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A novel method for state of charge estimation of lithium-ion batteries using a nonlinear observer

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HIGHLIGHTS

- A novel method for SOC estimation using a nonlinear observer is presented.
- State equations are derived from the first-order RC equivalent circuit model.
- The observer for SOC estimation is designed and its convergence is proved.
- The new method has merits in computation cost, accuracy and convergence rate.

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ABSTRACT

The state of charge (SOC) is important for the safety and reliability of battery operation since it indicates the remaining capacity of a battery. However, as the internal state of each cell cannot be directly measured, the value of the SOC has to be estimated. In this paper, a novel method for SOC estimation in electric vehicles (EVs) using a nonlinear observer (NLO) is presented. One advantage of this method is that it does not need complicated matrix operations, so the computation cost can be reduced. As a key step in design of the nonlinear observer, the state–space equations based on the equivalent circuit model are derived. The Lyapunov stability theory is employed to prove the convergence of the nonlinear observer. Four experiments are carried out to evaluate the performance of the presented method. The results show that the SOC estimation error converges to 3% within 130 s while the initial SOC error reaches 20%, and does not exceed 4.5% while the measurement suffers both 2.5% voltage noise and 5% current noise. Besides, the presented method has advantages over the extended Kalman filter (EKF) and sliding mode observer (SMO) algorithms in terms of computation cost, estimation accuracy and convergence rate.

1. Introduction

Electric vehicles (EVs), including pure electric vehicle (PEV), hybrid electric vehicle (HEV) and fuel cell electric vehicle (FCEV) are considered to be an effective way to ease energy crisis and environmental pollution. Comparing with other batteries, such as lead-acid battery and nickel–cadmium battery, lithium-ion battery (LIB) has been widely used in EVs due to its higher energy and power density, lower self-discharging rate and longer cycle life. However, LIB has higher requirements for the battery management system (BMS). For example, it has greater risk of burning or exploding than other batteries if it is over-charged or over-discharged. Estimating the SOC is one of the most key techniques in the design of BMS, especially for those used in EVs. An accurate SOC estimation approach will improve the efficiency of power distribution, extend the battery cycle life and prevent the battery from over-charging or over-discharging. Nevertheless, it is difficult to get an accurate value of SOC, because the SOC cannot be measured directly and its value is affected by various factors, such as the current, temperature and cycles (aging).

A number of methods have been proposed to estimate the SOC, such as the ampere-hour (Ah) counting, Kalman filter (KF), sliding mode observer (SMO), particle filter (PF), artificial neural network (ANN) and fuzzy logic (FL) methods. The Ah counting method [1] is the most common one and usually used as the basis of other methods. The merit of Ah method is that it is simple and easy to implement. However, it suffers accumulated errors from the integration process due to inaccurate measurement current.

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Furthermore, as an open-loop estimation method, it cannot deal with the initial SOC error problem. The original KF is a linear estimation method. To expand its application in the nonlinear battery systems, the extended Kaman filter (EKF) [2–7] and unscented Kalman filter (UKF) [8,9] have been developed. Both the EKF and UKF methods can estimate the SOC accurately if the battery model is accurate enough and the system is not highly nonlinear. However, they have poor applicability for highly nonlinear systems and have high requirements for hardware due to a large number of matrix operations. Furthermore, the KF method is based on an assumption that the noise is Gaussian white noise and the statistical property of the noise should be known before the SOC is estimated. However, this usually cannot be met in practice. The SMO [10,11] is a reliable and robust method for SOC estimation in terms of model error and external disturbance. However, it is difficult to design the SMO for SOC estimation because the optimal parameters are hard to obtain. The PF [12] method also needs numerous matrix operations and has high requirements for hardware. The ANN method [13–15] requires a large number of sample data and a reliable learning algorithm. The FL method [16] is difficult to design and its performance depends on the designer's experience.

In this paper, a novel method for SOC estimation using a nonlinear observer is presented. This method does not need complicated matrix operations and is robust against the measurement errors and parameter uncertainties. Comparing with EKF method, the presented method can reduce the computation cost with the similar SOC estimation accuracy and convergence performance. Comparing with SMO method, it can improve the SOC estimation accuracy and accelerate convergence simultaneously. Therefore, the proposed method has good performance and can be easily implemented in an online estimation system.

