## Applied Energy 155 (2015) 455-462

Contents lists available at ScienceDirect

# **Applied Energy**

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

# A comparative study and validation of state estimation algorithms for Li-ion batteries in battery management systems



AppliedEnergy

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HIGHLIGHTS

## • Description of state observers for estimating the battery's SOC.

• Implementation of four estimation algorithms in a BMS.

• Reliability and performance study of BMS regarding the estimation algorithms.

• Analysis of the robustness and code properties of the estimation approaches.

• Guide to evaluate estimation algorithms to improve the BMS performance.

#### ARTICLE INFO

Article history: Received 27 February 2015 Received in revised form 29 May 2015 Accepted 29 May 2015

Keywords: Lithium-ion battery Battery management system State of charge estimation Robustness analysis Sliding-mode observer Kalman-based SOC estimation

# ABSTRACT

To increase lifetime, safety, and energy usage battery management systems (BMS) for Li-ion batteries have to be capable of estimating the state of charge (SOC) of the battery cells with a very low estimation error. The accurate SOC estimation and the real time reliability are critical issues for a BMS. In general an increasing complexity of the estimation methods leads to higher accuracy. On the other hand it also leads to a higher computational load and may exceed the BMS limitations or increase its costs.

An approach to evaluate and verify estimation algorithms is presented as a requisite prior the release of the battery system. The approach consists of an analysis concerning the SOC estimation accuracy, the code properties, complexity, the computation time, and the memory usage. Furthermore, a study for estimation methods is proposed for their evaluation and validation with respect to convergence behavior, parameter sensitivity, initialization error, and performance.

In this work, the introduced analysis is demonstrated with four of the most published model-based estimation algorithms including Luenberger observer, sliding-mode observer, Extended Kalman Filter and Sigma-point Kalman Filter.

The experiments under dynamic current conditions are used to verify the real time functionality of the BMS.

The results show that a simple estimation method like the sliding-mode observer can compete with the Kalman-based methods presenting less computational time and memory usage. Depending on the battery system's application the estimation algorithm has to be selected to fulfill the specific requirements of the BMS.

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# 1. Introduction

Lithium-ion battery technologies are a very promising technology for both stationary energy storage and electro-mobility. The optimal operation to improve the performance, prolong the lifetime, and to prevent damage of the battery are key factors that have to be achieved by the battery management system (BMS).

http://dx.doi.org/10.1016/j.apenergy.2015.05.102 0306-2619/© 2015 Elsevier Ltd. All rights reserved. Therefore, a precise real time reliable, accurate estimation of battery parameters and internal states are needed. Some of these states cannot be measured directly by sensors, which means that they have to be estimated making use of available measured variables such as cell voltages, current load, and cell temperatures. One of these internal states with a particular interest is the battery state of charge (SOC). The SOC represents the available battery capacity that can be withdrawn from the battery. On the other hand the SOC is used to prevent battery over-discharge or over-charge as well as to operate the battery in such a manner that aging effects are

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reduced. One of the most implemented methods to estimate the SOC is the Coulomb counting method [1,2]. Although simple to carry out, an accurate estimation of the SOC cannot be achieved, mainly because of the initialization and accumulated measurement errors. The initialization error can be solved by having knowledge of the relation between SOC and the open circuit voltage (OCV) that can be obtained by characterization measurements [3–5] or by OCV estimation algorithms [6]. However, this requires long resting periods.

To solve these problems, many different model-based approaches have been developed and published in recent years, presenting high SOC estimation accuracy and reliability [7–9]. Although very precise, some of these methods compute complex equations that have to be processed by a microcontroller.

Besides the estimation of the battery state, the BMS has to fulfill other functions like protecting the battery from operating outside its safe operating area, collecting and reporting data, controlling its environment and cell balancing. These operations have to be executed within some few milliseconds to ensure the BMS functionality.

The focus of this work lies on the application of selected estimation algorithms and the study of their reliability regarding external disturbances and erroneous parametrizing as expected in a real battery system environment. Furthermore this paper proposes a study of some fundamental topics besides the estimation accuracy of the state estimation algorithms that have to be considered for the implementation in a BMS, mainly the BMS cycle time, code complexity and code memory usage which are different for every algorithm.

To address the issue of comparability of observer design implementations the following points are taken into account:

- The programming is carried out by the same programmer.
- Same workflow and compiler is employed.
- Same battery module, BMS and battery model is used.
- Same parameterization procedure is followed.

