Experimental Set-Up and Procedures to Test and Validate Battery Fuel Gauge Algorithms

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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°C to 40°C .

Index Terms

Battery management system (BMS), battery fuel gauge (BFG), state of charge (SOC) tracking, hardware-in-the-loop (HIL) validation.

I. 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

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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 I, 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.
- *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 I, 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], [10], [11], [12], [13], [14], [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 & 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 hours of talking time or 30 minutes 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, and
- 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.

A BFG can predict the time it takes to reach a certain voltage given a constant load or constant charging current. Time-to-shutdown (TTS) and time-to-full (TTF) are special cases of the TTV estimates. The error in the TTV estimate can be easily computed after the actual voltage in question is reached. We denote this error as the *TTV metric*. The advantage of the TTV metric is that it is computed based on an independent and accurate quantity, *measured time*. The BFG estimates of SOC, battery capacity, and the battery equivalent electrical circuit model parameters are required to compute the TTV metric. Hence, the TTV metric tests the BFG estimates of SOC, battery capacity and the equivalent electrical circuit model parameters; this is considered as a drawback because of the ambiguity in tracing the causes of errors.

It must be noted that the above three validation metrics are designed to validate the SOC and TTS estimate of a BFG. Both the SOC and TTS are fast varying quantities; the SOC changes from 1 to 0 within a cycle; the TTV is usually in minutes. The focus of the present paper is on validating the SOC and TTS outputs of a BFG.

The battery parameters, such as the capacity, impedance (dynamic equivalent model parameters) and hysteresis, vary in response to temperature changes [16], [11], [17]. In a typical battery operation, the cell temperature varies rapidly due to the load and due to possible changes in the environmental conditions. Hence, an accurate BFG evaluation requires that the battery be tested at varying temperatures. In this paper, however, we limit our BFG validation to various (but fixed) temperatures in the range from -20°C to 40°C .

In many Li-ion batteries, the OCV-SOC characterization [16] remains relatively flat and linear starting from a full battery (SOC=1) until a very low SOC (e.g., until SOC = 0.20). Below that, the OCV-SOC curves exhibit a sharp turn towards zero SOC. Consequently, the BFG validation should be performed in both high and low regions of the OCV-SOC curve. Our BFG evaluation scheme uses specific load patterns in order to validate it at high and low SOC values.

It must be noted that a HIL system is not a requirement for testing a BFG algorithm, since it does not

require any control inputs applied to the battery. However, testing the BFG algorithm on a realtime HIL system gives one useful insights into the required computing and memory requirements for real life BFG algorithm implementation. Further, BFG is an essential element of a battery management system (BMS), which aims to control temperature rise and battery aging through optimal charging waveforms; a HIL system is required to test a BMS. The details of the proposed HIL system in the present paper will be useful for testing any BMS algorithm.

The rest of this paper is organized as follows. Section II provides a description of the HIL setup and the software for the programmable load. Section III briefly introduces the BFG algorithm evaluated in this paper. Section IV formalizes the HIL validation metrics for the BFG. Section V provides a summary of HIL test results and the paper is concluded in section VI.

LIST OF NOTATIONS

C_{batt}	Battery capacity
OCV	Open circuit voltage
$\hat{s}_{\text{BFG}}[k]$	SOC estimate of the BFG at time k (8)
$i[k]$	Current through the battery (1)
$\hat{s}_{\text{cc}}[k]$	SOC estimate based on Coulomb counting (1)
$\hat{s}_{\text{bfg}}$	SOC estimate by BFG (2)
R_i	Resistances in the ECM, $i = 0, 1, \dots, N$ (5)
C_i	Capacitances in the equivalent circuit model (ECM), $i = 1, \dots, N$ (5)
SOC	State of charge
$\bar{\epsilon}_{\text{cc}}$	Averaged Coulomb counting error in % (2)
$\bar{\epsilon}_{\text{ocv}}$	Averaged OCV-SOC error in % (9)
$\bar{\epsilon}_{\text{ttv}}$	Averaged TTV error in % (14)
σ_i	Current measurement error s.d.
V_{cs}	Current sensing resistor
R_{cs}	Voltage across current sensing resistor

II. HIL EXPERIMENTAL SETUP

In this section, we summarize the essential elements of a BFG evaluation. Figure 1 shows the hardware set up used in our BFG evaluation experiments. The Lithium-ion cells are placed inside customized Aluminum casts. The Omega RTD Temperature Sensor Probe (PR-10) is calibrated with Omega CN9000 series temperature controller for battery temperature measurement. A nitrogen gas bath was constructed for the Aluminum casts and ultra high purity nitrogen gas (of 99.99% purity) is pumped into the Aluminum cast via a chamber and this helps to remove the moisture inside the cast – this is crucial for avoiding the formation of ice during cold temperatures. The temperature of the chamber can be varied from -25°C to $+45^\circ\text{C}$. Functional block diagrams of the above set up using PC and xPC target are described later.

