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Battery Management Systems—Challenges and Some Solutions

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Abstract: Electric vehicles are set to be the dominant form of transportation in the near future and Lithium-based rechargeable battery packs have been widely adopted in them. Battery packs need to be constantly monitored and managed in order to maintain the safety, efficiency and reliability of the overall electric vehicle system. A battery management system consists of a battery fuel gauge, optimal charging algorithm, and cell/thermal balancing circuitry. It uses three non-invasive measurements from the battery, voltage, current and temperature, in order to estimate crucial states and parameters of the battery system, such as battery impedance, battery capacity, state of charge, state of health, power fade, and remaining useful life. These estimates are important for the proper functioning of optimal charging algorithms, charge and thermal balancing strategies, and battery safety mechanisms. Approach to robust battery management consists of accurate characterization, robust estimation of battery states and parameters, and optimal battery control strategies. This paper describes some recent approaches developed by the authors towards developing a robust battery management system.

Keywords: battery management systems; battery fuel gauge; state of charge; state of health; power fade; capacity fade; robust estimation; predictive control

1. Introduction

Automobiles powered by gasoline engines account for nearly 25% of the global energy consumption [1]. Rechargeable batteries promise a way to replace them by electric vehicles (EVs) in the near future. In addition to EVs, rechargeable batteries have been widely adopted in portable electronic equipment, household appliances, power tools, aerospace equipment and renewable energy storage systems. A battery management system (BMS) ensures the safety, efficiency and reliability of a battery powered system. Research on BMS has been very intense in the last two decades and significant improvements were achieved in the safety, efficiency and reliability of battery systems [2,3]. However, there are challenges remaining and in this paper we describe a list of challenges and outline possible solutions.

Two schools of approaches for battery management systems have emerged over time; one models the battery through *electrical equivalent circuit model (ECMs)* [2,3] and the other seeks to model it through *electrochemical models* [4]. However, most practical systems adopt the electrical ECM based approaches due to their simplicity. The research challenges faced by the present day BMS are three pronged: *safety, efficiency* and *reliability*. Lithium ion batteries are susceptible to *thermal runaway* which is an irreversible chemical process triggered by several conditions including over-voltage and high temperature. The need to fast-charge the battery, which is important in electric vehicle applications, increases the possibility of thermal runaway and safety issues [5,6]. There are wide ranging issues affecting the efficiency of energy storage in batteries; particularly, electric vehicle applications strive to improve efficiency in every possible way. For example, charging efficiency is the percentage of the total energy needed during charing [7]; fast charging requirements results in significant energy waste in the form of heat. BMS algorithms attempt to enhance efficiency of batteries in multiple ways; optimal charging algorithms aim to reduce the amount of heat waste and the degradation of state of health; precise SOC estimation algorithms will help to improve the efficiency by helping to design minimal battery-pack configurations based on specific needs. Individual cells in a battery-pack are known to become imbalanced over time causing safety and reliability issues; short circuited cells are another common cause of safety and reliability issues in Li-ion batteries [8–10].

An emerging challenge for battery management systems comes in the form of battery reuse [11,12]. It is predicted that the electric vehicle sales are about to grow by nearly 500% in the next 10 years [13]. The state of the art BMS algorithms heavily depend on prior characterization carried out in laboratories [2,3]; Consequently, they are only effective for first time use of batteries. Considering the fact that the first use of the battery alters its electrochemical characteristics in unique ways, traditional BMS approaches that rely on empirical modeling, under the assumption that batteries of the same chemistry and size have similar characteristics, will be inadequate to manage used batteries.

The present manuscript is written in the form of an *expository paper* detailing the many solutions developed by the authors in the recent past in order to address specific challenges in battery management systems. Section 2 describes in more details about the specific goals of a state of the art battery management systems and the challenges it needs to overcome. Section 3 describes some specific solutions developed by the authors in order to address the challenges faced by the present day battery management system. Finally, the paper is concluded in Section 4.

2. Battery Management System: Goals and Challenges

In this section, some of the challenges faced in designing battery BMS are briefly described.

2.1. State of Charge Estimation

Coulomb counting is the easiest approach to estimate the state of charge (SOC) of a battery [2,3]. Figure 1a gives the approximate Coulomb counting equation that is used to compute SOC in a recursive manner. However, Coulomb counting method suffers from the following sources of errors:

1. *Initial SOC error.* Since it is a recursive integration, any errors in the initial SOC assumption will remain as a bias.
2. *Current measurement error.* Current sensors are corrupted by measurement noise; simple, inexpensive current sensors are likely to be more noisy and possibly biased.
3. *Current integration error.* Coulomb counting methods employ a simple, rectangular approximation for current integration. Such an approximation results in errors that increase with sampling interval as the load changes rapidly.
4. *Uncertainty in the knowledge of battery capacity [14].* Coulomb counting method assumes perfect knowledge of the battery capacity, which is known to vary with temperature, usage patterns and time (age of the battery) [15,16].
5. *Timing oscillator error.* Timing oscillator provides the clock for (recursive) SOC update, that is, the *measure of time* comes from the timing oscillator. Any error/drift in the timing oscillator will have an effect on the measured Coulombs.

