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State of charge estimation of lithium-ion batteries using an optimal adaptive gain nonlinear observer

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ABSTRACT

Accurate state of charge (SOC) estimation is very crucial to guarantee the safety and reliability of lithium-ion batteries, especially for those used in electric vehicles. Since the SOC is unmeasurable and nonlinearly varies with factors (e.g., current rate, battery degeneration, ambient temperature and measurement noise), a reliable and robust algorithm for SOC estimation is expected. In this paper, an optimal adaptive gain nonlinear observer (OAGNO) for SOC estimation is proposed. The particle swarm optimization (PSO) algorithm is employed to optimize parameters of the adaptive gain nonlinear observer (AGNO). A combined error is presented as the fitness function to evaluate the search performance of the PSO algorithm. To perform the PSO-based parameter optimization of the AGNO, a combined dynamic loading profile consisting of the Federal Urban Driving Schedule, the New European Driving Cycle and the Dynamic Stress Test is developed. The proposed approach is verified by experiments performed on Panasonic NCR18650PF lithium-ion batteries and compared with different parametric AGNOs. Experimental results indicate that the proposed OAGNO is helpful to improve the accuracy of battery SOC estimation compared with the non-optimal AGNO methods. Additionally, the OAGNO approach is robust against initial SOC error, current noise and different driving cycles.

1. Introduction

Nowadays, lithium-ion battery is becoming more and more popular in energy storage systems, especially for those used in electric vehicles and distributed power generation. Compared with other kinds of batteries, lithium-ion battery has the merits of high power/energy density, high cell voltage, pollution-free, no memory effect, long lifespan, and low self-discharge rate [1]. However, it has high requirements on the battery management system (BMS) to guarantee the safety and reliability of battery operation. The BMS is in charge of monitoring the battery operating parameter (e.g., voltage, current and temperature) and estimating the battery states, e.g., state of charge (SOC), state of energy (SOE), state of health (SOH) and state of power (SOP). SOC defined as the ratio of battery remaining capacity to its nominal capacity decides how long the battery can be used before recharging. It is regarded as the most key parameter to be monitored by the BMS. Nevertheless, SOC is immeasurable and influenced by amount of factors, such as current rate, ambient temperature, battery degeneration, parameter uncertainties and external disturbance. Thus estimation via measureable variables (e.g., current, voltage and temperature) is a commonly used method to obtain the approximate value of SOC.

1.1. Review of the SOC estimation approach

To get the accurate value of SOC, a number of approaches have been developed, such as the Ampere-hour integral or Coulomb counting method [2,3], open-circuit voltage method [4], electrochemical impedance spectroscopy method [5], machine learning-based methods (e.g., artificial neural network [6–8] and support vector machine [9,10]), KF-based methods (e.g., extended Kalman filter (EKF) [11–19] and unscented Kalman filter (UKF) [20–28]), sliding mode observer (SMO) method [29–31], and particle filter method [32–34]. The first four methods need not establish the battery models, so they are usually called as non-model based methods. These methods featured by open-loop cannot correct errors caused by inaccurate initialization of SOC, measurement noise and external disturbance. Besides, the estimation accuracy of the machine learning-based methods highly depends on quantity of the training data. In practice, however, it is nearly impossible to collect an adequate number of training data, which can cover all loading scenarios of the battery. Besides, collection of the training

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data is time-consuming. Thus, the estimation accuracy of these methods cannot be guaranteed for online application. Because of the aforementioned factors, the application of the non-model based and open-loop methods in accurate SOC estimation is limited. Instead, the last four methods are categorized as model-based and close-loop method, because they need to establish a battery model for SOC estimation and have the ability of correcting errors due to inaccurate initialization of SOC, model uncertainties, measurement noise and external disturbance. Accordingly, compared with the open-loop and non-model based methods, these methods are more attractive to be used for accurate SOC estimation and more investigated in recent years.