A. Batteries for BFG Evaluation

Batteries made for the same application by different manufacturers differ in chemistry and other characteristics. A desirable feature of BFG is that it should be able to perform equally well regardless of the manufacturer or the type of battery. In this paper, we evaluate the BFG algorithm [2], [18], [9] using different commercially available batteries LG LGIP 530B, Nokia BP-4L, Samsung EB555157VA (used in Samsung Galaxy 3) and Samsung L1G6LLAGS (used in Samsung Galaxy 4).

B. Battery Loading and Charging

The HIL experimental set up needs to be designed to load and charge the battery with typical loads and typical charging methods. In this section, we explain how typical battery usage data can be simulated and collected for a BFG validation.

The applied loads should be comparable to the loads the batteries in a typical phone experience as mentioned in section II-A. Using a phone for BFG evaluation requires a person to engage the system simulating typical phone activities, e.g., making calls, typing, playing video, sending text messages, etc. The load profiles generated in this fashion will be inconsistent (hence not desirable) for BFG evaluation of several batteries at the same time. A desirable approach is to be able to use the same load profile on all the batteries. This is done by simulating load profiles using a *programmable load*; we used a programmable load manufactured by Kikusui (part number PLZ-4WA¹). The device is operated in 0 – 3.3 A constant current mode with a slew rate of 1 A/1 μ s. Based on the available capabilities of the load box, we describe next how a load profile resembling a typical phone usage is created.

First, five different profiles representing typical phone usage are created (see profiles A to E in Figure 2(a)-(e), respectively.) Table II shows the mean of each of the profiles and denotes which one of the actual load profiles it resembles. Then, a programmable dynamic load profile is created by repeating Profile A for three minutes, Profile B for two minutes, Profile C for two minutes, Profile D for two minutes, and Profile E for one minute. Figure 2(f) shows the resulting 10 minute dynamic load profile that is programmed into the Kikusui PLZ-4WA load box for automatic BFG evaluation.

A LabVIEW based graphical user interface (GUI) was developed to automate the Kikusui PLZ-4WA programmable load using instrument I/O assistant. The back-end for this automation is implemented with the help of virtual instrument software architecture (VISA), a standard language for instrument programming.

¹Kikusui Electronics Corp., PLZ-4WA Multifunctional DC Electronic Load.

C. Data Acquisition

The current, voltage and temperature values are measured from the battery using a *PC-based* or *xPC target-based* data acquisition system as described below.

1) *PC Based HIL Validation*: Figure 3 shows a block diagram of the PC-based HIL validation setup.

For data acquisition, we used a device manufactured by National Instruments; the part number of this device is DAQ 6281². The resolution of the data acquisition device is 18 bits; this translates to approximately $19\mu\text{V}$ resolution in the $0 - 5\text{ V}$ measurement range to which it was set. As a result, the voltage measurement standard uncertainty is computed as $\sigma_v \approx 5.5\mu\text{V}$ (obtained by dividing the resolution by $\sqrt{12}$, based on the s.d. of a uniformly distributed random variable.)

The data is collected at a sampling frequency of 10 Hz (100 ms sampling interval) and stored for future simulations as well. BFG algorithm is modeled in Simulink³ and implemented in the PC which runs on a non real-time operating system (such as Microsoft Windows and Mac OSX), which do not guarantee real time execution of the Simulink model. As a result, the time stamps in the collected data (which is crucial for accurate SOC tracking) may have jitters. Next, we discuss a HIL validation setup using xPC target⁴, which guarantees real-time data acquisition.

2) *Realtime HIL Validation*: Figure 4 shows the block diagram of the Real-time HIL validation setup. We used MPC term 50 I/O interface board for real-time data acquisition. Real-time data acquisition is facilitated by xPC Target. The xPC Target we used has 16 bit resolution; this results in $\sigma_v \approx 22\mu\text{V}$. We used the “differential input” functionality to reduce the noise level. The Simulink model of the BFG algorithm can be automatically converted into C (language) and downloaded into xPC Target via a LAN connection. Interrupt mode is the default real-time execution mode for the xPC Target kernel. The interrupt driven real-time scheduler ensures execution of tasks according to their priorities. Latency period between the interrupt and the device served is minimal and is consistent in a real-time OS.

3) *Current Sensing*: An accurate current sensor is designed to acquire the current regardless of polarity. Voltage across the external sensing resistor is amplified by a current sensing amplifier. In this circuit, a Maxim 4069 current sensing amplifier with gain $G=100$, $V_{\text{ref}} = 1.845$ and $R_{\text{CS}} = 20\text{ m}\Omega$ is used to convert current into voltage; R_{CS} of $20\text{ m}\Omega$ is obtained by connecting four $5\text{ m}\Omega$ resistors in series. Each of these $5\text{ m}\Omega$ resistor has 1% tolerance specified by the manufacturer. The voltage and current relation is

²National Instruments, NI USB-6281, M Series Multifunction Data Acquisition System (DAQ).

