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Kalman filter for onboard state of charge estimation and peak power capability analysis of lithium-ion batteries

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HIGHLIGHTS

- A linearized battery model is developed for on-board implementation.
- A KF-based co-estimator for battery SOC and SOF is proposed.
- The robustness of joint estimator is evaluated under various scenarios.
- The statistical analysis for influential mechanism of SOF factors are performed.

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ABSTRACT

To evaluate the continuous and instantaneous load capability of a battery, this paper describes a joint estimator for state-of-charge (SOC) and state-of-function (SOF) of lithium-ion batteries (LIB) based on Kalman filter (KF). The SOC is a widely used index for remain useful capacity left in a battery. The SOF represents the peak power capability of the battery. It can be determined by real-time SOC estimation and terminal voltage prediction, which can be derived from impedance parameters. However, the open-circuit-voltage (OCV) of $LiFePO_4$ is highly nonlinear with SOC, which leads to the difficulties in SOC estimation. To solve these problems, this paper proposed an onboard SOC estimation method. Firstly, a simplified linearized equivalent-circuit-model is developed to simulate the dynamic characteristics of a battery, where the OCV is regarded as a linearized function of SOC. Then, the system states are estimated based on the KF. Besides, the factors that influence peak power capability are analyzed according to statistical data. Finally, the performance of the proposed methodology is demonstrated by experiments conducted on a $LiFePO_4$ LIBs under different operating currents and temperatures. Experimental results indicate that the proposed approach is suitable for battery onboard SOC and SOF estimation.

1. Introduction

Rechargeable batteries are becoming more and more popular for various applications in on-board energy storage systems for electric vehicles (EVs) and smart grids. Lithium-ion batteries (LIBs) have been more attractive for the aforementioned applications because of their higher specific or volumetric power and energy density, higher cycle lifetime and decreasing costs. For instance, Ma et al. [1] focused on quantitative analyses of cell aging path dependence in a repeatable laboratory setting, considering the influence of duty cycles, depth of discharge (DOD), and the frequency and severity of the thermal cycle, as reflected in pure electric buses operated in Beijing. Wang et al. [2] proposed a novel active equalization method based on the remaining capacity of cells which is feasible for LIB packs in EVs. Shang et al. [3] proposed a direct cell-to-cell battery equalizer based on quasi-resonant LC converter and boost dc-dc converter.

Due to demanding vehicle operations in daily driving and complex interactions with electricity grids, their operation strategy needs to be optimized in order to extend their lifetime (durability) and prevent critical operating conditions (e.g., overcharging, charging at low temperatures or high currents rates), which yield accelerated aging [4]. Therefore, Battery Management Systems (BMSs) have been designed to guarantee safe, efficient, reliable and durable battery operations. These BMSs must be capable of accurately predicting the remaining useful capacity (represented by SOC – amount of charge available in the battery at any time to sink, is

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employed to indicate the remaining mileage) and state-of-function (SOF – power capability of the battery, is utilized to regulate the propelling power and coordinate the regenerative braking and friction braking) of an EV [5].

