Journal of Power Sources 279 (2015) 439–449

Contents lists available at ScienceDirect

Journal of Power Sources

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

State of charge estimation for $LiMn_2O_4$ power battery based on strong tracking sigma point Kalman filter

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HIGHLIGHTS

- A battery model was built for the estimation of the battery State of Charge (SOC).
- Test data of battery was used to obtain accurate parameters for the battery model.
- A improve Sigma Point Kalman Filtering (SPKF) algorithm was used to estimate the SOC.
- Strong Tracking Factor was used to enhance the accuracy of the SPKF algorithm.
- Adequate experimental and simulated data based on the improve SPKF were discussed.

ARTICLE INFO

Article history:
Received 13 March 2014
Received in revised form
22 November 2014
Accepted 1 January 2015
Available online 2 January 2015

Keywords:
Equivalent circuit model
Strong tracking sigma point Kalman filtering algorithm
State of charge estimation
Battery management system
Lithium-ion battery

ABSTRACT

The State of Charge (*SOC*) estimation is important since it has a crucial role in the operation of Electrical Vehicle (EV) power battery. This paper built an Equivalent Circuit Model (*ECM*) of the $LiMn_2O_4$ power battery, and vast characteristics experiments were undertaken to make the model identification and thus the battery *SOC* estimation was realized. The *SOC* estimation was based on the Strong Tracking Sigma Point Kalman Filter (STSPKF) algorithm. The comparison of experimental and simulated results indicates that the STSPKF algorithm performs well in estimating the battery *SOC*, which has the advantages of tracking the variables in real-time and adjusting the error covariance by taking the Strong Tracking Factor (STF) into account. The results also show that the STSPKF algorithm estimated the *SOC* more accurately than the Extended Kalman Filter (EKF) algorithm.

1. Introduction

As concerns for global warming and depletion of natural resources continue to grow, the Electric Vehicles (EVs) are establishing as the most promising solution to the increasing problems associated with the transportation. The internal combustion engines based automobile industry is gradually transitioning to EVs [1] and Hybrid Electric Vehicles (HEVs). These EVs taking advantage of the renewable sources of electricity have been widely accepted as important transitional technologies for sustainable transportation [2].

The power battery is an important component of EVs and HEVs and plays a crucial role in their successful application. Among the various types of power batteries, the Lithium-ion battery possesses the higher energy to weight ratio and long operating life, which is recognized as the most promising for EV applications. However, due to its unique characteristics, the Lithium-ion power battery must be used with the support of Battery Management System (BMS) to ensure safe and reliable operations. The BMS should prevent over-discharging or over-charging under all operating conditions, extend the lifetime and protect the battery from permanent damage thereby facilitating its safe and efficient discharging and charging [3]. The functions of BMS include the battery parameter measurement, State of Charge (*SOC*) estimation, safety management, battery pack equilibrium, thermal management, etc. The *SOC* is defined as the ratio of capacity at a given time to the nominal capacity of the battery [4]. The estimation of *SOC* is one of the most important functions of BMS.

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http://dx.doi.org/10.1016/j.jpowsour.2015.01.002

Generally, the *SOC* estimation methods can be divided into two categories. The first category is based on the direct measurement, in which the *SOC* is estimated by a simple relationship between the measurements and the *SOC*. In our view, the following methods belong to this category. 1) The discharge test is the most reliable method under the laboratory conditions. However, it is too time-consuming and hard to use in practice. 2) The open-circuit voltage is a promising method in applications with relatively long rest periods. Since the rest periods will occur only occasionally, it is used in combination with other techniques for ensuring continuous indication of the *SOC* [5]. 3) The ampere hour counting (current integration) method has been widely used, which has reasonable accuracy and is cost effective when a sufficiently accurate current sensor is adopted. This method was reported to have several drawbacks [6–8]. It fails to estimate coulombic efficiency accurately, determine the initial *SOC*, or indicate the variations in initial *SOC* resulting from self-discharge and other factors. In addition, the error becomes large when the battery operates at high and low temperature or when the current sharply fluctuates. Also, it is an open loop *SOC* estimator that will accumulate the error [9].

