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A model-based adaptive state of charge estimator for a lithium-ion battery using an improved adaptive particle filter ☆

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HIGHLIGHTS

- Propose an improved adaptive particle swarm filter method.
- The SoC estimation method for the battery based on the adaptive particle swarm filter is presented.
- The algorithm is validated by the case study of different aged extent batteries.
- The effectiveness and applicability of the algorithm are validated by the LiPB batteries.

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ABSTRACT

Obtaining accurate parameters, state of charge (SoC) and capacity of a lithium-ion battery is crucial for a battery management system, and establishing a battery model online is complex. In addition, the errors and perturbations of the battery model dramatically increase throughout the battery lifetime, making it more challenging to model the battery online. To overcome these difficulties, this paper provides three contributions: (1) To improve the robustness of the adaptive particle filter algorithm, an error analysis method is added to the traditional adaptive particle swarm algorithm. (2) An online adaptive SoC estimator based on the improved adaptive particle filter is presented; this estimator can eliminate the estimation error due to battery degradation and initial SoC errors. (3) The effectiveness of the proposed method is verified using various initial states of lithium nickel manganese cobalt oxide (NMC) cells and lithium-ion polymer (LiPB) batteries. The experimental analysis shows that the maximum errors are less than 1% for both the voltage and SoC estimations and that the convergence time of the SoC estimation decreased to 120 s.

1. Introduction

Using a battery management system (BMS) is critical for electric vehicles [1,2], especially those with a lithium-ion battery (LIB). Based on the foundation of BMS control topology, accurate model estimations including the parameters, the capacity and the state of charge (SoC) of the battery are important for the safety, power and economic performance of the vehicle. Currently, most BMSs for electric vehicle use the static equivalent circuit model to estimate the battery condition [3]. For example, in the R_{in} and RC [4], Thevenin [5], Partnership for a New Generation of Vehicles (PNGV) [6] and nonlinear equivalent circuit models [7], the battery parameters are tested using the offline hybrid pulse power characterization (HPPC) experiments. However, the model structure and the model parameters will vary largely for the entire BMS lifetime. As a result, these models cannot reflect the effects of the working current, SoC, state of health (SoH), temperature or the self-discharge on the internal characteristics of the battery [8]. Another drawback of this modeling method is that the model parameters are identified using offline data. Therefore, the battery parameters cannot dynamically change over the lifetime of the battery. The variances in the battery model parameters that follow its degradation and varying operation conditions are neglected. Thus, the reliability and applicability of these models should be discussed further.

LIBs have become the dominant battery type for electric vehicles due to their many merits. Compared with other types of batteries, LIBs have outstanding energy density, charging velocity, robust health conditions and use cycles. SoC is a crucial index for LIBs but is difficult to measure directly due to the electrochemical process that occurs during working operation. Considerable effort has been expended to investigate the estimation methods, and

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the advantages of each are reviewed in [9–12]. The ampere-hour (A h) integral algorithm is a very precise and low-cost approach if the initial SoC is accurate and if the current measurement electronics have high fidelity. However, the strong dependence on model corrections and the trade-off between model complexity and estimation accuracy are concerning. In addition, some intelligent algorithms [13,14] have been used to estimate the SoC. For example, the sliding mode method [3], proportional-integral (PI) method [15], and Kalman filter method can somewhat reduce the error of SoC estimation. Although these models can achieve desirable results, the necessary a priori knowledge is their primary weakness. The model error of the battery defines the accuracy of the SoC estimation. The system error, which is caused by the variation in the internal parameters of the battery, is not considered. A novel online method that can estimate the SoC and can dynamically and adaptively follow the parameter variation of the battery was then proposed. To overcome the abovementioned shortcomings, a previous study used the uncertainty quantification method to innovatively solve the uncertainty modeling problems of a dynamic battery system [16]. With an accurate battery pack model and an adaptive filter based on the battery SoC estimator, the SoC of the battery group can be accurately estimated. Then, a novel battery temperature field forecasting method was proposed for an online LIB, including the electrochemical impedance and the internal battery characteristics [1]. This novel method is a key contribution to excellence in BMS energy research. Furthermore, the authors of [17] proposed a novel systematic state-of-charge estimation method that considers both the open circuit voltage (OCV) and the SoC of the batteries. This method can be used to not only predict the state of a single battery cell but also accurately model the battery pack; furthermore, this method can be used to balance the energy flow of the hybrid energy system (HES) of an electric vehicle in order to optimize the energy efficiency of the HES. The above cases [16,1,17] have made some progress in the SoC estimation for a single LIB in a pack of batteries. However, the inconsistency of the battery is neglected. Thus, the above cases are can handle flat noise with a zero average value, but their weakness is attenuating disturbance in the uncertainty of the battery model and parameters.