1.1. Review of the SOC estimation approaches

In order to accurately estimate the battery SOC, many methods have been presented. The Ampere hour counting methods [6] obtain SOC estimation through the accumulation of the battery current. This kind of methods is easy to implement, but it is an open-loop estimation so that its estimation accuracy can suffer from initial value errors and accumulated errors from incorrect measurements [7]. The electrical model based methods take SOC as a state variable, so they can solve the accumulated error of the Ampere hour counting methods by updating SOC based on the difference between the measured and the predicted value of the terminal voltage [8]. These methods are closed-loop, and many algorithms such as EKF (extended Kalman filter) [9,10], UKF (unscented Kalman filter) [4,11], PF (particle filter) [2,12], UPF (unscented particle filter) [13,14] and SMO (slide mode observer) [15,16] are used in SOC estimation. Some other works develop the artificial neural networks [17], the fuzzy logic method [18] and support vector machine [19]. These approaches have been widely used in SOC estimation of Li-ion batteries, and most of them have achieved acceptable results. However, these algorithms are often too heavy for on-board implementation on a microcontroller. For example, the computational effort of the PF based algorithm increases linearly with the amount of defined samples [4]. In EKF method, the highly non-linear state transition and observation models cannot be applied to the covariance directly. Instead a matrix of partial derivatives (the Jacobian) is computed, which is computationally costly if done numerically. UKF method uses a deterministic sampling technique known as the unscented transform to pick a minimal set of sample points around the mean, which removes the requirement to explicitly calculate Jacobians [20]. However, the introduced sigma points also increase the computational effort. A standard KF method can be a candidate [21] to reduce computational complexity. However, the standard KF method requires an accurate linear system model. Ref. [21] thus employed one coefficient based linear equation to model open-circuit-voltage (OCV) function. However, the existence of OCV hysteresis is not taken into consideration. And the OCV estimate error is slightly larger using one parameter to linearize the SOC-OCV curve. To avoid these problems, this paper proposed a basic KF based estimation method, where the OCV and model parameters are piece-wise linearized. The OCV-SOC curves with hysteresis effect are modeled using two parameters linear equations. Therefore, the battery model can be regarded as a linear time invariant system. KF can provide an optimal estimation and minimal computational effort.

1.2. Review of the SOF estimation approaches

On the other hand, the power capability information of battery is necessary in many application scenarios since it can determine the power available in the moment to meet the acceleration, regenerative braking and gradient climbing power requirements without fear of over-charging or over-discharging the battery and thus reducing its lifespan [22]. The power capability is often called as SOF or state-of-power (SOP). With the development of EVs technology, some SOF estimation approaches are presented. As reviewed in Ref. [22], the most commonly used method is the hybrid pulse power characterization (HPPC) method, which is employed in laboratory environments [5]. Ref. [23] proposed a voltage – limited method for continuous SOP prediction to overcome the drawbacks of the HPPC method. Considering the state-of-energy (SOE) – limit or SOC – limit, and online parameter identification, Ref. [5,24] proposed an online model-based method. However, how the factors, such as SOC/SOE limit, manufacture limits (power, current) and terminal voltage based limits influence peak power capability has not been analyzed. Therefore, the influential mechanism of these factors is analyzed according to statistical data in this paper.

1.3. Contributions of this paper

The above methods for battery SOC and SOF estimation have achieved their own advantages. However, these algorithms are often too heavy for on-board implementation on a microcontroller. The main contribution of this paper is that an onboard SOC estimation method is proposed based on KF. Firstly, a simplified linearized equivalent-circuit-model is developed to simulate the dynamic characteristics of a battery, where the open-circuit-voltage (OCV) is regarded as a linearized function of SOC. In addition, the model parameters are identified off-line with battery pulse test. Besides, the battery peak power capability is determined by combining SOC estimation results, terminal voltage prediction results and manufacture power/current limits. Finally, the influential mechanism of these factors is analyzed according to statistical data.

1.4. Organization of this paper

The outline of this paper is as follows: the lumped parameter battery model and the implement flowchart of the parametric modeling approach are given in Section 2. The implement flowchart of the joint estimator for battery SOC and SOF is given in Section 3. The test bench and datasheets of IFP1865140-type cells are described in Section 4. The experiments, simulation results and evaluation of the proposed method are reported in Section 5. Finally, some conclusions and final remarks are given in Section 6.

2. Battery modeling

2.1. The lumped parameter battery model

It is always difficult to obtain an accurate battery model, because LIB is a very complex electrochemical system with physical/chemical processes and some extra side reactions, such as aging, diffusion and self-discharge effects [10]. Many different kinds of battery models have been established. However, for the data-driven demand of BMS, many researchers have chosen the data-driven model, which means that the parameters of battery model are updated online according to the measured data, such as Ref. [11,12]. Min et al. [33] suggested an accurate and comprehensive electrical model for LIB (see Fig. 1(a)). This battery model can be divided into two parts: the battery Runtime-based part and Voltage-Current characteristics-based part. The first part models capacity, SOC and runtime of the LIB, which is comprised of a capacity (C_N), a current-controlled current source