of battery management systems (BMS) are developed to monitor battery health states, elevate battery safety and even enhance battery useful life for practical operation.

The SoH is applied to describe how an aged battery differs from a fresh battery [4]. It is an internal parameter which cannot be measured directly, but just estimated. The same problem occurs in control theory where indirect effects of system internal state can only be inferred from the system outputs [5,6]. In this paper, the system is a Li-ion battery, whose internal state is the SoH, which cannot be measured directly. And the system outputs are the external features of the battery. Thus, the resolution of SoH estimation can be separated into 3 steps. The first step is to select suitable outputs (representative external features) of the battery, whose measurable quantities would be obtained by sensors in the BMS. The second step is to establish a model to describe the relationship between the internal state and external feature using mathematical functions. And the third step is to compute the internal state by using selected algorithms, e.g. nonlinear filters [7–10], machine learning methods [11–13]. Peculiarly, the second and the last step are usually combined into one in machine learning methods.

Several different types of battery external features have been employed for SoH estimation. The features, e.g. the double layer

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capacitances, the charge transfer resistances, the Warburg impedances and the electrolyte resistances, were extracted from electrochemical impedance spectroscopy (EIS) data and used as system output to describe SoH in Ref. [14]. A large amount of battery charge/discharge data of voltage at a low current (e.g. C/3) has been used by Feng et al. [15]. And, with the help of probability density function, the relationship between battery SoH and voltage data was revealed. The equivalent direct current resistances of Li-ion batteries under different health conditions during charging period have been obtained and utilized for SoH determination by Tsang et al. [16]. Currents, terminal voltages and state of charges (SoCs) were measured and computed in Ref. [17], and were then used to estimate battery SoH. Six critical factors of the battery, i.e. the peak power at 30% SoC, the capacity, the open circuit voltage, the voltage drop at 30% SoC with a C/3 pulse, the temperature rises at the end of discharge and charge at 1C, were required in Ref. [18] to describe SoH.

Likewise, many valuable models and algorithms have been presented for SoH estimation in recent years. SoC and SoH were detected by a dual-sliding-mode observer based on the RC model which was presented using data of charge/discharge current, terminal voltage and temperature in Ref. [19]. Adaptive neural network and linear prediction error method were used by Rezvani et al. [20] for the SoH quantification and remaining useful life prediction of Li-ion battery cells. Hu et al. [21] presented a hybrid of coulomb counting and extended Kalman filter techniques to estimate battery capacity which indicates cell SoH. Chen et al. [22] established a battery model including the diffusion capacitance which was used to determine SoH. Then Genetic Algorithm (GA) was employed to identify model parameters and estimate SoH. Weng et al. [23] provided a quantitative relation between incremental capacity peaks and faded battery capacity using support vector regression (SVR), which was also developed to accomplish the task of SoH observation. In Ref. [24], a mixture of Gaussian process (MGP) was used to capture the time-varying degradation behavior of Li-ion battery, and particle filter was applied in the implementation of SoH monitor based on the MGP model.

However, considering the limitation of the measurement devices in present BMS, many external features of the battery are hard or even impossible to be obtained in actual operation. Moreover, the applications of the above mentioned methods are also limited by the computational capability of real BMS. To address these issues, a suitable feature and an effective machine learning algorithm are utilized to estimate SoH in this paper. Specifically, terminal voltage curve at constant charge current is set as the feature to reflect SoH. A differential geometry based approach (DGA) is exploited to acquire featured parameters from thousands of sample points in the experimental data, followed by the application of GMDH polynomial neural network to establish the relation between voltage curves and SoH and the detection of SoH. Furthermore, experimental data from different Li-ion battery cells are applied to validate the SoH estimation method presented in the paper.

The rest of this paper is organized as follows: In Section 2, battery external feature from CC charge subprocess is expressed by parameters using DGA. Section 3 introduces the GMDH polynomial neural network. Experiment results are presented and analyzed in Section 4. The conclusion is given in Section 5.

2. SoH reflection based on battery external features

Battery external properties and features would change with the degradation of the battery. It is important to find a set of appropriate battery outputs to depict the variation of the SoH.

2.1. SoH definition

A universal definition of the battery SoH is given in Eq. (1).

$$SoH = \frac{C_{bat}}{C_0} \times 100\% \tag{1}$$

where C_{bat} is the present capacity, C_0 is the capacity when the battery is fresh.

Experimental data from NASA battery data set [25] is used in this paper. 3 18650-size Li-ion battery cells with same type are tested through 3 operational profiles (charge, discharge and impedance measurement) at room temperature of 25 °C. The repetitive cycles of charge and discharge process are stopped when a certain cycle number is reached. The operating condition of NASA battery data set is shown in Table 1. Among them, battery # 6 has been over-discharged badly in every cycle. Moreover, SoH of the experimental battery cells from cycle 1 to cycle 168 are plotted in Fig. 1.

As shown in Fig. 1, battery SoH changes as cycle number increases. Moreover, the curves in Fig. 1 also indicate that battery in different cycle number would have a same value of SoH, which means that SoH and cycle life are not equivalent for the batteries used by NASA. This phenomenon is easy to understand from the perspective of human health and kinesiology: health state and athletic ability may be similar for people in different ages.

In the area of medicine and kinesiology, the health state and athletic ability of a person can be reflected by a set of indices whose parameters can be acquired through tests of specific process. For example, VO_2max is used for evaluating the effects of aerobic exercise programs and classifying individuals for health risks. In Ref. [26], VO_2max is predicted through the selected experimental data from a submaximal exercise test. Similarly, battery SoH can also be estimated based on the data of specific charging or discharging process. Thus, battery SoH is described and estimated based on the abovementioned philosophy in this paper.

2.2. External feature selection

There are only a limited number of battery external features which can be captured by sensors in actual BMS to depict SoH. Some of them can be measured directly, e.g. terminal voltage, current, temperature, while some of them are obtained through calculation, e.g. open circuit voltage, incremental capacity and differential capacity. Moreover, to the best of our knowledge, charging process of the Li-ion battery during common actual application consists of 2 subprocesses, constant current (CC) charge and constant voltage (CV) charge. In practical operation, the value

Table 1
Test condition of NASA battery data set.

Battery no.	Constant charge current (A)	Charge cut-off voltage (V)	Discharge current (A)	Discharge cut-off voltage (V)	Nominal capacity (Ah)
5	1.5	4.2	2.0	2.7	2.0
6	1.5	4.2	2.0	2.5	2.0
7	1.5	4.2	2.0	2.2	2.0

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