Alternatively, the open circuit voltage (OCV) can be modeled as a function of the SOC of the battery. This OCV-SOC model [17] can be exploited to estimate the SOC based on voltage measurements. However, measuring the OCV in real-time during battery operation is not feasible because the battery needs to be rested for several hours before the OCV can be measured. While the battery is operational a measure of OCV can be obtained by estimating the voltage across the battery ECM; this requires the estimation of the ECM parameters as well. Once the OCV is estimated, the SOC can be looked-up [17] using the OCV-SOC characterization parameters. Figure 1b summarizes the voltage based approach to SOC estimation. The following errors are encountered by the OCV-SOC based state of charge estimation approach:

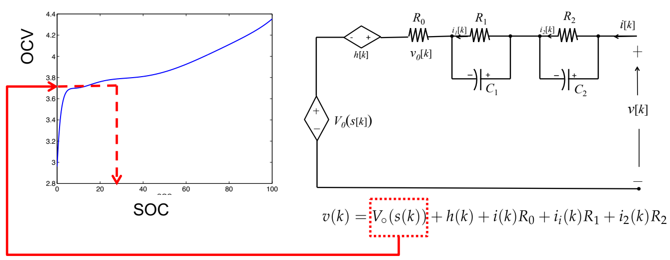
1. Errors in the parameters estimated for the electrical ECM of the battery.
2. Voltage and current measurement error.

Most of the advanced BFG's use a *fusion based approach* where both the Coulomb counting method and the OCV-lookup method a combined in an efficient manner.

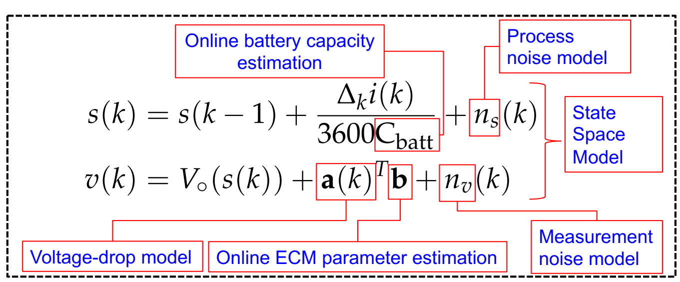
$$s(k) = s(k-1) + \frac{1}{3600C_{\text{batt}}} \int_{t(k-1)}^{t(k)} i(\tau)d\tau$$

$$s(k) \approx s(k-1) + \frac{\Delta_k i(k)}{3600C_{\text{batt}}}$$

(**a**) Current based approach



(**b**) Voltage based approach



(**c**) Fusion based approach

Figure 1. State of charge estimation. The fusion based approach is one of the most robust approaches to accurate battery SOC estimation.

Th fusion approach to SOC estimation (more appropriately, SOC tracking) is modelled as a recursive Bayesian estimation problem and by employing a nonlinear filtering approach (such as an extended Kalman filter) for online SOC tracking [2,3]. A complete SOC tracking solution involves the following:

(i) *Estimation of the OCV parameters that form part of the state space model through offline OCV characterization:* The OCV-SOC characterization is stable over temperature changes and aging of the battery. Once estimated, these parameters form part of a state-space model with known parameters.
(ii) *Estimation of the dynamic ECM parameters:* These parameters can change depending on the battery age, temperature, and SOC, therefore, they must be estimated in real time.
(iii) *Estimation of battery capacity:* Even though the the manufacturer provides the nominal capacity of the battery, it changes over time. Some important factors that cause *capacity fading* are, elevated temperature, cycling (usage), depth of discharge patterns, and calendar aging. Due to this, the battery capacity needs to be estimated in real-time for an accurate BFG. Capacity estimation is still being actively investigated in the literature [14].
(iv) *Model parameter-conditioned SOC tracking:* As soon as the model parameters are estimated, a filtering approach can be used to track the SOC using the state-space model discussed above. In order to do this, numerous filtering approaches, including extended Kalman filter, Unscented Kalman filter and particle filter, were experimented in the literature. However, it is observed that the resulting state-space model contains correlated process and measurement noise processes. Properly addressing the effect of these correlations will yield better SOC tracking accuracy.

Figure 1c illustrates the fusion based approach to SOC estimation. The fusion based approach needs to have the knowledge of OCV parameters, battery capacity, ECM parameters as well as the sensitivity of the voltage and current measurement sensors. Section 3 briefly describes the approaches to estimate them.