The remains of this paper are organized as follows. Section 2 introduces the first-order resistor–capacitor battery equivalent circuit model, based on which the state-space equations are derived. Section 3 illustrates the design of the nonlinear observer for the SOC estimation and proves the convergence of the observer. Section 4 shows the experimental configurations. Experimental results and discussion are presented in Section 5. Finally, Section 6 concludes the paper.

2. Battery modeling

2.1. Equivalent circuit model of a battery

A common definition of SOC is formulated as.

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_0) - \frac{\int_{t_0}^{t} i\mathrm{d}t}{C_n} \tag{1}$$

Based on Eq. (1), the derivative of SOC can be obtained as.

$$\dot{\mathrm{SOC}}(t) = -\frac{i(t)}{C_n} \tag{2}$$

where i represents the battery current, whose value is positive while discharging and negative while charging; and C_n is the battery nominal capacity.

An accurate battery model that can simulate the dynamic characteristic of a LIB is essential to the SOC estimation. Therefore, many battery models have been proposed, among which the most common are the equivalent circuit models, including the resistor model [9], first-order resistor–capacitor (RC) model [17–19], second-order RC model [3,11] and complicated RC models [20–22]. The resistor model is the simplest model and has the lowest computation cost. However it cannot accurately reflect the dynamic voltage characteristic of a battery. The complicated electrical models can reduce model errors, but increase system complexity and computation cost. In Refs. [19], a comparative study of twelve equivalent circuit models for LIB was presented. The results indicate that the first-order RC model is a good choice to balance between model robustness and complexity since it is almost as good as more complex models. Therefore, in this paper, the first-order RC model is utilized to make a trade-off between the model error and computation cost. As shown Fig. 1, the first-order RC model consists of an open-circuit voltage $U_{\mathrm{oc}}(\mathrm{SOC})$, a resistor R_o, and an RC network R_1 and C_1. The resistor R_o is used to represent the electrical resistance of battery components with the accumulation and dissipation of charge in the electrical double-layer, and it is called as ohmic resistance. While the RC network is employed to describe the mass transport effects and dynamic voltage performance, the elements of R_1 and C_1 are accordingly called as the diffusion resistance and diffusion capacitance, respectively [5].

The electrical behavior of the first-order RC model can be expressed as.

$$\dot{U}_1 = -\frac{U_1}{R_1 C_1} + \frac{I_L}{C_1} \tag{3}$$

$$U_L = U_{\mathrm{oc}}(\mathrm{SOC}) - U_1 - I_L R_o \tag{4}$$

where U_1 is the terminal voltage of capacitor C_1, U_L is the load voltage, and I_L is the load current.

2.2. Model parameters identification

For the first-order RC equivalent circuit model shown in Fig. 1, the values of parameters R_o, R_1 and C_1, as well as the relationship expression between the open circuit voltage (OCV) and the SOC have to be identified. To do so, pulse discharge experiment has been carried out based on the ICR18650–22F typed lithium-ion batteries. More details about the battery parameters and the test bench configurations will be illustrated in Section 4. With the exponential-function fitting method, the values of parameters R_o, R_1 and C_1 are obtained, as shown in Table 1.

An accurate relationship expression between the OCV and the SOC is crucial to improve the SOC estimation accuracy. Various approaches have been developed to describe the relationship between the OCV and the SOC. For instance, a straight–line fitting method was used in Ref. [10], while a broken–line fitting method was utilized in Ref. [11]. Both of the two methods are simple, but not accurate enough to capture the dynamic voltage behavior of a battery. In this paper, a ninth–order polynomial fitting method is employed to improve the model accuracy. The profile of COV versus

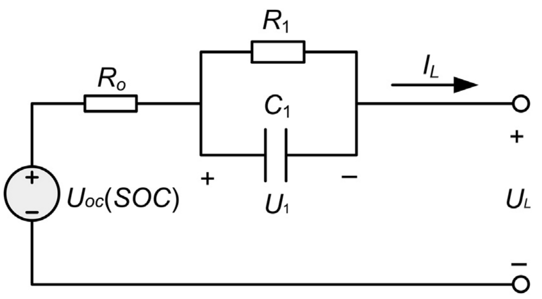

Fig. 1. Schematic diagram of the first-order RC equivalent circuit model.