Journal of Power Sources 301 (2016) 277–286

Contents lists available at ScienceDirect

Journal of Power Sources

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

An online model-based method for state of energy estimation of lithium-ion batteries using dual filters

Guangzhong Dong, Zonghai Chen*, Jingwen Wei, Chenbin Zhang, Peng Wang

Department of Automation, University of Science and Technology of China, Hefei 230027, PR China

HIGHLIGHTS

- A novel open circuit voltage model is developed in considering temperature.
- Temperature and current are considered to model total available energy capacity.
- A novel model-based state of energy estimator is established using dual filters.
- The robustness of new method is validated under dynamic experimental conditions.

ARTICLE INFO

Article history:
Received 30 July 2015
Received in revised form
20 September 2015
Accepted 5 October 2015

Keywords:
State-of-energy
Lithium-ion battery
Particle filter
Model-based

ABSTRACT

The state-of-energy of lithium-ion batteries is an important evaluation index for energy storage systems in electric vehicles and smart grids. To improve the battery state-of-energy estimation accuracy and reliability, an online model-based estimation approach is proposed against uncertain dynamic load currents and environment temperatures. Firstly, a three-dimensional response surface open-circuit-voltage model is built up to improve the battery state-of-energy estimation accuracy, taking various temperatures into account. Secondly, a total-available-energy-capacity model that involves temperatures and discharge rates is reconstructed to improve the accuracy of the battery model. An extended-Kalman-filter and particle-filter based dual filters algorithm is then developed to establish an online model-based estimator for the battery state-of-energy. The extended-Kalman-filter is employed to update parameters of the battery model using real-time battery current and voltage at each sampling interval, while the particle-filter is applied to estimate the battery state-of-energy. Finally, the proposed approach is verified by experiments conducted on a $LiFePO_4$ lithium-ion battery under different operating currents and temperatures. Experimental results indicate that the battery model simulates battery dynamics robustly with high accuracy, and the estimates of the dual filters converge to the real state-of-energy within an error of ±4%.

1. Introduction

Nowadays, rechargeable batteries have been finding applications in on-board energy storage for electric vehicles and smart grids. Li-ion (Lithium-ion) based rechargeable batteries have been widely adopted for high energy density and a considerably long life. For instance, Wang et al. [1] established a temperature composed battery model based on commercial $LiFePO_4$ cells which can be used for SOC (state of charge) estimation at dynamic temperatures. Liu et al. [2] introduced a novel remaining discharge capacity estimation method through different voltage analysis for Li-ion batteries. Zhong et al. [3] developed a new method for SOC estimation of a pack that considered the differences among the cells and the impact of balance control. Due to demanding vehicle operations in daily driving and complex interactions with electricity grids, BMSs (Battery Management Systems) have been designed to guarantee safe, efficient, reliable and durable battery operations. A critical variable that must be estimated in the BMS is the battery SOE (state of energy). SOE represents residual energy in a battery compared with its maximum value, and it provides the essential basis of energy deployment, load balancing, and security of electricity [4].

Traditionally, the energy left in a battery is measured by SOC. However, with the increasingly widespread application of Li-ion

* Corresponding author.
E-mail address: chenzh@ustc.edu.cn (Z. Chen).

http://dx.doi.org/10.1016/j.jpowsour.2015.10.011
0378-7753/

batteries, the functional demand of BMS appears a more sophisticated and complex trend. Therefore, SOC is not appropriate to predict the residual energy of power battery systems [4]. Compared to SOC, SOE is a more significant indicator for residual energy. Meanwhile, SOC denotes the state of the electrical charge rather than the energy of a battery. Therefore, it changes linearly with operating currents, while SOE has direct link with the battery real-time voltage. As a result, SOE is hard to be accurately estimated. An assortment of techniques have previously been reported to estimate SOE, adopting almost the same methods for SOC estimation. As to SOC estimation method, Xiong et al. [5] used an adaptive extended Kalman filter (EKF)-based method to jointly estimate SOC and peak power capability of a Li-ion battery. Liu et al. [6] built a dual-particle-filter (PF) estimator to obtain simultaneous SOC and drift current estimation. Plett et al. [7] and Hu et al. [8] adopted EKF for online estimation of SOC and the identification of a battery empirical model. Hu et al. [9] presented an integrated method for the capacity of a Li-ion battery and remaining useful life throughout the whole life-time based on the Gauss-Hermite PF method. Charkhgard et al. [10] presented a method for modeling and estimation of SOC of Li-ion batteries using neural networks and EKF. Some other works developed the fuzzy logic method [11] and the support vector machine [12] for SOC estimation.

