Applied Energy 164 (2016) 387–399

Contents lists available at ScienceDirect

Applied Energy

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

A comparative study of three model-based algorithms for estimating state-of-charge of lithium-ion batteries under a new combined dynamic loading profile

Fangfang Yang [a,*], Yinjiao Xing [b], Dong Wang [a], Kwok-Leung Tsui [a]

[a] Department of Systems Engineering and Engineering Management, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong, China
[b] Center for Advanced Life Cycle Engineering, University of Maryland, College Park, MD 20742, USA

HIGHLIGHTS

- Three different model-based filtering algorithms for SOC estimation are compared.
- A combined dynamic loading profile is proposed to evaluate the three algorithms.
- Robustness against uncertainty of initial states of SOC estimators are investigated.
- Battery capacity degradation is considered in SOC estimation.

ARTICLE INFO

Article history:
Received 4 May 2015
Received in revised form 14 October 2015
Accepted 26 November 2015

Keywords:
State of charge
Lithium-ion batteries
Extended Kalman filter
Unscented Kalman filter
Particle filter
Degradation

ABSTRACT

Accurate state-of-charge (SOC) estimation is critical for the safety and reliability of battery management systems in electric vehicles. Because SOC cannot be directly measured and SOC estimation is affected by many factors, such as ambient temperature, battery aging, and current rate, a robust SOC estimation approach is necessary to be developed so as to deal with time-varying and nonlinear battery systems. In this paper, three popular model-based filtering algorithms, including extended Kalman filter, unscented Kalman filter, and particle filter, are respectively used to estimate SOC and their performances regarding to tracking accuracy, computation time, robustness against uncertainty of initial values of SOC, and battery degradation, are compared. To evaluate the performances of these algorithms, a new combined dynamic loading profile composed of the dynamic stress test, the federal urban driving schedule and the US06 is proposed. The comparison results showed that the unscented Kalman filter is the most robust to different initial values of SOC, while the particle filter owns the fastest convergence ability when an initial guess of SOC is far from a true initial SOC.

1. Introduction

With the increasing development of electric vehicles (EVs), lithium-ion batteries are gradually becoming dominant in energy storage systems due to their advantages, such as high energy and power density, long lifespan [1]. To guarantee safe and reliable battery operation, a battery management system (BMS) is required to monitor and control lithium-ion batteries so as to provide a longer lifetime of a battery [2]. State of charge (SOC) estimation is one of the main concerns in the BMS. The SOC quantifies remaining charge of a battery at the current cycle and indicates how long the battery will sustain before the battery is recharged [3]. It can be regarded as a “Gas Gauge” or “Fuel Gauge” function by analogy to a fuel tank in a car [4]. A precise automotive fuel gauge will relieve drivers’ anxious about an unexpected fuel range. In addition, accurate estimation of SOC is strongly helpful to determine the end of charge and discharge. And it will effectively keep a battery operating within desired operation limits and slow down battery failures caused by over-charging and over-discharging. However, SOC cannot be directly measured. Even though SOC can be estimated from some measurable parameters, such as current and voltage, an explicit relationship is not concluded. In other words, voltage and current can only be used to provide a rough indication of SOC. To achieve a higher SOC estimation accuracy, other factors in operation conditions, such as ambient

* Corresponding author.
E-mail addresses: fangfyang2-c@my.cityu.edu.hk (F. Yang), yxing3@calce.umd.edu (Y. Xing), dongwang4-c@my.cityu.edu.hk (D. Wang), kltsui@cityu.edu.hk (K.-L. Tsui).

http://dx.doi.org/10.1016/j.apenergy.2015.11.072

temperature, battery voltage and temperature, charge and discharge rate, self-discharge rate should be taken into consideration [5].

Currently, existing SOC estimation algorithms can be divided into non-model based approaches mainly including Ampere-Hour integral, open-circuit voltage (OCV), machine learning methods and model-based approaches. By directly accumulating battery current over time, Ampere-Hour integral methods can give approximate SOC estimation [6–8]. However, errors caused by inaccurate initialization of SOC, low precision of current sensor, and discretization of sample time are inevitable and difficult to be reduced because of open-loop estimation [9]. In practice, an OCV-based method is often adopted to estimate an initial SOC via the monotonic relationship between OCV and SOC [5]. Machine learning methods, such as artificial neural networks [10], fuzzy logic [11], and support vector machine [12], regard a battery as a black box and they are able to model the nonlinear relationship between inputs and outputs on the basis of large quantities of training data available [1,13]. Because these methods lack of specifications of lithium-ion batteries, estimation accuracy of these methods strongly depends on quantity and quality of training data. Besides, these methods are time-consuming.

