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A parameter adaptive method with dead zone for state of charge and parameter estimation of lithium-ion batteries

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HIGHLIGHTS

- A parameter adaptive method with dead zone is developed for battery system.
- The proposed approach improves the robustness and accuracy of SOC estimation.
- The proposed approach reduces the computation for parameter adaptive method.
- The proposed approach is validated under dynamic and constant current cycles.

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ABSTRACT

It is very important to estimate the state of charge accurately and to achieve the on-line updating of the battery parameter for the battery management system of electric vehicles. This research aims to develop a novel parameter adaptive method with dead zone for estimation of state of charge and other parameters of lithium-batteries. The dead zone refers to the definition of an interval based on the error of the battery model terminal voltage and the measured terminal voltage. When the error is no longer in the interval, the battery parameters are not estimated. Otherwise, the battery parameters are estimated. This research can be summarized as follows. First, the proposed method is applied to estimate all battery parameters including battery capacity, battery impedance and open circuit voltage. Second, the use of dead zone solves the problem of poor robustness of parameter adaptive algorithm when the initial state error is large, and the problem of instability. Finally, the experimental results indicate that the proposed method can achieve estimation accuracy with an error of 1%. Moreover, compared with the method used the same sampling time for estimating battery state and parameters, the dead zone method reduces the computation.

1. Introduction

Lithium-ion batteries are important energy storage devices that have been widely used in pure electric vehicles (EV) and hybrid electric vehicles (HEV) due to their high performance in cycle life and energy density [1]. The core functionality of battery management system (BMS) in the vehicle is to estimate the state of charge (SOC). A robust and accurate estimation of the battery's SOC is necessary in order to ensure the vehicle's stability and reliability.

There is a brief summary of the SOC estimation methods given in Ref. [2], which can be divided into three categories: the conventional method such as open circuit voltage (OCV) method and ampere-hour counting method; The model-based estimation method such as Kalman filter (KF) [3], particle filter (PF) [4], H-infinity filter [5,6], and non-linear observer [7–10]; The learning algorithm such as neural network (NN) [11], fuzzy logic (FL) [12], support vector machine (SVM) [13] and genetic algorithm (GA) [14,15]. The OCV method and ampere-hour counting method are very simple methods, but their shortcomings are obvious. The OCV method is based on a one-to-one relationship between battery OCV and SOC, but it requires a long time resting in order to reach balance and it is difficult to use this method when the electric car is in operation. Ampere-hour counting method is a simple calculation method using low-cost sensor measurement, but its main drawback is easily affected by initial error and electric current measurement noise. Therefore, the ampere-hour counting method is difficult to guarantee the sustained time accuracy [16,17], so in practice it is often used in combination with other model-based estimation methods. There are many model-based SOC estimation methods, e.g. a number of

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Kalman filter methods and their variations for SOC estimation [18]. A common drawback of the model-based methods is that the model parameters are identified or estimated by offline data. Due to the fact that the parameters of the battery will change with the aging of the battery and there are fitting error for the parameter identified offline, it is imperative to calibrate battery parameters on-line to estimate SOC accurately for practical applications. The learning algorithm based methods can be used for SOC estimation, which require a lot of training data and a large amount of computation efforts.

The parameter adaptive method can improve battery SOC estimation accuracy through updating battery parameters. The recursive least square (RLS) algorithm is employed to estimate the battery parameters with the help of the forgetting factor [19]. A dual/joint Kalman filters method to estimate the battery SOC and capacity concurrently is proposed in Refs. [20–23]. In Refs. [24–26], the unscented Kalman filter (UKF), the particle filter (PF), and the unscented particle filter (UPF) are respectively used to estimate battery SOC, battery capacity and battery impedance simultaneously while the OCV is still based on off-line data. The approach of multi-scale dual Kalman filters to estimate the battery SOC, battery capacity and battery impedance is given in Ref. [27], where the battery state and parameters are estimated by different sampling time. In Ref. [28], it can be found that the multi-scale dual H-infinity filters is applied to estimate battery SOC, battery capacity and battery impedance. A combined method is presented in Ref. [29] where the battery state and battery impedance are estimated by using PF and extended Kalman filter (EKF), respectively. In general, the battery parameters include battery capacity, OCV and battery impedance. However, all above-mentioned methods can only estimate partial parameters of the battery. Although all parameters of the battery would affect the estimation of battery SOC, it is difficult to guarantee the robustness and stability of the algorithm by estimating all battery parameters simultaneously. Especially in some segments of OCV-SOC curve, OCV changes dramatically with the SOC, which shows different characteristics from other battery parameters. It is reasonably assumed that the battery capacity and battery impedance are the slow time-varying parameters compared to battery SOC, so most of the methods use OCV off-line data to ensure the stability of the algorithm. The estimation of OCV directly by dual Kalman filters can be found in Ref. [30], but the other parameters of battery use off-line data to ensure the stability of algorithm. A part of parameters identification using offline data can improve the robustness of the algorithm with respect to the initial value of SOC.