2.2. Real-Time State of Health Estimation

Today's BMS technology is inadequate to accurately predict the state of health (SOH) of a battery. The available choices are either to prematurely replace the battery or to wait until an explicit failure event occurs. Both of these choices have undesirable consequences: premature replacement will result in increased cost to the end user and excessive waste to the environment; waiting out will negatively impact the safety and quality of experience to the end user.

Many of the methods proposed in the literature for SOH estimation are data driven methods. The existing approach to SOH estimation differ in terms of the features used to train and the machine learning topology used. For instance, both approaches presented in References [18,19] used neural networks; in Reference [18], the following features were used: change in the SOC, current, temperature and the internal circuit parameters; in Reference [19] the voltage curve was used as a feature. In References [20–22], support vector machines approach was employed for SOH classification. Feng et al. [20] used partial charging voltage curves as there feature to estimate the SOH online while [21] identified the charging time and capacity to be the features in order to estimate the SOH. In Reference [23], a sample entropy algorithm is used identify the measured terminal voltage under hybrid pulse power characterization current profile; this is then used as a feature to estimate the SOH using a sparse Bayesian predictive modeling. Yun and Qin [24] proposed the use of the time required for the terminal voltage to drop from and to a certain value as the feature to train.

Real-time SOH estimation remains one of the open problems in battery management system research.

2.3. Optimal Charging

The state of the art in battery charging is primitive: time consuming, less efficient and less safe compared to gasoline refueling. Research on optimal charging algorithms (OCA) received significant attention in the recent past. One of the most common method of charging is the constant trickle current based charge strategy. Because a low charging current is used, it requires a long charging time (around 10 h) [25]; charging time can be reduced by increasing the charging current, however, as the batter OCV increases due to charging, this will cause the battery terminal to reach a voltage that is above the safety threshold. Hence, the higher current that is applied at the initial stage needs to be reduced when the terminal voltage reaches a certain threshold value. Consequently, the *constant-current constant-voltage (CC-CV)* [25] strategy has become one of the widely used approaches to fast charging. In order to shorten the charging time and perpetuate the cycle life of the battery a multi-step constant-current charging is used in References [26,27]. The Taguchi-based methods for battery charging [28,29] uses orthogonal arrays to put forward a systematic method to find the optimal solution with guidelines for choosing the design parameters. Another strategy to use is the boost charging strategy, where a very high current is applied to close-to-fully discharged batteries [30]. In pulse-charging methods [31–35], the battery is exposed to very short rest or even deliberate discharging periods during the charging process. Soft-computing approaches can also be used to optimize the battery charging profile. In Reference [36], optimal charging is achieved by simplifying the problem to be in the form of an optimization problem with the objective function of maximizing the charge within 30 min. Through the use of a multistage constant current charging algorithm, the optimal solution can be obtained by using an ant-colony approach. The authors of Reference [37] proposed a universal voltage protocol, its goal is to enhance the charging efficiency and cycle life by applying a certain charging profile, this charging profile is determined based on the SOH of the battery, which is estimated during the optimization process [38]. Recently, in Reference [39], to find the optimal charging strategy, an optimization approach with cost function of time-to-charge and energy loss is used. However, an analytical solution has not been presented; rather a numerical solution is given to the problem. Many other approaches are presented in the literature for battery charging, such as data mining [40,41], genetic algorithm and neural network based strategies [42], Grey-predicted charging system [43].

2.4. Fast Characterization

Two important offline characterizations required in a BMS are the SOC and SOH characterizations. In SOC characterization, the SOC is modelled against the OCV by collecting one full cycle of data (fully charged battery $\rightarrow$ fully discharged battery $\rightarrow$ fully charged battery) whereas the state of the art SOH characterization is done against the number of cycle requiring hundreds and even thousands of cycles of data. This makes SOC ans SOH characterization a time-consuming process. Hence, it is important to find ways to reduce characterization time.

One approach to reduce characterization time is to do it in real-time while the battery is in use. Some approaches for real-time SOC characterization were proposed in the past [44,45]. One of the drawbacks of these approaches is due to the fact that simpler OCV-SOC models need to be employed (due to computational bottlenecks in the BMS) for online estimation of parameters; this will lead to loss of accuracy [46]. Secondly, different sources of error can accumulate from other estimated parameters, that will be incorporated during OCV estimation [47]. Lastly, based on the SOC range that the battery goes through, the estimated OCV model will cover that SOC portion—which depends on the battery usage pattern. In orderfor OCV-SOC model to cover the entire SOC range, the battery has to undergo a complete discharge/charge profile—this cannot be guaranteed. In Reference [48], an approach that uses the data pieces-based parameter identification was proposed to estimate the entire OCV-SOC model. However, this approach has its own drawbacks where the modelling error can be high at the initial stages and the the convergence is not always insured.