³Mathworks Inc., *Matlab Simulink*.

⁴MathWorks, xPC Target User’s Guide Version 2.

given by $V_{cs} = G \times I + V_{ref}$. The schematic of the current sensing amplifier is shown in Figure 5.

4) *Voltage Sensing*: The voltage across the +ve and -ve terminals of the battery gives the terminal voltage of the battery.

5) *Temperature Sensing*: A resistance temperature detector (RTD) has the temperature-dependent resistance. The resistance of the RTD increases linearly for the given range of temperature and hence the voltage of RTD can be used to give accurate temperature readings. The Omega RTD Temperature Sensor Probe (PR-10) is used in our experiment.

The accuracy table (against temperature) can be found on the manufacturer's website.⁵ Our operating range is from -25°C to $+45^{\circ}\text{C}$. The accuracy is $+/- .55^{\circ}\text{C}$.

D. BFG Validation Procedure

For each battery, the HIL test was performed as follows:

- A) The battery was fully charged at room temperature using a compatible commercial mobile battery charger.
- B) Battery was kept in the custom designed Aluminum cast, which was made vacuum tight.
- C) Ultra high purity Nitrogen gas was continuously pumped through the Aluminum cast to prevent formation of ice over the Battery during negative temperature scenarios.
- D) The Aluminum cast was then immersed into the temperature controlled bath (see Figure 1).
- E) Desired test temperature is set and sufficient time is given until the battery temperature stabilizes at the desired test temperature; the battery temperature can be seen on Omega RTD temperature probe display.
- F) Desired *BFG validation load profile* is selected using the Kikusui load automation GUI.
- G) The NI DAQ acquires voltage and current over time and provides as input to the Simulink model (either in PC or xPC Target).
- H) The BFG outputs (such as SOC, TTS and other intermediate variables) are stored.
- I) The acquired data (time stamp, voltage, current and temperature) is also stored; this enables us to test new modifications to the BFG algorithms in future without repeating the data acquisition process.
- J) The experiment is repeated under different temperatures and for different batteries.

⁵<http://www.omega.com/prodinfo/rtd.html>.

We use simulated load profiles described in Section II-B for automated BFG evaluation of several batteries. An advantage of the simulated load profiles is that the exact amount of Coulombs taken from the battery could be computed; hence, any errors due to sampling and current sensing are minimized.

An actual load profile, shown in Figure 6, is created using a smartphone as a load. The following activities are performed while the load is connected to the battery under evaluation: phone Call (15 min), web surfing, reading email, game playing, etc.(20 min), texting (10 messages), listening to music or watching a video using speaker phone (30 min video), standby– cell radio enabled pinging of tower (1 hour).

III. BFG ALGORITHM

The primary function of a BFG is to track the SOC. There are two basic approaches to SOC tracking: current based (Coulomb counting) and voltage based. The Coulomb counting approach requires the initial SOC and accurate knowledge of battery capacity. The voltage based approach uses the OCV-SOC characterization in order to “look up” SOC corresponding to the voltage between battery terminals. Figure 8 shows a general block diagram of a BFG. Other BFG outputs, such as TTS are computed based on the estimated values of SOC, battery electrical ECM parameters and the (estimated) battery capacity. The proposed BFG validation approach is best suited to validate BFGs that are both current and voltage based (i.e., the state-space model based BFG algorithms [18], [2], [19], [20]), so that all three validation metrics can be computed. However, it must be noted that at least one of the three validation metrics can be computed for *any* BFG algorithms summarized in Table I of this paper.

IV. BFG VALIDATION METRICS

In this section, we discuss the three BFG validation metrics introduced in Section I.

A. CC Metric

Given the exact knowledge of battery capacity, C_{batt} , and the initial SOC, $\hat{s}_{\text{cc}}[0]$, the present SOC $\hat{s}_{\text{cc}}[k]$ can be recursively computed by the Coulomb counting (CC) method as follows

$$\hat{s}_{\text{cc}}[k] = \hat{s}_{\text{cc}}[k-1] + \frac{\Delta_k}{3600\hat{C}_{\text{batt}}} \left(\frac{i[k] + i[k-1]}{2} \right) \quad (1)$$

where $\hat{C}_{\text{batt}}$ is the estimate of the battery capacity and for simulated load profiles, the current measurement error can be neglected, i.e., $\sigma_i = 0$. The BFG validation is performed in such a way that the initial SOC as

well as the battery capacity are known for computing $\hat{s}_{cc}[k]$ whereas *the BFG algorithm is not permitted to use this information*. The BFG error (in %) related to Coulomb counting is then defined as

$$\bar{\epsilon}_{cc} = \frac{\sqrt{\sum_{k=1}^T (\hat{s}_{cc}[k] - \hat{s}_{bfg}[k])^2}}{T} 100 \quad (2)$$

where the CC metric is computed over T samples; usually, several hours of data are used in computing the CC metric.