In terms of SOE estimation, Mamadou et al. [13] proposed a new criterion for direct evaluating the residual energy of a battery, where the discharge stages of the battery were considered. Mamadou et al. [14], Stockar et al. [15], and Kermani et al. [16] presented a definition of SOE and a method to follow-up SOE based on a direct power integral method which used power integral to estimate SOE. However, this method suffered from a significant estimation error because of an erroneous initial value and the measurement noises of currents and terminal voltages of battery cells. Liu et al. [4] proposed an improved direct SOE estimation method at dynamic currents and temperatures based on Back-Propagation Neural Network (BPNN). In the input layer, the input parameters consisted of the battery terminal voltage, the current and the temperature. The output was the estimated SOE. However, the estimation accuracy of this method may become poor due to the incorrect measurements, because it was an open-loop estimation. Wang et al. [17] used PF to jointly estimate SOC and SOE of a battery, and PF had been verified under both constant and dynamic current conditions. However, the SOE estimation accuracy depended on the SOC estimation accuracy in this method. Dong et al. [18] presented a method for SOE estimation based on a wavelet-neural-network-based battery model and a PF based estimator. To further reduce the hardware cost, the complexity of the proposed algorithm needed to be decreased. He et al. [19] employed the central difference Kalman filter to estimate the real time SOE. In considering that different kinds of battery showed different open circuit voltage behaviors, a Gaussian model was employed to construct the battery model in this study. What was more, the genetic algorithm was employed to locate the optimal parameter for the selected battery model. All the aforementioned methods for SOE estimation have achieved acceptable results. However, batteries used in EVs and electricity grids would inevitably experience uncertain operating currents and temperatures. Therefore, the real-time performance of a battery model should be enhanced. To solve this problem, Zhang et al. [20] established a joint estimator for SOE and SOP (state of power), where parameters of the battery model were estimated online using RLS (recursive least square algorithm) method. However, it did not take the influence of temperature and discharge rate on total available energy into account, while the total available energy is a critical parameter directly limit the pack performance through “capacity fade”. Moreover, when the system models are not linear in the parameters, the RLS method becomes inappropriate. To solve this problem, the dual EKF method for SOC estimation presented in Plett [7] can be a candidate. Moreover, in contrast to Kalman filter, PF is a completely nonlinear state estimator based on the probability. It is noted that PF has become a popular method in solving optimal estimation problems for nonlinear non-Gaussian state space models, such as SOC estimation problems. For instance, Wang et al. [21] employed PF to estimate the cell SOCs during equalization in order to eliminate the drift noise of the current sensor. Compared to EKF and UKF, the advantages of PF in solving SOC or SOE estimation problems are also demonstrated in Zhong et al. [3] and Wang et al. [17].

In this paper, to determine SOE of a battery, an online model-based estimator using EKF-PF dual filters is developed. In the proposed method, EKF method is used to identify parameters of the battery model through real-time battery currents and voltages due to its high accuracy and quick convergence in estimating unknown parameters. In addition, PF is applied to estimate battery SOE. In conclusion, the proposed EKF-PF based approach has the potential to accurately estimate battery SOE and eliminate the drawback of parameter variations. Further more, the performance of this estimator has been verified and evaluated by experiments conducted on $LiFePO_4$ cells.

The outline of this paper is as follows: Section 2 gives the lumped parameter battery model and the implement flowchart of the parametric modeling approach. Section 3 presents a review of the EKF-PF based dual filters algorithm, and then gives the model-based approach implement flowchart of battery SOE. The test bench and datasheets of IFP1865140-type cells are described in Section 4. The experiment, 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. Parametric modeling approach

2.1. Battery model

SOE provides information of the remaining available energy of a battery. In this study, SOE is defined as the ratio of the residual energy to the total original energy capacity of a Li-ion battery. A common definition of SOE is formulated as the following equation [17,22]:

$$\mathrm{SOE}(t) = \mathrm{SOE}(t_0) - \frac{\int_{t_0}^{t} P(\tau)\mathrm{d}\tau}{E_N} \tag{1}$$

Based on Eq. (1), the discrete-time recurrence can then be written as.

$$z_k = z_{k-1} - \Delta E_{k-1}/E_N = z_{k-1} - I_{L,k-1}U_{t,k-1}\Delta t/E_N \tag{2}$$

where z denotes SOE of a battery, z_k and z_{k-1} denote the SOE at sample time k and$k-1$. ΔE_k is the consumed energy at time k. E_N denotes the maximum available energy of the battery. I_L represents the load current of the battery. U_t represents the terminal voltage of the battery.

An accurate battery model that can simulate the dynamic characteristic of a battery is essential to dynamic state estimation. Therefore, many battery models have been proposed, among which the most commonly used are the equivalent circuit model. In most cases, researchers choose to use a data-driven model, which means that the battery model is established according to the measured data, such as Xiong et al. [23] and Sun et al. [24]. As shown in Fig. 1, the first-order RC model is utilized to make a trade-off between the model error and the computation cost in this paper. This battery