Journal of Energy Storage 7 (2016) 38–51

Contents lists available at ScienceDirect

Journal of Energy Storage

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

# Validation and benchmark methods for battery management system functionalities: State of charge estimation algorithms

Christian Campestrini *, Max F. Horsche, Ilya Zilberman, Thomas Heil, Thomas Zimmermann, Andreas Jossen

*Chair of Electrical Energy Storage Technology, Technical University of Munich (TUM), Arcisstr. 21, 80333 Munich, Germany*

ARTICLE INFO

*Article history:*
Received 2 March 2016
Received in revised form 21 April 2016
Accepted 12 May 2016
Available online

*Keywords:*
Battery management system
State of charge
Kalman filter
Lithium-ion battery

ABSTRACT

Several state of charge estimation algorithms have been developed and validated in the past. However, due to varying validation methods, the results cannot be compared. This paper presents an approach for a generalised validation and benchmark method for state of charge estimation algorithms. The independence of standardised driving cycles is obtained by developing a synthetic load cycle. To do so, a frequency analysis is performed for 149 different driving cycles and the five major time constants are identified at 55.8 s, 9 s, 5.1 s, 3.8 s and 1 s. Using the synthetic load profile, three validation profiles are created. In addition to low- and high-dynamic behaviour, long-term stability is considered at five different temperatures (−10 °C, 0 °C, 10 °C, 25 °C and 40 °C). During the long-term test, the temperature varies between −10 °C and 40 °C. To ensure comparability, a quantitative rating technique is introduced for estimation accuracy, transient behaviour, drift, failure stability, temperature stability and residual charge estimation to evaluate the performance of different state estimation algorithms. Furthermore, the benchmark can be used to optimise the state estimator, such as a linear and an extended Kalman filter examined within this study.



## 1. Introduction

With the necessity of high-energy and high-power battery packs for different applications, such as stationary energy storage systems (SESS) or electric vehicles (EV), cells must be connected in series and parallel. Due to safety reasons (e.g. over and under voltage), cell balancing and ageing issues, supervision of each cell is indispensable. For this purpose, the battery management system (BMS) is used. The BMS supervises single-cell voltages, current and temperatures in a battery pack to guarantee compliance with cell limits. When a cell exceeds the so-called safe operating area (SOA), the BMS limits the power, or shuts down the system completely before an uncontrollable state is obtained. Beside safety management and cell balancing, other required functions including thermal management, communication with a higher-level control unit, state of charge (SOC) estimation, state of health (SOH) estimation and state of available power prediction are important features of a BMS. All these functions are currently being investigated and reported in the literature [1–3]. Due to different applications and purposes of these functions, their validation and test procedures differ, which not allows a comparison of the algorithms or functionalities. Therefore, we introduce the first proposal for the validation of BMS functionalities. The developed methods are open for discussion and are available on our homepage for open usage.[1] As the first part, a method for the validation and evaluation of SOC estimation algorithms is presented.

Within the literature, various algorithms for SOC estimation are validated by different methods without further benchmarking. However, a comparison of these algorithms is not possible. Since the area of application is multilateral, shortcomings of the estimators are often not considered in the validation process. An important issue in the validation is the determination of a reference SOC to compare the estimated SOC with a reliable value. A common method to measure the reference SOC is the coulomb counter (Eq. (1)). In this study the resulting SOC is defined as

$$SOC(t) = SOC_0 + \frac{1}{C_{act}} \int_{t=0}^{t} i(\tau) d\tau \qquad (1)$$

* Corresponding author.
*E-mail address:* c.campestrini@tum.de (C. Campestrini).
*URL:* http://www.ees.ei.tum.de

[1] Manual, benchmark calculation script and example data are available at www.ees.ei.tum.de/en/media/downloads/validation/.

http://dx.doi.org/10.1016/j.est.2016.05.007
2352-152X/

**Acronyms**

| | |
|---|---|
| BMS | battery management system |
| CC | constant-current |
| CCCV | constant-current constant-voltage |
| CV | constant-voltage |
| DC | direct current |
| DFT | digital Fourier transformation |
| ECM | equivalent circuit model |
| EKF | extended Kalman filter |
| EV | electric vehicle |
| FFT | fast Fourier transformation |
| KF | Kalman filter |
| LFP | lithium-iron-phosphate |
| LIB | lithium-ion battery |
| NCA | nickel-cobalt-aluminium |
| OCV | open circuit voltage |
| SESS | stationary energy storage system |
| SLC | synthetic load cycle |
| SOA | safe operating area |
| SOC | state of charge |
| SOH | state of health |

where $SOC_0$ corresponds to the initial SOC, $C_{act}$ to the actual measured capacity of the cell, $i(\tau)$ to the load current and $t$ to the time of operation.