Remarks:

1. The validation needs to be performed relative to “known initial SOC” condition, such as a fully charged battery.
2. Typical CC-CV chargers terminate the charging operation at a pre-specified charging current; the charger we used stops at 125 mA. This means that the battery is not charged to 100% SOC. The SOC at this point can be computed as

$$\text{SOC}_{\text{initial}} = f_{\text{ocv-soc}}^{-1}(V_{cv} - I_{cv}R_0) \quad (3)$$

where the CV mode of the charger is set to V_{cv} volts, $I_{cv} = 125$ mA in this case, and R_0 is the estimated internal resistance of the battery at the temperature at which it is charged (in our experiments, we have always charged the battery at room temperature).

3. The discharged capacity C_r , defined below, can be used to compute the total capacity of the battery (needed for computing $\hat{s}_{cc}[k]$).

$$C_r = \text{Amount of discharged Coulombs (in Ah) from a fully charged battery until the terminal voltage reaches } V_{sd} \text{ at a discharge rate of } r \text{ measured in amperes} \quad (4)$$

The total capacity can be obtained from the discharge capacity C_r using the following procedure.

- a) Compute the OCV when the battery was “emptied” at r -rate

$$\hat{V}_0[k] = V_{sd} - \hat{h}[k] - g(r, \{\hat{R}_i\}, \{\hat{C}_i\}) \quad (5)$$

where $\hat{h}[k], \{\hat{R}_i\}, \{\hat{C}_i\}$ are quantities estimated by the BFG algorithm. See [2], [18], [9] for more details.

- b) Compute the corresponding SOC using the OCV-SOC curve

$$s_r = f_{\text{ocv-soc}}^{-1}(\hat{V}_0) \quad (6)$$

c) Now, the estimated total capacity of the battery is given as

$$\hat{C}_{\text{batt}} = \frac{C_r}{1 - s_r} \quad (7)$$

B. OCV-SOC Metric

The OCV-SOC error is computed as

$$\epsilon_{\text{ocv}} = \hat{s}_{\text{bfg}}[k] - f_{\text{ocv-soc}}^{-1}(v_r[k]) \quad (8)$$

where $v_r[k]$ is the terminal voltage (after resting the battery) at time k .

The OCV-SOC metric is computed by averaging the OCV-SOC error in the high and low SOC regions as (in %)

$$\bar{\epsilon}_{\text{ocv}} = \left[\frac{|\epsilon_{\text{ocv}}(s_L) + \epsilon_{\text{ocv}}(s_H)|}{2} \right] 100 \quad (9)$$

where $\epsilon_{\text{ocv}}(s_L)$ indicates the error computed in the low SOC region and $\epsilon_{\text{ocv}}(s_H)$ indicates the error computed in the high SOC region. Lower the $\bar{\epsilon}_{\text{ocv}}$, better is the BFG algorithm.

Remarks:

1. The OCV metric is corrupted by the hysteresis effect in the battery; in the present paper, we ignore this and suggest to use batteries with little hysteresis effect for BFG validation.⁶
2. One quick fix is to employ the method suggested in [21] to estimate the hysteresis voltage and account for it before computing the OCV metric.

C. TTV Metric

Given the SOC estimate of a BFG algorithm at time k as $\hat{s}_{\text{bfg}}[k]$, the time it takes to reach the terminal voltage v can be written as follows

$$T_{\text{bfg},v}[k] = \frac{[f_{\text{oct-soc}}^{-1}(\hat{V}_o[k]) - \hat{s}_{\text{bfg}}[k]]}{I} C_{\text{batt}} \cdot 3600 \quad (10)$$

where

$$\hat{V}_o[k] = v - \hat{h}[k] - g(I, \{\hat{R}_i\}, \{\hat{C}_i\}) \quad (11)$$

⁶Indeed, all the existing methods that used a similar (OCV based) approach for BFG validation ignored this as well. We, for the first time, have identified this flaw and currently working on developing a solution.

The current I is assumed to be constant until the terminal voltage v is reached.

