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# Experimental set-up and procedures to test and validate battery fuel gauge algorithms

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## HIGHLIGHTS

- Novel approach and procedures for battery fuel gauge validation are presented.
- Three battery fuel gauge validation metrics are presented.
- Details of implementation of each battery fuel gauge validation metric is described.
- Sample battery fuel gauge validation results are presented at multiple temperatures.

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## ABSTRACT

A battery fuel gauge (BFG) helps to extend battery life by tracking the state of charge (SOC) and many other diagnostic features. In this paper, we present an approach to validate the SOC and time-to-shutdown (TTS) estimates of a BFG. Hardware-in-the-loop (HIL) testing under realistic usage scenarios provides a means for BFG algorithm evaluation and provides insights into practical implementation and testing of BFG algorithms in battery management systems. We report the details of a HIL system that was designed to validate the SOC and TTS estimation capability of BFG algorithms; different current load profiles were synthesized to replicate typical battery usage in portable electronic applications; the HIL system is automated with the help of programmable current profiles and is designed to operate at various controlled temperatures; three performance validation metrics are formulated for an objective assessment of SOC and TTS tracking algorithms. The HIL setup and the performance validation metrics are used to evaluate a BFG developed by the authors using three different batteries at temperatures ranging from $-20\,^{\circ}$C to $40\,^{\circ}$C.



## 1. Introduction

Li-ion batteries are known for high power density, high capacity and light weight [1]. With the proliferation of portable electronic devices and electric vehicles, Li-ion batteries have become the most common rechargeable batteries. Consequently, it is important to have an accurate estimate of the state of charge (SOC) in order to avoid overcharging or deep discharging conditions in a battery. Further, the knowledge of the state of health (SOH) of the battery is critical in many applications, such as in electrical vehicles (EV), where the battery replacement is costly and must be planned well in advance to avoid unanticipated breakdowns. The battery fuel gauge (BFG) estimates the SOC, SOH, the time to shut down (TTS) and the remaining useful life (RUL) of the battery. The knowledge of battery capacity has significant impact on the estimation of SOC, SOH, TTS and RUL. The battery capacity fades over time depending on environmental, usage and charging patterns and, as a result, BFG becomes a challenging system identification and state estimation problem.

There has been tremendous interest in the past decade on developing BFG algorithms that involve the solution to a joint state and parameter estimation problem. In Table 1, we have summarized the features of existing ECM-based BFG algorithms under the following topics:

- *Type of ECM.* Many of the early BFG algorithms modeled the ECM as a resistor and OCV only; this is inadequate as shown in [2]. For better accuracy, BFG algorithms should employ appropriate ECM.

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**Table 1**
Features of the existing SOC tracking approaches.

| | | | |
|---|---|---|---|
| ECM | $R_0$ | | [23–26] |
| | $R_0$, $R_1$, $C_1$ | | [3,27–32] |
| | $R_0$, $R_1$, $C_1$, $R_2$, $C_2$ | | [30,33,34] |
| | Higher order | | [35,36] |
| Model identification | Online | | [3,23,24,27,36,37] |
| | Offline | | [26,28,29,32,33,38,39] |
| SOC estimation method | Nonlinear filter | EKF | [3,27,29,30,33–35,37,39,40] |
| | | UKF | [24,32] |
| | | PF | [23,25,26,38] |
| | | Leunberger observer | [29] |
| | Coulomb counting | | [41] |
| | Data driven | | [42] |
| | Voltage lookup | | [3,24,28] |
| Capacity | Estimated online | | [28,36–38,42] |
| | Rated capacity | | [3,26,27,29,31,33] |
| Validation method | Coulomb counting | | [3,24,26,28–30,33,34,36,37,40,42] |
| | OCV lookup | | [43,14] |
| | Simulated models | | [11,17,44,13] |
| | Empirical evaluation of SOC | | [45,15,46] |

- *Model identification techniques.* The ECM parameters vary with temperature and load; offline estimated ECM parameters cannot provide adequate BFG functionality. For better accuracy, BFGs should employ online ECM identifications methods [3].
- *SOC estimation method.* There are many possible ways to devise an SOC estimation scheme. This has been well reported in the literature.
- *Capacity estimation approach.* The battery capacity fades with age and changes with temperature; hence, online capacity estimation is required to ensure accurate BFG output. Several BFG algorithms reported in the literature employ online capacity estimation.
- *Validation methods.* Most of the existing SOC tracking approaches use a Coulomb counting based method for BFG validation.