One issue is that, mostly, the same current signal is used to calculate the reference SOC and to estimate the SOC with the algorithm [4–8]. An offset-afflicted measurement causes a drift in the reference, calculated by Eq. (1). When the algorithm is not able to correct this drift, the estimation follows the offset-influenced reference. Other algorithms, for example, open circuit voltage (OCV)-based algorithms, may correct the error, but when using only one current sensor, it is not possible to distinguish between the correct and incorrect SOC (Fig. 1a). This shortcoming can be addressed by using two different sensors for the reference and for the algorithm [9–12]. Thereby, the current sensor for the reference must be more accurate than the sensor for the algorithm. In Fig. 1b, this concept is depicted schematically. The estimation based on the BMS current measurement (Fig. 1b, sensor 1) drifts apart, while the algorithm partly compensates for the error.

By determination of the reference SOC using a coulomb counter, the finite sample rate causes an error during dynamic loads. In Fig. 1c the real current (dashed blue line) and the discrete current measurement (red line) is shown. The green area symbolises the resulting error, caused by the discrete measurement. Furthermore, temperature changes and high currents can cause temporary capacity ($C_{act}$) variations, which can affect the SOC calculation (Eq. (1)). A possibly more accurate way to define a reference SOC is a residual charge determination at the end of each test. Due to the constant-current (CC) discharge, the accumulated error caused by the finite sample rate and other influences can be minimised. This approach is mandatory for long-term tests [12].

The behaviour of a battery is dependent on temperature, SOC and current rate. Furthermore, the OCV changes with temperature, depending on chemistry and SOC [13,14]. This is especially important for OCV-based algorithms. Xing et al. [9] show the influence of the temperature-dependent OCV of a lithium-iron-phosphate (LFP) cell during state estimation with a Kalman filter (KF). They showed high errors resulting from an incorrect OCV–SOC relationship. To resolve this problem, different OCVs at

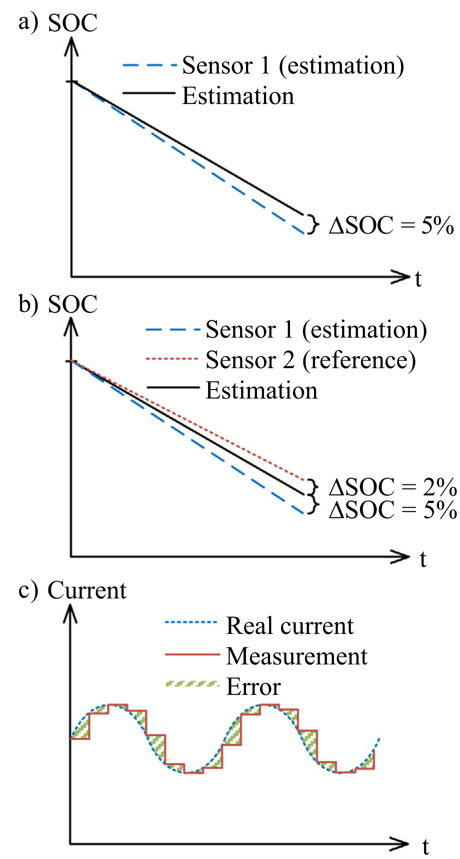


**Fig. 1.** Validation issues: (a) validation with one current sensor; (b) validation with an additional, more accurate, current sensor; (c) shortcomings of discretising and resulting error.

different temperatures were implemented in the battery model. Consequently, due to possible temperature variations during operation, the validation has to be performed at different and varying temperatures. Otherwise, a reliable and accurate function cannot be guaranteed [12].

The algorithms present in the literature are rarely validated during the charging process. In common applications, the discharge current is highly dynamic, while in the charge direction, the current is comparably constant. As an example for neural networks, this also leads to the need for separate training data for the charge period. Other algorithms such as the dual KF [15–17] or the sliding mode observer [18] also behave differently without any dynamics [12,19]. These behaviours are often neglected.

Due to the wide measurement range of current sensors, the measurement accuracy of small currents can be disturbed by noise or by an offset of the sensor. These errors can affect the SOC estimation. To address these issues, pauses and long-term tests [20] are necessary. During these tests, the SOC based on the coulomb counter increases due to the current sensor offset, while the SOC estimation of the algorithm follows the reference SOC [12]. Further investigations showed the estimation accuracy and stability concerning variable ambient temperatures as well as ageing effects. Additionally, the influence of initialisation and parameter errors is mandatory for a proper validation [8].

The rest of the paper is organised as follows. To show the necessity of validation under different conditions battery parameters and their dependency on temperature, current rate and SOC are shown in Section 2. The independence of standardised driving cycles is obtained by developing a synthetic load cycle (SLC) for the validation scenarios in Section 3. All three scenarios are performed at five different temperatures. Furthermore, an evaluation system