For resistance only models (which corresponds to *Model 1* in [2]), (11) can be written as

$$\hat{V}_o[k] = v - IR_0 \quad (12)$$

The actual time at which the terminal voltage v is reached, $T_v[k]$, can be noted once that voltage is reached during the experiment. Let us say that the voltage v is reached at time sample T . Now, the following TTV validation metric can be computed

$$\epsilon_{\text{ttv}} = \frac{1}{60N_T} \sqrt{\sum_{i=1}^{N_T} \left(T_{\text{bfg},v}[i] - T_v[i] \right)^2} \quad (13)$$

where $T_v[i] = (T - i)T_s$ is the actual time it took from time epoch i to reach the voltage v and T_s is the sampling interval. The ϵ_{ttv} value above is in minutes. Now, we define the following metric (which is in %)

$$\bar{\epsilon}_{\text{ttv}} = \frac{\epsilon_{\text{ttv}}}{(T_{\text{ttv}}/60)} 100 \quad (14)$$

where $T_{\text{ttv}} = N_T T_s$ is the duration of time during which the TTV metric is computed.

It must be noted that the TTV metric defined above is dependent on the duration of the validation T_{ttv} . Let us assume that $T_{\text{ttv}} = 100$ min and that the average TTV error during this period is $\epsilon_{\text{ttv}} = 2$ min; the TTV metric becomes $\bar{\epsilon}_{\text{ttv}} = 2\%$. Now, let us assume that $T_{\text{ttv}} = 10$ min and that the average TTV error during this period is unchanged at $\epsilon_{\text{ttv}} = 2$ min; the TTV metric now becomes $\bar{\epsilon}_{\text{ttv}} = 20\%$. Hence, a standardized T_{ttv} must be used in all the BFG evaluations. We use $T_{\text{ttv}} = 100$ min in our evaluations.

Remarks:

1. The TTV metric is computed based on the accuracy of “prediction” by the BFG. For a given value of current, the BFG predicts how long the battery will last in the current cycle; this is computed by predicting the SOC at the shut-down voltage under the assumption that the voltage drop will remain constant since the current is constant.
2. During practical battery operation, the current is unlikely to be constant; hence, computation of TTV metrics by the BFGs for “self evaluation/calibration” is not feasible; the TTV metric can be computed only during validation, by applying a constant current.
3. Typical BFGs generate a prediction table; for each possible type of load, such as voice, text, video, typing and gaming, they compute and display the predicted remaining TTVs. For each type of

application, they use typical mean current values, similar to the one shown in Table II.

We summarize the requirements and capabilities of the BFG validation method presented in this paper in Table III.

Finally, we would like to conclude this section by discussing the following aspects of the proposed validation metrics.

- *Suitability.* The proposed BFG validation metrics are developed as part of BFG algorithm development for (portable) Li-ion batteries; however, the metrics are suitable to validate any BFG algorithm that is based on the electrical equivalent circuit model.
- *Targeted applications.* Regardless of the application (such as portable electronics, EV or storage) the basic structure of the BFG algorithm remains the same; all three metrics presented in this paper are suitable in any of these applications; however, validation in each application needs to be customized. For example, realistic load profiles need to be used in each application; details of simulated load profiles for EV applications can be found in [22].
- *Limitations.* Main limitation of the proposed BFG validation approach is that it is unable to evaluate the SOH and RUL estimates of a battery. We are presently working on developing a validation method for these BFG outputs. Further, due to the specific requirements on load profiles, the proposed validation approach has to be performed in a laboratory set up, i.e., the BFG cannot be evaluated on the go. Also, the proposed BFG validation approach assumes fixed temperature.
- *Use cases.* BFG validation is done by device manufacturers. For example, a smart phone manufacturer needs to evaluate different BFG algorithm before selecting one for inclusion in the device. In most cases, the BFG algorithm is implemented in hardware; hence, it cannot be “updated” during regular software (OS) updates. The use of BFGs are critical in EV applications where the TTS estimates determine the remaining mileage of the vehicle; a less accurate BFG results in increased “buffer” allocated in the “safety tank.” On the other hand, an accurate BFG will enable the EV manufacturers to reduce the buffer zone, which will result in increased mileage. A reliable BFG validation method is required to compare different BFG algorithms and evaluate their performance; the proposed metrics are steps in this direction.

V. RESULTS

In this section, first we present and discuss a BFG validation load profile and explain how each validation metric is computed. Then, we present all three BFG evaluation metrics computed on three different commercially available portable Li-ion batteries using the BFG algorithm in [18], [2], [19], [20].

In Figure 9, we present a load profile that was obtained using real life load using a Samsung Galaxy S4 phone; similar profile can be generated by “stitching” and applying the simulated load profile shown in Figure 2 as well. This profile allows one to compute the CC metric through the entire region of SOC; two OCV metrics can be computed – both close to high SOC region; and TTV metric can be computed at the low SOC region. The exact region (or places) where each metric is computed is denoted using arrows and text boxes. The validation profile shown in Figure 9 is collected at 25°C using a Samsung Galaxy 4 (GS4) battery, which has a rated capacity of 2.65 Ah.