In summary, as illustrated in Table 1, the existing literature has diverse methods and approaches related to types of ECM, model identification methods, SOC estimation methods and online capacity estimation methods. However, when it comes to validating the SOC estimates, a vast majority of the existing approaches solely depend on the Coulomb counting method. Our objective in this paper is to show the necessity of having robust BFG validation strategies.

Evaluating a BFG is challenging due to the fact that there are no reliable mathematical models in order to represent the complex features of a Li-ion battery, such as hysteresis and relaxation effects, temperature effects on parameters, aging, power fade (PF), and capacity fade (CF) with respect to the chemical composition of the battery. To the best of our knowledge, there is little literature focusing on BFG algorithm evaluation under realistic usage conditions; the importance of BFG evaluation is discussed in [4]; in [5], the need to minimize power dissipation and to extend battery run-time for portable devices is discussed; the advantages of hardware-in-the-loop (HIL) testing to validate a battery management system (BMS) under various failure conditions was motivated in [6]; and a HIL test to validate the BFG using a multi-cell battery pack was proposed in [7,8].

In this paper, we argue that a single BFG evaluation metric is inadequate for a thorough validation of BFG algorithms. Next, we discuss two such metrics and discuss the drawbacks of each of them. Finally, we propose a third validation metric and discuss its merits. Our proposed validation strategy is based on all three metrics. We also propose improvements to metrics 1 and 2 in order to improve their effectiveness.

*Metric 1: Coulomb counting error.* The majority of the existing BFG algorithms, such as the ones in [9–15], utilized this evaluation metric. Given the knowledge of battery capacity and the starting SOC point of the experiment, Coulomb counting method provides an accurate estimate of the state of charge of a battery. The RMS error between Coulomb counting based SOC estimate and the SOC estimate of the BFG serves as an evaluation metric, referred hereafter as the *CC metric*. The drawback of the CC metric stems from the inaccuracies in the knowledge of battery capacity and the initial SOC. Later, we describe an approach to design an evaluation load profile that allows one to estimate the battery capacity.

*Metric 2: OCV–SOC error:* The OCV–SOC characterization of a battery gives a look-up procedure for finding the SOC. Hence, the SOC estimate from a BFG can be compared with the OCV–SOC characterization by bringing the battery to a fully rested state and by measuring its voltage. We refer to this evaluation metric as the *OCV–SOC metric*. The OCV–SOC metric suffers from the hysteresis effect in the battery. Later, we discuss some ways to compensate for this drawback. Further, the OCV–SOC metric assumes perfect knowledge of the OCV–SOC characterization, which, as we discussed in [16], is prone to errors.

The metrics 1 and 2 are computed based on the assumed (perfect) knowledge of battery parameters such as battery capacity, initial SOC at the start of the validation period and the parameters of the OCV–SOC characterization curve. Metric 3, described below, is computed based on a quantity that is independent of all the battery parameters.

*Metric 3: Predicted time-to-voltage (TTV) error.* In mobile applications, the remaining charge of the battery translated to the remaining operational time is a very useful quantity. For example, knowing that the remaining battery (SOC) level is 40%, this may translate into 2 h of talking time or 30 min of texting time. This knowledge gives the user an option to prioritize his/her usage. Similarly, given an initial state, mobile users desire to know the estimates of

- Time-to-full charge
- Time-to-shutdown
- Time to reach a specific voltage

of the battery at constant charging/loading levels. These estimates will provide information about the battery status and help the user to manage the mobile usage.