In view of the above problems, a key contribution of this study is that a parameter adaptive method with dead zone is proposed. Based on the error between the actual terminal voltage and the terminal voltage calculated by the battery model, two dead zones are designed. The algorithm stops battery parameter estimation when the battery model error is too large or too small. The use of dead zone solves both the problem of poor robustness of parameter adaptive algorithm when the initial state error is large, and the problem of instability. In particular, the estimation of OCV is converted into the OCV fitting parameters while the fast time-varying parameter OCV is converted into several slowly time-varying parameters. In this way, it ensures that the algorithm can obtain accurate OCV values when the parameters estimation occurs in dead zone. Moreover, the effectiveness of the parameter adaptive method with dead zone has been validated by dynamic and constant current loading profile. In comparison with the EKF method, the experiments verify the correctiveness of the two dead zones.

The paper is organized as follows: Section 2 provides battery modeling. Section 3 describes the implementation of the parameter adaptive method with dead zone. The battery tests, experiments, simulation results and evaluation of the proposed method are illustrated in Section 4. Finally, the conclusions are drawn in Section 5.

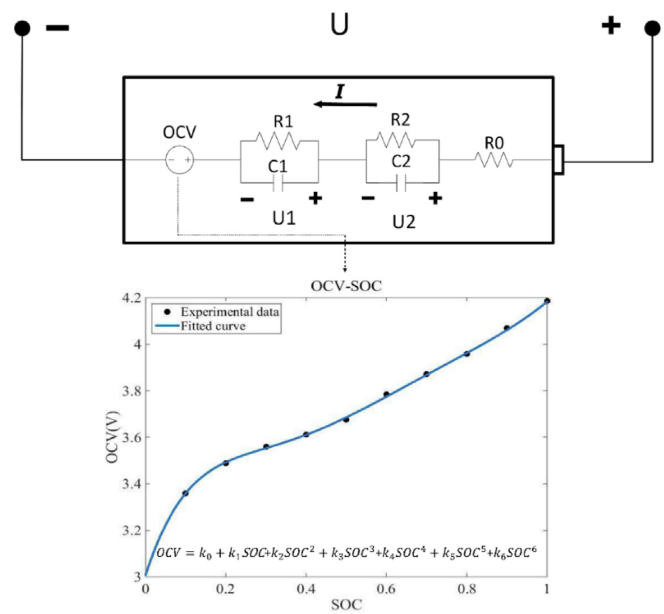

Fig. 1. The circuit of the second-order RC model.

2. Battery modeling

It is well known that the accuracy of the battery model of electric vehicle has a great impact on the estimation of SOC [31]. The equivalent circuit model (ECM) is widely used for Li-Ion Battery, in particular the second-order resistor–capacitor (2RC) battery equivalent circuit model maintains good accuracy and is not very complicated [32].

Here we consider the second-order resistor–capacitor (2RC) battery equivalent circuit model as shown in Fig. 1. The model consists of the open circuit voltage (OCV), the terminal voltage U, the ohmic resistance R_0 and two RC branches. R_1 and C_1 are the activation polarization resistance and capacitance, respectively; R_2 and C_2 are the concentration polarization resistance and capacitance, respectively; U_1 and U_2 describe the diffusion voltage over the RC network; Q is the battery capacity; U is the terminal voltage; I is the load current (assumed positive for charge, negative for discharge). The electrical behavior of the 2RC battery equivalent circuit model can be expressed as:

$$\begin{cases} \dot{U}_1 = \frac{1}{R_1C_1}U_1 + \frac{1}{C_1}I \\ \dot{U}_2 = \frac{1}{R_1C_1}U_1 + \frac{1}{C_1}I \\ \dot{SOC} = -\frac{1}{Q}I \end{cases} \tag{1}$$

$$U = OCV + U_1 + U_2 + IR_0 \tag{2}$$

Open circuit voltage (OCV) refers to the voltage source, which is related to the battery SOC. The OCV function takes SOC as variable. So the OCV is typically represented by a polynomial fitted equation containing SOC. The relationship between SOC and OCV is fitted by least squares method (LSM). The OCV function can be expressed by the following equation:

$$OCV = K_0 + K_1SOC + K_2\,SOC^2 + K_3\,SOC^3 + K_4\,SOC^4 + K_5\,SOC^5 + K_6\,SOC^6 \tag{3}$$

Where K_i $(i = 0,1,2,3,4,5,6)$ are slow time-varying parameters which correlate the SOC-OCV data. The OCV varies with the change of SOC. If we assume the OCV as an estimated parameter, the estimation of the parameter and state of battery must be maintained at the same sampling time. Thus we estimate the slow time-varying parameter K_i instead of directly estimating OCV.