Just before applying the BFG validation load profiles, the battery was charged using a commercial charger using a CC-CV charging profile, which set the CV charging at 4.35 V until the current reduced to 125 mA. The estimated internal resistance of the battery at 25° C was found to be 190 mΩ. Using (3), the initial SOC is found to be (see Figure 7)

$$\text{SOC}_{\text{initial}} = f_{\text{ocv-soc}}^{-1}(4.3262) = 0.9834 \quad (15)$$

The above $\text{SOC}_{\text{initial}}$ and the estimated battery capacity $\hat{C}_{\text{batt}}$ (using 7) are used to compute $\hat{s}_{\text{cc}}[k]$ for validation.

Figure 10 shows the computed BFG outputs for the load profile shown in Figure 9. The top plot shows the SOC output and the plot at the bottom shows the TTV output; the TTV output is computed by setting the desired shutdown voltage $v = V_{\text{sd}} = 3 \text{ V}$; in other words, the TTS estimate is used for computing the TTV metric. It can be noticed that the TTV estimate is very high and noisy during idling periods; the TTV estimate steeply drops during heavy loads; and the TTV estimate is very smooth during constant current discharge periods (approximately last four hours of the validation profile).

Figure 11 shows the *BFG validation data*, that are accurate estimates of the SOC and TTS obtained through “controlled means”, i.e., based on the specially designed BFG validation load profiles. The Coulomb counting based SOC estimate, shown at the top of the plot, is estimated based on the knowledge of the initial SOC and estimated battery capacity. The OCV look-up based SOC is computed at the end of each rest period (zero current period) in the profile. The OCV-SOC curve of the battery is computed based on the *normalized OCV modeling approach* of [16]. The TTV validation data is computed by subtracting the current time from the time at which the particular voltage is reached.

Figure 12 shows the computed BFG validation metrics. The CC error is computed throughout the entire validation data; the OCV error can be computed at the end of rest periods; even though the BFG continuously computes TTV, the predicted TTV can be validated against the true one only when the

current remains constant.

The SOC error in the top plot of Figure 12 shows a constant bias of approximately 0.6%; this bias is due to errors in $\hat{C}_{\text{batt}}$ estimation and due to ECM model mismatch in the BFG algorithm. It was reported in [2] that the ECM of the battery employed in BFGs changes based on the load; four possible ECMs were presented in [2] that could cover typical battery loads in mobile applications. The BFG evaluated in this paper uses model 3 of [2] as a primary model and does a “hard switch” to model 1⁷ at very low SOC; this could be attributed to the changing of the bias in SOC error towards 0 at the end.

In Figure 13, we show a close up detail of the TTV error towards the end of the validation period. It shows a matching trend similar to the bias in the SOC error; the amount of bias in TTV error is approximately 5.8 minutes (ideally, the TTV error is zero for constant current discharge). Based on (10), let us compute the bias in TTV error based on the bias in SOC error, i.e.,

$$\begin{aligned} b_{\text{ttv}} &= \frac{b_{\text{soc}} \hat{C}_{\text{batt}}}{I} \\ &= \frac{0.006 \times 2.70}{.240} = 0.0663 \text{ hrs} = 4.05 \text{ min} \end{aligned} \quad (16)$$

where b_{ttv} denotes the bias in TTV error and b_{soc} denotes the bias in SOC error; the observed bias in the TTV error (see Figure 13) is close to 5.8 minutes; the difference could be attributed to the errors in $\hat{C}_{\text{batt}}$ estimation and ECM parameter estimation.

Now, we present some preliminary results of a systematic BFG evaluation on three different batteries corresponding to Samsung Galaxy S3, Nokia and LG mobile devices. All three of these batteries are purchased through commercial vendors; the manufacturer data sheets were not available for any of the batteries. Table IV lists the nominal capacity and nominal voltage of these batteries.

Figure 14 shows the validation data collected from the three different batteries. The applied load profiles were not the same as the one shown in Figure 9 since the internal impedance rapidly rises at low temperatures and prevents the dynamic load profiles to be applied for long due to voltage protection circuits. Hence, waveforms had to be changed for each battery type, resulting in slightly different load profiles for each battery type. As a result, we employed a slightly modified load profile. Please refer to [20] for different types of load profiles and their applicability in BFG validation.

The summary of BFG evaluation is presented in Tables V, VI and VII. The empty cells imply that the data were removed from analysis due to identified instrumentation errors (marked as “IE”). The results

⁷Model 1 acts nearly as a “SOC look-up” using the measured voltage. The shape of the estimated SOC using model 1 follows the form of voltage; employing model 1 in dynamic data is insufficient and will result in very noisy (and inaccurate) SOC estimates.

show that the Coulomb counting error (the most commonly used validation approach throughout the literature) is always below 1% whereas the OCV lookup error and TTV error are more than 1% at times. This indicates the inadequacy of using Coulomb counting as the sole BFG validation method.

