ARTICLE IN PRESS

Applied Energy xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

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

A novel parameter and state-of-charge determining method of lithium-ion battery for electric vehicles

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HIGHLIGHTS

- The improved method is accurate and stable when the sample interval is long.
- The LMS algorithm, which requires less computational capability, is made effective by the improved method.
- An HIL test is conducted to verify the accuracy of the improved method.
- The improved method shows high accuracy and stability in the determination of the SoC.

ARTICLE INFO

Article history:
Received 7 February 2017
Received in revised form 2 May 2017
Accepted 8 May 2017
Available online xxxx

Keywords:
Electric vehicles
Battery
On-line parameter identification
State-of-charge
Hardware-in-the-loop validation

ABSTRACT

To improve the estimation accuracy of a battery's inner state for a battery management system, an improved online model-based parameter identification algorithm is proposed. To reduce the computation cost, the existing methods regard the open circuit voltage over a certain time as a constant value. However, the battery state-of-charge (SoC) estimation error with the traditional method will deteriorate with larger sampling intervals. Compared with the existing parameter identification method, a new online estimation method is proposed, and both recursive least squares (RLS) and least mean square (LMS) algorithms are employed and compared systematically. The LMS algorithm, which requires less computational capability and storage space but performs worse than the RLS algorithm, is also invalid for the wide sampling interval in the traditional method. The improved method using LMS can maintain the maximum SoC estimation error at less than 10%. The simulation results show that the proposed approach can accurately identify the model parameters within 5% SoC estimation error. Finally, a hardware-in-the-loop validation experiment is carried out to prove the accuracy and superiority of the improved method.

1. Introduction

Electric vehicle technology is a good choice to solve the problems of energy shortage and environmental pollution. The battery pack, which plays a critical role in electric vehicles, is also the critical technological bottleneck of electric vehicles. It determines the performance of the electric vehicle, influencing economy, power, reliability and other aspects of performance [1,2]. The state-of-charge (SoC), which reflects the usable energy of the battery pack, is vital for the energy control and state estimation of the EVs (electric vehicles). As a result, the estimation of the SoC is an important function of the battery management system (BMS) [3–5].

The existing SoC estimation methods are primarily of two types: the direct method and the indirect method [6]. The direct method remains the most popular method today. The direct method usually uses an ampere-hour integral to obtain the SoC [7,8]. The advantages of this method include low calculation requirements and high reliability, although its accuracy is very poor [9,10]. The lack of accuracy is caused by two reasons, the accuracy of the electric current cannot be guaranteed because of the sensor limit, and the initial SoC is difficult to obtain [11,12].

To address this inadequacy, some studies put forward indirect methods. Indirect methods obtain the SoC according to the battery's intrinsic relationship between the SOC and some electrical parameters, usually the open-circuit voltage (OCV) [13–15]. During the battery charging or discharging process, there is always a

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http://dx.doi.org/10.1016/j.apenergy.2017.05.081
0306-2619/

Please cite this article in press as: Li Z et al. A novel parameter and state-of-charge determining method of lithium-ion battery for electric vehicles. Appl Energy (2017), http://dx.doi.org/10.1016/j.apenergy.2017.05.081

one-to-one relationship between the OCV and the SoC, so we can build an OCV-SoC table. The problem is transformed into how to obtain the OCV. Measurement of the OCV is difficult because it is infeasible to wait a long time for the battery to reach a steady state [16–18]. To solve this problem, some studies have built equivalent circuit models, which consist of voltage sources, resistors and capacitors to describe the operational performance of the battery [19,20]. The OCV can be identified as a parameter of the equivalent circuit model [21–23].

The indirect methods include two types: the offline estimation method and the online estimation method [24,25]. The offline estimation methods generally use optimization algorithms such as the extended Kalman filter (EKF), a genetic algorithm (GA), particle swarm optimization (PSO) or other methods to identify the battery parameter [26–29]. Offline methods can provide good results, but they requires too many calculations, taking dozens of hours to complete a single time and making it difficult to adopt in EVs [30,31]. Conversely, the online estimation method is a widely applied method. The online estimation method can track the state of the battery in real time [2,32,33]. In addition, it requires less time to perform the calculations and occupies only a small amount of memory. Ref. [34] puts forward a model-based, online estimation method for the SOC and the OCV. This method is widely used and accepted by scholars. First, an equivalent circuit model with n RC networks is used to model the polarization characteristic and the dynamic behavior of the battery. Generally, the estimation results have the best accuracy when there are fewer than two RC networks. Next, the corresponding equations are built to describe the electric behavior of the battery. A Laplace transformation and a bilinear transformation are used for system discretization. The recursive least squares (RLS) method is used to identify the battery parameters, including the open-circuit voltage (OCV). Finally, the SoC can be obtained from the OCV-SoC lookup table, which is built based on experimental data.

The traditional method can obtain a satisfactory result when the system sampling interval is small, but there is a critical shortcoming. The traditional method assumes the change in the OCV between two adjacent sample points is negligible. Therefore, the traditional method supposes $\partial SoC/\partial t \approx 0$ and the OCV of two adjacent sample points are equal. This supposition is reasonable with a small sampling interval. However, if the sampling interval is large, the change in the OCV is not small enough to be ignored. As a result, this traditional method works poorly with a moderate or a large sampling interval. Experiments show that the maximum SoC error is greater than 10% when the sampling interval is only 5 s. It is unrealistic and wasteful for EVs to adopt a very short sampling interval. The sampling interval is usually more than 5 s in practical applications.