Four estimation algorithms including Luenberger observer, sliding-mode observer, Extended Kalman Filter and Sigma-point Kalman Filter, are analyzed and compared in this work. At first the model-based estimation method theory as well as the approaches under study are presented. The results of validation tests regarding accuracy, robustness and computational time are demonstrated and discussed.

This work serves as a guide for analyzing, testing, and validating state estimation algorithms to assure the BMS reliability and performance for an optimal operation of lithium-ion batteries.

## 2. Cell model and model-based state estimation algorithms

# 2.1. Cell model

Model-based state estimation algorithms are very promising approaches for reliable battery monitoring [10,11]. These sorts of algorithms make use of an equivalent circuit, e.g. depicted in Fig. 1 which describes the battery's dynamic, electrical behavior with a constant nonlinear voltage source for the OCV, a cell ohmic resistance and a *RC*-circuit connected in series.

For the presented equivalent circuit the current is defined positive for charging and negative for discharging. The relationship between the input values, current *I*, ambient temperature *T*, and the voltage output  $U_{cell}$  of the model leads to the estimation of internal cell states, e.g. SOC. Thinking of the system having a state vector that outlines the effect of past inputs on the system the cell model can be expressed in the following state space representation



**Fig. 1.** Electrical equivalent circuit of a cell with open-circuit-voltage, cell ohmic resistance  $R_0$  and  $R_1$  and  $C_1$  of the *RC*-circuit.

$$\boldsymbol{x}_{k+1} = \boldsymbol{f}(\boldsymbol{x}_k, \boldsymbol{u}_k, \boldsymbol{d}_{u,k}), \tag{1}$$

$$y_k = g(\mathbf{x}_k, \mathbf{u}_k, \mathbf{d}_{y,k}), \tag{2}$$

where *k* is the discrete-time index,  $\mathbf{x}_k$  the system state vector as a function of the system input  $\mathbf{u}_k$  and the input disturbances  $\mathbf{d}_{u,k}$ . The system output  $y_k$  depends on the state vector, the system input and the output disturbances  $\mathbf{d}_{y,k}$ . In this work the SOC and the voltage drop  $U_1$  at the *RC*-circuit from Fig. 1 are the selected system states

$$\boldsymbol{x}_{k} = \begin{pmatrix} \boldsymbol{x}_{1,k} \\ \boldsymbol{x}_{2,k} \end{pmatrix} = \begin{pmatrix} \text{SOC}_{k} \\ \boldsymbol{U}_{1,k} \end{pmatrix},\tag{3}$$

and are defined as the discrete current integration

$$SOC_{k+1} = SOC_k + \frac{\Delta t}{C_N} \cdot I_k,$$
 (4)

and as the voltage at the capacitance

$$U_{1,k+1} = \left(1 - \frac{\Delta t}{R_1 C_1}\right) \cdot U_{1,k} + \frac{\Delta t}{C_1} \cdot I_k,\tag{5}$$

where  $\Delta t$  is the time increment, and  $C_N$  the nominal cell capacity. In steady state (no current flow) the cell behavior is characterized by the OCV of the equivalent circuit. The dynamic response due to a change in current is described by the parameters  $R_0$ ,  $R_1$  and  $C_1$ . These values identified from characterization tests can be stored in look-up tables [3]. Hence the system output is defined as the cell voltage

$$y_k = U_{\text{cell},k},\tag{6}$$

where  $U_{\text{cell},k}$  is calculated using the Kirchoff's second law as

$$U_{\text{cell},k} = \text{OCV}(\text{SOC}_k) + R_0 \cdot I_k + U_{1,k}.$$
(7)

Then the battery's dynamic and electrical behavior is given through the linear state Eqs. (4) and (5) and the nonlinear system's output Eq. (7).

#### 2.2. Model based state estimation principle

Since SOC is a non-measurable variable it has to be estimated by an algorithm that is capable to fully reconstruct the internal system states using a state observer. As seen in the structure of the SOC estimation in Fig. 2, the observer calculates the cell voltage  $\hat{U}_{cell,k}$  and compares it with the measured voltage  $U_{cell,k}$ . The difference  $e_k$  between modeled and measured voltage is fed back through an observer gain into the model to correct the estimated system states and output. The variable  $\Theta_k$  contains all the internal cell parameters used in the model.

Beside the input current  $I_k$  and temperature  $T_k$  the disturbances  $d_k$  affect the estimation of the internal states. In this approach the disturbances are seen as sensor uncertainties. Their influence to the estimated SOC is analyzed further in this work.

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