VI. CONCLUSIONS

In this paper, a systematic approach is presented to validate battery fuel gauging (BFG) algorithms. We discussed the complexities of evaluating a BFG algorithm and discussed why a single validation metric is inadequate to fully evaluate it. This paper developed three BFG evaluation metrics: *Coulomb counting (CC) metric*, *OCV-SOC metric*, and the *TTV metric*. The CC metric measures the error between the BFG reported SOC and the SOC computed by Coulomb counting based on a “measured” battery capacity. The OCV-SOC metric computes the error between the BFG reported SOC and the SOC estimated from the OCV-SOC curve of a rested battery. The TTV metric computes the error between the predicted time to shutdown (or the time to reach a certain voltage) reported by the BFG and the actual time to shutdown (or to reach a certain voltage). The proposed metrics are demonstrated through experimental data collected from commercially available Li-ion batteries.

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APPENDIX A

OCV-SOC CHARACTERIZATION METHOD

The open circuit voltage (OCV) of a battery increases monotonically with SOC. Determining the non-linear relationship between OCV and SOC plays a key role in adaptive SOC tracking algorithms. In this appendix, we briefly summarize the OCV parameter estimation approach that was presented in detail in [16].

The voltage across the battery terminals can be represented as

$$z_v[k] = V_o(s[k]) + h[k] + i[k]R_0 + n_v[k] \quad (17)$$

where, k indicates time index, $V_o(s[k])$ is the OCV corresponding to the SOC $s[k]$ of the battery, $h[k]$ is the hysteresis or voltage "pull" which is a function of current and SOC of the battery, $i[k]$ is the current through the battery, R_0 is the internal resistance of the battery, and $n_v[k]$ accounts for the voltage measurement error.

As the OCV experiment is performed at low current (usually at C/30 rate), the hysteresis effect can be considered approximately proportional to the current only [16], i.e.,

$$h[k] \propto i[k] \quad (18)$$

Then (17) simplifies to

$$z_v[k] = V_o(s[k]) + i[k]R_{0,h} + n_v[k] \quad (19)$$

where the effective resistance

$$R_{0,h} = R_0 + R_h \quad (20)$$

is the sum of the series resistance R_0 and the constant hysteresis equivalence resistance, R_h .

The OCV-SOC curve is represented by the following Combined+3 model [16]

$$V_o(s[k]) = K_0 + \frac{K_1}{s[k]} + \frac{K_2}{s[k]^2} + \frac{K_3}{s[k]^3} + \frac{K_4}{s[k]^4} + K_5 s[k] + K_6 \ln(s[k]) + K_7 \ln(1 - s[k]) \quad (21)$$

For a given temperature, the OCV parameters $K_i \in \{K_0, K_1, K_2, K_3, K_4, K_5, K_6, K_7\}$ and $R_{0,h}$ are estimated offline using the procedures described next.

$$z_v[k] = \underbrace{\begin{bmatrix} \mathbf{p}_o(s[k])^T & i[k] \end{bmatrix}}_{\mathbf{p}[k]^T} \underbrace{\begin{bmatrix} \mathbf{k}_o \\ R_{0,h} \end{bmatrix}}_{\mathbf{k}} + n_v[k] \quad (22)$$

where

$$\mathbf{p}[k]^T = \left[1 \quad \frac{1}{s[k]} \quad \frac{1}{s^2[k]} \quad \frac{1}{s^3[k]} \quad \frac{1}{s^4[k]} \quad s[k] \quad \ln(s[k]) \quad \ln(1 - s[k]) \right] \quad (23)$$

By considering a batch of N voltage observations, (22) can be written as

$$\mathbf{v} = \mathbf{P}\mathbf{k} + \mathbf{n} \quad (24)$$

where

$$\mathbf{v} = [v[1] \ v[2] \ \dots \ v[N]]^T \quad (25)$$

$$\mathbf{P} = [\mathbf{p}[1] \ \mathbf{p}[2] \ \dots \ \mathbf{p}[N]]^T \quad (26)$$

$$\mathbf{n} = [n[1] \ n[2] \ \dots \ n[N]]^T \quad (27)$$

$$\mathbf{k} = [\mathbf{k}_o \ R_{0,h}]^T \text{ an } (M+2) \text{ vector} \quad (28)$$

The least squares estimate of the parameter vector is given by

$$\hat{\mathbf{k}} = (\mathbf{P}^T \mathbf{P})^{-1} \mathbf{P}^T \mathbf{v} \quad (29)$$

Now, the OCV parameters at any temperature can be estimated by following the steps below.

1. Fully charge the battery
2. Collect the measured voltage $z_v[k]$ during
 - a) Slow-discharge the battery at $C/30$ rate until empty
 - b) Slow-charge the battery at $C/30$ rate until full
3. Compute battery capacity by accumulating the discharged Coulombs
4. Compute SOC $s[k]$ at each time step k using Coulomb counting
5. Use (29) to estimate the OCV model parameters

Remarks.