This paper presents an improved adaptive particle swarm filter (improved-APF) that can achieve better convergence performance and robustness under outer/inter disturbance than the abovementioned methods. Not only can the estimation performance be guaranteed but lower computation cost can also be realized; in particular, the improved-APF method has less hardware requirements.

1.1. Contributions of the paper

A data-driven adaptive SoC estimator was built by combining the particle swarm filter and the adaptive estimation method. The effectiveness and feasibility of this method have been verified using different battery loading profiles. The applicability of the algorithm has been further verified using different types of batteries, particularly lithium-ion polymer batteries (LiPB). In the proposed SoC estimator, the error analysis method is added into the adaptive particle filter method, and the improved-APF is embedded. The improved-APF algorithm can improve the robustness and the convergence speed by adaptively updating the model parameters. The proposed method can deal with the model variation with both a random time series and random white noise covariance.

1.2. Organization of the paper

The outline of the paper is as follows: The introduction is presented in Section 1. Section 2 describes the fundamental battery model and some intelligent estimation methods. In Section 3, the particle swarm optimization (PSO) based on the online parameter identification method is presented. Then, an error analysis method for the state estimation of the batteries is proposed. In Section 4, a data-driven adaptive SoC estimator using the APF algorithm is presented. To verify the proposed approach, 3.6 V/2 A h lithium-ion polymer battery (LiPB) cells with different ages are used to execute the characteristic test; this experiment is described in Section 5. Section 6 verifies the proposed adaptive SoC estimator using the Urban Dynamometer Driving Schedule (UDDS) test and DTS test on a LiPB battery and discusses the analysis in detail. Section 7 provides conclusions and suggestions.

2. Lithium-ion battery model

Section 2.1 presents the lumped parameter battery model in detail, which allows for the optimization of the proposed APF algorithm. Section 2.2 elaborates each step of the PSO algorithm.

2.1. Lumped parameter battery model

To model the dynamic characteristics of the battery under the variable working mode, the Thevenin model is adopted in this paper, as shown in Eqs. (1) and (2). The equivalent electrical circuit of a battery can be simplified as a resistor R_0 and a capacitor C_0 in parallel; then, the RC network is connected to the OCV in series. However, the battery parameters will change with time and working conditions, so the diffusion resistance R_p and diffusion capacitance C_p are used here to dynamically respond to the battery characteristics.

$$U_t = U_{ocv}(z) - IR_0 - U_d \tag{1}$$

$$U_d = \exp(-\Delta t/(R_pC_p))U_d + R_p(1 - \exp(-\Delta t/(R_pC_p)))I \tag{2}$$

where U_{t} represents the terminal voltage of the battery that changes with time, as shown in Eq. (1), U_{ocv} is the diffusion voltage, and U_{d} is the resistance dependency. Furthermore, the diffusion voltage U_{d} can be represented by an exponential function. According to the authors of [17], U_{ocv} can be induced from the electrochemical equation of the battery and can be written as

$$OCV = K_0 + K_1z + K_2z^2 + K_3z^3 + K_4/z + K_5\log(z) + K_6\log(1-z) \tag{3}$$

where K_{i} ($i = 0, 1, \ldots, 6$) are seven parameters that can accurately depict the OCV of the battery under different battery SoCs. For different types of battery, these parameters can be polyfitted by the current and voltage of the experimental results.

2.2. Parameter identification method for the battery model

Eqs. (1) and (2) of the battery state are in the continuous form. To identify the SoC of the battery, the algorithm must be implemented in a digital processor. The state equations should be discretized by linear transformation, as shown in Eqs. (4) and (5).

$$U_{d,k+1} = \exp(-\Delta t/\tau)U_{d,k} + R_p(1 - \exp(-\Delta t/\tau))I_k \tag{4}$$

$$U_{t,k} = U_{ocv}(z_k) - I_kR_0 - U_{d,k} \tag{5}$$

where Δt is the sampling time interval, which is a constant value here; the subscript k represents the sampling moment, which is an integer number; the subscript d represents the diffusion voltage and t represents the time variable. Other parameters can be indexed in Eqs. (1) and (2). $U_{d,k+1}$ denotes the terminal diffusion voltage at the sampling time interval $k + 1$, and τ is a time constant that can be calculated from the RC circuit, $\tau = R_p \times C_p$.