EKF and UKF were firstly introduced to estimate SOC of lithium-ion batteries by Plett in 2004 [11] and 2006 [20] respectively. Although the KF-based SOC estimation methods showed satisfying results in terms of accuracy and robustness to measurement noise, they have some shortcomings. For instance, the EKF suffers large linearization error and needs to calculate the Jacobian matrix, which may lead to instability of the filter and then reduce estimation accuracy for strongly nonlinear battery systems [30], e.g., the LiFePO4 battery. The studies of Li et al. [35] and He et al. [36] indicated that the UKF performs better in terms of accuracy and robustness compared with the EKF, however, the UKF takes more computation time due to a large number of matrix operations. In addition, the KF-based methods assume that the noise in the system follows the Gaussian distribution, which is usually inconsistent with the conditions in practical battery systems. Furthermore, they require statistic knowledge of the system and measurement noises, which is represented as covariance. As a result, the accuracy of SOC estimation is strongly dependent on the selection of the covariance. That is to say, an inappropriate selection of covariance is likely to result in large estimation error. To overcome this problem, adaptive EKF [16–19] and adaptive UKF [27,28] were further developed, which can adaptively update the covariance according to the observation error. Nevertheless, the addition of update law significantly increases the computation complexity. The SMO method can guarantee the reliability and robustness of SOC estimation when the battery systems suffer model uncertainties and stochastic disturbances. Nevertheless, it is difficult for the designers to select the reliable parameters of SMO, e.g., the switching gains and the uncertainty boundaries, which obviously affect performance of the SMO [29]. Furthermore, the SMO asks observation equation of the system to be linear, so the relationship between OCV and SOC has to be approximated by a linear function, which will reduce the SOC estimation accuracy. Compared with the aforementioned methods, the PF can be applied for SOC estimation of high-order nonlinear battery systems suffered non-Gaussian distributed disturbances. Nevertheless, its implementation is a great challenge to onboard systems because it requires a large number of particles and massive matrix operations. Furthermore, the PF-based method may result large estimation error due to particle degeneration. In our previous studies [37,38], a nonlinear observer-based algorithm has been developed to efficiently estimate the battery SOC. In order to improve the estimation performance, a modified SOC estimation algorithm based an adaptive gain nonlinear observer was further proposed in [39]. Nevertheless, the selection of the gain coefficients having significant influence on the estimation performance was not solved in the previous works.

1.2. Contribution of the paper

In this paper, we propose an optimal adaptive gain nonlinear observer for SOC estimation of the lithium-ion batteries. Firstly, the widely used 2nd-order equivalent circuit model is selected to simulate the dynamic behaviors of the lithium-ion battery, and parameters of the battery model are identified based on the voltage response of pulse current discharging process and the exponential-function fitting method. Then, the optimal adaptive gain nonlinear observer for SOC estimation is developed. In this method, the particle swarm optimization (PSO) algorithm is introduced to optimize parameters of the adaptive gain nonlinear observer. Accordingly, a combined error is presented to be the fitness function to evaluate the search performance of the PSO algorithm. To perform the PSO-based parameter optimization of the adaptive gain nonlinear observer, a combined dynamic loading profile composed of the Federal Urban Driving Schedule, the New European Driving Cycle and the Dynamic Stress Test is developed. Finally, the proposed approach is verified by experiments performed on Panasonic NCR18650PF lithium-ion batteries and compared with different parametric adaptive gain nonlinear observers. Experimental results indicate that the proposed OAGNO algorithm can accurately estimate the battery SOC with a mean absolute error about 0.74% and a maximum error less than 3.1%, which are lower than that of non-optimal AGNO methods. Robustness of the OAGNO algorithm against factors, including initial SOC error, current noise and different driving cycles are further investigated, and results indicate that the proposed OAGNO always performs better compared with the non-optimal AGNO approaches.

1.3. Organization of the paper

The rest of this paper is organized as follows. Section 2 introduces the 2nd-order battery model and the identification of its parameters. In Section 3, detail of the optimal adaptive gain nonlinear observer for SOC estimation is presented. Section 4 illustrates the experimental configuration and verification of the proposed method. Finally, the paper is summarized in Section 5.

2. Battery modeling

2.1. Definition of SOC

Generally, SOC of the battery is defined as a ratio of the remaining capacity to its nominal capacity formulated as

$$SOC(t) = SOC(t_0) - \frac{1}{C_n}\int_{t_0}^{t} \eta_c i_L(\tau)d\tau \qquad (1)$$

where $SOC(t)$ and $SOC(t_0)$ represent the current SOC at time t and initial SOC at time t_0 respectively, C_n denotes the nominal capacity of the battery, η_c is the Coulombic efficiency defined as the ratio of the discharging capacity to the charging capacity, i_L represents the current flowing through the load which is positive for discharging and negative for charging.

Based on Eq. (1), the SOC estimation accuracy is affected by factors summarized as follows

(1) Inaccurate initial SOC: It is difficult to get an accurate initial SOC due to self-discharging, voltage recovering and nonlinear OCV-SOC relationship.
(2) Inaccurate discharging capacity: Usually, the practical discharging capacity C_d is not equal to the nominal capacity C_n as it varies with current rate, ambient temperature and battery degeneration, etc.
(3) Inaccurate measurement: i_L cannot be accurately measured in practice due to electromagnetic interference and sensor drift.
(4) Inaccurate Coulombic efficiency: Similarly with C_d, η_c varies with current rate, ambient temperature and battery degeneration, so it cannot be obtained online.

As open-loop methods, the non-model based estimation approaches cannot correct errors caused by above factors.