1. We reported in [16] that the OCV curve remains the same regardless of the temperature as far as the *normalized OCV modeling approach* of [16] is followed. The normalized OCV modeling approach suggests to use the estimated capacity at each temperature for OCV parameter estimation. Hence, the above technique can be used in any temperature to estimate the OCV parameters, however, the effect of the resistance R_0 is lesser at higher temperature. Hence, it is suggested to collect the data for the OCV characterization at high temperatures.
2. Figure 15(c) shows how the effect of hysteresis is marginalized by taking the OCV characterization

voltages by applying smaller current during charging and discharging.

3. In order to avoid ill conditioning associated with the natural logarithm near $s=0$ or $s=1$, SOC is scaled between $[0.15, 0.85]$. Details may be found in [16]

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Fig. 13. **TTV metric (in minutes) at close.** The TTV metric shown at the bottom of Figure 12 is shown in close-up; only the portion of TTV corresponding to the constant current discharge at the end of the validation profile is shown.

(a) Data from the LG battery

(a) Data from the Samsung battery

(a) Data from the Nokia battery

Fig. 14. Validation data.

(a) Applied current $i[k]$ and measured terminal voltage $z[k]$ (b) Measured terminal voltage $z[k]$ and modeled OCV against SOC

(c) Zoomed version of dashed box in (b) showing voltage drop and hysteresis of the battery

Fig. 15. **Data for OCV parameter estimation.** Applying the same (low) magnitude of current results in the hysteresis approximately the same at a certain SOC during charging and discharging.

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TABLE I
FEATURES OF THE EXISTING SOC TRACKING APPROACHES

ECM	R_0		[23],[24],[25],[26]
	R_0, R_1, C_1		[3],[27],[28], [29], [30],[31],[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],[34],[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],[37],[38],[42]
	Rated capacity		[3],[26][27],[29],[31],[33]
Validation method	Coulomb counting		[3],[24],[26],[28],[29],[30],[33],[34],[36],[37],[40],[42]
	OCV lookup		[43], [14]
	Simulated models		[11], [17], [44], [13]
	Empirical evaluation of SOC		[45], [15], [46]

TABLE II
SIMULATED CURRENT PROFILES

Profile	Mean (mA)	Similar to
Profile A	80	Active screen
Profile B	56	Idle state
Profile C	280	Active phone call
Profile D	324	Video and texting
Profile E	492	Camera and web surfing

TABLE III
SUMMARY OF BFG METRICS PRESENTED IN THIS PAPER

	CC Metric	OCV Metric	TTV Metric
Required load profiles for validation	Low discharge until the shut down voltage V_{sd} is reached (in order to computed C_{batt})	Rested battery ($I_{batt} \leq \epsilon$ for an hour)	Constant current discharge/charge for few minutes
BFG output tested	SOC	SOC	SOC & TTS

TABLE IV
LIST OF BATTERIES USED IN BFG VALIDATION

Battery	Model	Nominal Capacity (Ah)	Nominal voltage (V)
Samsung	EB555157VA	1.75	3.7
LG	LGIP	1.1	3.7
Nokia	BP 4L	1.5	3.7

TABLE V
CC METRIC (ERRORS IN %)

	Temperature								
	-20°C	-15°C	-10°C	-5°C	0°C	10°C	20°C	30°C	40°C
Samsung EB555157VA	0.44	0.86	0.44	0.86	0.35	0.02	0.75	IE	IE
LG LGIP	0.39	0.52	0.90	0.11	0.66	0.53	0.28	0.25	0.49
Nokia BP 4L	0.23	0.42	0.59	IE	IE	0.14	IE	0.88	IE

TABLE VI
OCV METRIC (ERRORS IN %)

	Temperature								
	-20°C	-15°C	-10°C	-5°C	0°C	10°C	20°C	30°C	40°C
LG LGIP	-0.58	-0.06	2.40	0.38	0.61	-0.32	-0.98	IE	IE
Nokia BP 4L	3.15	5.29	0.26	2.97	1.49	4.19	0.23	1.99	1.12
Samsung EB555157VA	4.76	1.22	0.38	IE	IE	-0.59	IE	0.02	IE

TABLE VII
TTV METRIC (ERRORS IN %)

	Temperature								
	-20°C	-15°C	-10°C	-5°C	0°C	10°C	20°C	30°C	40°C
LG LGIP	1.4	0.7	3.8	3.8	3.0	3.8	3.7	IE	IE
Nokia BP 4L	1.5	0.7	4.0	6.1	14.2	1.6	4.6	5.3	4.5
Samsung EB555157VA	8.7	17.7	1.9	IE	IE	8.9	IE	6.0	IE