The second category combines the battery model, measurement data and control algorithm. As a whole, there are the following four types of battery models to describe the functioning and operation of the battery:

1) The electrochemical model, which describes the internal reactions of the battery by adopting a certain mathematical equation. Reinhardt Klein et al. presented a full macro-homogeneous 1-D model of a Li-ion battery as well as its reduction, suitable for the purpose of estimation and control [10]. MengGuo et al. designed a multi-geometry and physical model for Li-ion battery module [11], which predicts 3-D profiles of the electrical potential and temperature in the battery. However, the electrochemical model is too complicated for most practical applications.
2) The specific factor model is designed for describing a specific factor (e.g., temperature model, and cycle life model) of the battery. Quanshi Chen et al. proposed the temperature model which could describe the decrease in battery capacity with decreasing temperature without the knowledge of best working temperature [12]. The authors also gave a relationship between the cycle life and the depth of discharge. However, one specific factor model can only describe one aspect of the battery.
3) The Electrochemical Impedance Spectroscopy (EIS) model is on the basis of an experimental method that characterizes electrochemical systems of the battery. The amplitude and phase of electrochemical impedance are measured when a small AC current flows through the battery. The EIS also can be obtained by repeating this procedure for a certain range of frequencies [13]. It is a unique technique for the analysis of the very slow dynamics of the batteries [14]. In Refs. [14–19] the authors used several methods to build the EIS models, and based on them estimated the *SOC* of the battery.
4) The Equivalent Circuit Model (*ECM*) is an external characteristic model that can be used to predict battery behavior [20]. The *ECM*'s mathematical expression as transfer functions could be introduced to describe only the behavior of the input and output variables of the battery, such as current and voltage [21]. The *ECM* generally includes an *n*th-order *RC* network to simulate the battery behavior, and offers best compromise between the time for computations, parameterization effort, and precision of the simulation [22]. A first-order *RC* network was used to simulate the battery [23–25], which saved the computational time but lacked accuracy. Low Wen Yao et al. compared the first-, second-, and third-order *RC* networks, reducing the complexity of battery modeling and multi-cell analysis [26]. Their studies also show that notable modeling error existed in the relaxation effect modeling when first-order *RC* network is applied, and that the accuracy improved when second- or third-order *RC* network is used. The prediction of battery behavior using *n*th-order *RC* network was also discussed in Refs. [27–29]. It can be concluded that increasing the *RC* networks, subjected to *n*th-order not exceeding 5th improves the precision of dynamic voltage estimation. At higher values of *n*th, a large error will arise from the linear discrete method. In addition, the excessive computational costs caused by the complex structure of the model make this method unsuitable for nonlinear parameters' identification [28].

Currently, several combinations of battery models and adaptive control algorithms are used in battery characteristics research, such as the *SOC* estimation and state of health evaluation. Several control algorithms, such as the Artificial Neural Network (ANN), fuzzy logic, Support Vector Machine (SVM), and system filtering theory, have been used to estimate the *SOC*. The ANN was first used for depicting the available capacity, estimating the *SOC*, and describing the nonlinear relationships in a lead-acid battery [30–34]. Since the degree of battery degradation was used as one of the input signals, this model showed accurate results for batteries of different sizes and degradation states [34]. Another control algorithm is fuzzy logic. It was applied for estimating the battery *SOC* [35–37] based on the training datasets obtained from impedance spectroscopy, coulomb counting techniques, and voltage recovery measurements. Finally, the SVM was also used successfully to estimate the battery *SOC* [38–42]. While the SVM model gives good accuracies, its disadvantages are the offline establishment and heavy computational training processes.

Compared to the above methods, the system filtering theory has the advantages of being closed-loop and real-time, which has attracted the wide attention recently. The widely used system filtering theory is Kalman Filter (KF). However, as KF are linear in filtering process, several modifications have been proposed for their applications to non-linear battery system. Saeed Sepasi et al. established the Extended Kalman Filter (EKF) algorithm [43–48] and Rui Xiong et al. designed the Adaptive EKF algorithm [49–51]. Both of the two methods, which are based on the non-linear state-space functions with first-order Taylor accuracy, are used to estimate the *SOC* of Li-ion battery. However, the EKF has several shortcomings. For example, it has highly unstable characteristics during the linearization when the assumption of local linearity is in violation [52]. Additionally, the derivation of the Jacobian matrices is nontrivial and error-prone in many applications [53]. Consequently, as an alternative approach to the state estimation for non-linear systems, the Sigma Point Kalman Filter (SPKF), which overcomes the theoretical limitations of EKF algorithm, was proposed. This method has at least second-order Taylor accuracy. The Refs. [1,2,53–55] proposed the SPKF method used for estimating the *SOC* of the battery, and demonstrated that SPKF method has more accuracy than EKF method in estimating the *SOC* of the battery.

This paper will adopt the combination of *ECM* and Strong Tracking Sigma Point Kalman Filter (STSPKF) algorithm to estimate the *SOC* of $LiMn_2O_4$ power battery. The STSPKF algorithm as a improve algorithm of SPKF has many advantages, e.g. requires less computation, the system nonlinear function can be a discontinuous function, the measured online error can be adjusted for dynamic *SOC* estimation.

The remainder of this paper is organized as follows. The Section 2 conducts the power battery characteristics experiments. The Section 3 builds an *ECM* for the $LiMn_2O_4$ power battery, describes its application scenarios and uses the experimental data to identify