In opposition to the aforementioned non-model based approaches, model-based SOC estimation approaches featured by a closed-loop are able to self-correct and overcome unexpected disturbances. A battery dynamic behavior can be described either by an electrochemical model [14,15] or by an equivalent circuit model. The design of observers for SOC estimation can be conducted by using Kalman filter family, sliding observer [16,17] and H-infinity observer [18–20], etc. [21,22]. Among all the designed observers, a Kalman filter family takes up a large percentage due to its advantage in finding an optimal solution for a linear Gaussian system. Variants of the Kalman filter emerge for a non-linear battery system. Extended Kalman filter (EKF) was introduced to estimate SOC of a lithium-ion polymer battery pack by Plett [23–25]. Later, he implemented and tested two sigma-point Kalman filters (SPKFs), including the unscented Kalman filter (UKF) and the central difference Kalman filter, on a battery pack based on a fourth-generation prototype lithium-ion polymer battery because these two SPKFs did not require a Jacobian matrix, compared with the EKF [26,27]. Subsequently, the methodologies to enhance the Kalman filter family's performance on SOC estimation emerge, such as dual EKF [28], adaptive EKF (AEKF) [29], iteratively EKF [30], adaptive UKF (AUKF) [31,32], square-root UKF [33], square-root spherical UKF [34], strong tracking SPKF [35], and adaptive cubature Kalman filter [36]. Meanwhile, some efforts have been made to compare the performance of these model-based estimation approaches. Sun et al. [32] compared AUKF with AEKF, EKF, and UKF and showed the AUKF has a superior performance with a low computational load and a better accuracy of SOC. Li et al. [37] compared three model-based filtering algorithms, including the Luenberger observer, EKF, and SPKF, and concluded that the classical Luenberger observer relies mostly on the accuracy of the battery model and is less accurate, while the SPKF provides better SOC estimation results in the most cases. Tian et al. [38] compared the performance of AUKF against an adaptive slide mode observer in terms of convergence ability, tracking accuracy, and estimation robustness and the AUKF was shown to have better tracking accuracy and convergence ability in the comparison results. Other similar work can be found in [39,40].

Although the Kalman filter family yields satisfying results, it requires the noise in the system to follow Gaussian distribution. Particle filter (PF) is free of this constraint and it can be applied to non-linear and non-Gaussian systems [41]. The PF has been widely applied in object tracking and navigation, machine vision, and automatic control, whereas it is rarely exploited until the recent years in SOC estimation. In 2011, Gao et al. [42] used the PF with the combined model to estimate the SOC of a lithium-ion battery and showed the proposed method is effective and efficient. In 2013, Schwunk et al. [43] used the PF for SOC and state-of-health (SOH) estimation of lithium-ion batteries. Other related works based on PF for SOC estimation of lithium-ion batteries can be found in [44–46]. In our paper, to further explore its potential application to SOC estimation, PF is investigated and is compared with UKF and EKF.

However, several existing issues are seldom addressed in the literature. Firstly, a battery degradation issue is seldom discussed in SOC estimation. Often, experiments are carried out on brand fresh batteries. Practicable capacity, as an indicator of battery degradation, will decline due to irreversible physical/chemical reactions during normal operation [47–49]. Thus, an aged battery much more common-seen in reality, with a capacity loss, not only induces to reduction of a vehicle driving range, but may results in a large error when estimating SOC [50]. That is the motivation to study the effect of the aging level of the battery on SOC estimation. Secondly, SOC can only be inferred from some measurable parameters and thus the precise initial value of SOC is always unknown in reality. The accuracy and performance of a SOC estimator will be influenced by the uncertainty of initial values of SOC in two aspects: on one hand, improper initial guesses of a certain initial SOC may require different estimation times to track true SOC; on the other hand, lithium-ion batteries have a relatively flat OCV curve over the SOC, especially for lithium iron phosphate ($LiFePO_4$) batteries. Inferring SOC from the flat region will cause a larger error comparing with that from other relatively steep regions. However, in most of the works on SOC estimation, only some certain initial values of SOC were used to validate the developed algorithms. Therefore, it makes great sense to test robustness of the model-based filtering algorithms in terms of uncertainty of initial values of SOC [5]. What's more, computation time is an important factor to evaluation the performance of estimators as estimation of the current state is often required to be finished before the next measurement arrives in an online estimation case.

In this paper, we compare the performances of three popular combined model-based filtering algorithms, including EKF, UKF, and PF, for SOC estimation. First of all, we propose a new combined dynamic loading profile for the simulation of real EV driving behaviors. Taking battery degradation into consideration, we collect data from a new battery and an aged battery based on the proposed profile. Using data collected from the batteries, we consider uncertainty of initial values of SOC and test robustness of the three filtering algorithms to SOC estimation in terms of various initial values of SOC and various initial guesses of SOC. The performances of EKF, UKF, and PF are then compared in terms of tracking accuracy, convergence behavior, and computation time.

The rest of this paper is organized as follows. Section 2 introduces the battery test bench and the combined dynamic loading test. The implemented procedure and the details of algorithms are presented in Sections 3 and 4, respectively. The experimental results and discussions are presented in Section 5. Conclusions are drawn at the last section.

2. Experiments

The battery test bench, which composes of a battery test system (Arbin BT2000 tester) for loading and sampling the battery, a host computer with Arbin MITS Pro Software for on-line experiment control and data recording, and a computer with Matlab R2012b Software for data analysis, is shown in Fig. 1. The cylindrical A123 18650 battery ($LiFePO_4$), was used in the test, and the key specifications are shown in Table 1. Two separate test schedules