Based on the previous analysis, this paper proposes an improved online estimation method that will address the issues of the traditional method. In this improved method, the supposition that the OCV is unchanging has been abandoned. The improved method has almost no difference from the traditional method in commonly encountered conditions, but it does not generate large peaks as can occur with the traditional method. In addition, the new method has astringency and will approach the correct result rapidly if there is a false initial value or signal disturbance. It also has better stability and will not generate large mini waves on the second time scale as occurs with the traditional method.

The remainder of this paper is organized as follows. Section 2 discusses the improved method in detail and proves its astringency and reliability. A verifying experiment is carried out based on a dynamic stress test (DST) in Section 3. The results and errors of the improved method are presented and discussed in Section 4. A hardware-in-the-loop validation test is conducted to prove the superiority of the improved method in Section 5. Finally, conclusions are drawn in Section 6.

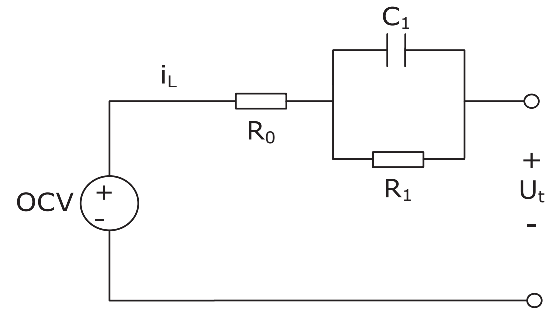

Fig. 1. The schematic of the Thevenin model.

2. The traditional method and the improved method

2.1. The traditional method

To model the polarization characteristic and the dynamic behavior of the battery, an equivalent circuit model with n RC networks is built. Parameter n represents the number of RC networks. If the model is too complex, it will have reduced accuracy. Therefore, n is usually less than 5. When n = 1, the equivalent circuit model is reduced to the Rint model, and when n = 2, the equivalent circuit model is reduced to the Thevenin model. According to the experimental verification, in most cases, the model has the best accuracy when n = 1 or n = 2. Consequently, this paper uses the Thevenin model, shown in Fig. 1, to simulate the behavior of the battery.

Eqs. (1) and (2) are built to describe the electrical behavior of the Rint model based on Kirchhoff's laws.

$$U_{ocv} = U_t + i_L R_o + U_1 \tag{1}$$

$$i_L = C_1 \frac{dU_1}{dt} + \frac{U_1}{R_1} \tag{2}$$

where U_{OCV} is the OCV, U_t is the terminal voltage, i_L is the load current, R_0 is the equivalent ohmic resistance, U_1 is the voltage across the RC network, R_1 is the resistance in the RC network, and C_1 is the capacitor in the RC network.

To discretize the continuous time system, a Laplace transformation and a bilinear transformation are carried out based on Eqs. (1) and (2), as shown in Table 1.

Table 1
The mathematical derivation process of the continuous time system discretization.

I. Laplace transform	
$i_L(s) = C_1 s U_1(s) + \frac{1}{R_1} U_1(s)$	(3)
$U_1(s) = i_L(s) \cdot \frac{R_1}{1+R_1 C_1 s}$	(4)
$U_{OCV}(s) - U_t(s) = i_L(s) \cdot \left(R_0 + \frac{R_1}{1+R_1 C_1 s}\right)$	(5)
II. Bilinear transformation	
$s = \frac{2}{T} \cdot \frac{1-z^{-1}}{1+z^{-1}}$	(6)
$U_{OCV}(z^{-1}) - U_t(z^{-1}) = i_L(z^{-1}) \cdot \frac{\frac{R_0 T + R_1 T + 2R_0 R_1 C_1}{T+2R_1 C_1} + \frac{R_0 T + R_1 T - 2R_0 R_1 C_1}{T+2R_1 C_1} z^{-1}}{1 + \frac{T-2R_1 C_1}{T+2R_1 C_1} z^{-1}}$	(7)
III. Inverse Z-transform	
Define $a_1 = -\frac{T-2R_1 C_1}{T+2R_1 C_1}$, $a_2 = -\frac{R_0 T + R_1 T + 2R_0 R_1 C_1}{T+2R_1 C_1}$ and $a_3 = -\frac{R_0 T + R_1 T - 2R_0 R_1 C_1}{T+2R_1 C_1}$	
$U_t(k) = U_{OCV}(k) - a_1 U_{OCV}(k-1) + a_1 U_t(k-1) + a_2 i_L(k) + a_3 i_L(k-1)$	(8)
Define $M(k) = U_{OCV}(k) - a_1 U_{OCV}(k-1)$	
$U_t(k) = M(k) + a_1 U_t(k-1) + a_2 i_L(k) + a_3 i_L(k-1)$	(9)
IV. Transform into vector notation	
Define $\varphi(k) = [1 \quad U_t(k-1) \quad i_L(k) \quad i_L(k-1)]$ and $\theta(k) = [M(k) \quad a_1 \quad a_2 \quad a_3]^T$	
$U_t(k) = \varphi(k)\theta(k)$	(10)

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