Compared to SOC characterization, SOH characterization is nearly impossible to do in real-time locally for a particular battery pack. However, the abundance today's connectivity offers an alternative solution for real-time SOC characterization. Figure 2 depicts how a *cloud assisted BMS* can collect data from numerous batteries to estimate crucial parameters for real-time management of battery packs.

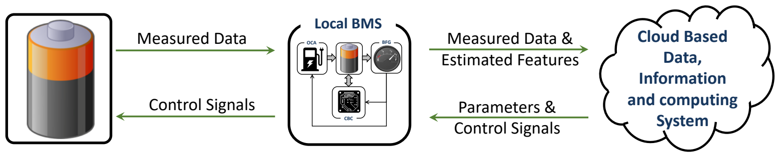


Figure 2. Cloud assisted battery management system. The abundance of todays connectivity allows crucial parameters related to SOC and SOH characteristics of battery packs in real-time. (image from Reference [49] being reprinted with permission from IEEE).

2.5. Battery Reuse

As counties race towards decreasing their green house gas emissions, the public is being encouraged to use EVs by offering various incentives. As a result, the manufacturing of Lithium-ion (Li-ion) batteries is expected to increase very rapidly in the next few decades due to their expected use in electric vehicles [50]. Battery packs used in electric vehicles are expected to be replaced when they reach about 80% of their original capacity [11], since range is an important quality in EVs. Research on BMS algorithms so far has predominantly focused on the first use of the battery-pack. The batteries retired from the EVs are still an excellent medium of renewable energy storage in other applications, such as renewable energy storage systems [11]. However, it is still not well understood as to how usage affects the SOC and SOH characterizations of a battery pack. Environmental and usage conditions affect battery characteristics; based on how, when and where an EV was predominantly in use, its battery-pack might have significantly different reliability, efficiency and safety compared to another battery-pack that was made by the same manufacturer during the same assembly process. In other words, even though two batteries were identical twins out of the assembly line, after their first retirement, they would possess two different characteristics based on the patterns of environmental and usage conditions that they experienced. Hence, there is a need to invest in research and to develop BMS that ensure safe, reliable and efficient operation of EV batteries during their second use as renewable energy storage systems. Even though the electric vehicle production is expected to grow exponentially in the next few decades [13], research on battery reuse is still in early stages [51,52]. Figure 3 demonstrates the overall block diagram of a BMS during battery reuse. One of the important challenges here is that each used battery pack is different from one another.

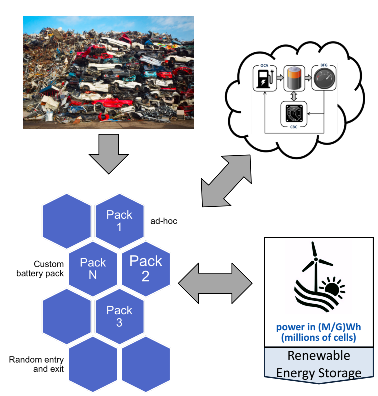


Figure 3. Battery reuse: from scrapyard to powering living rooms. Millions of vehicles are scrapped each year due to accidents. In the case of electric vehicles, the batteries could be reused store renewable energy. However, more research needs to be done about managing used batteries of various size, chemistry and manufacturers.

2.6. Universality

Existing BFG algorithms depend on prior characterization for accurate estimation of SOC and SOH [2,3]; as a result, their application is limited to certain type of batteries to which they have the parameters for. The state of the art BMS is constrained to a particular chemistry, manufacturer, and size of the battery to which it is characterized for, that is, the present-day BMS is not universal; this restricts battery selection and results in increased cost; also, such a restrictive BMS does not allow one to repurpose used battery packs for energy storage. In smaller, household, applications, custom battery chargers generate excessive electronic clutter and environmental waste.

The first ones to think about the universal battery systems were the battery charger designers who had to address the huge number of different chemistry and types of batteries that in each application requires its own customized charger; this increases the amount of electronic wastage and adds to the cost of the device. Hence, the problem of *universal battery charger* received attention in the literature [7,53–55]. Earlier versions of universal battery chargers are programmed to look for appropriate voltage to terminate the charging process. Most of them used a look-up table of incremental voltage in response to charging by a certain number of Coulombs [7,53–55].

A preliminary achievement regarding the universality objective is reported in Reference [52] where a probabilistic data association filter [56,57] was employed to associate the online measurements from batteries to their model parameters, thus, resulting in a *chemistry-adaptive BFG*. Further research needs to be done on this topic so that reliable algorithms can be developed to extend adaptivity for load-range, size, temperature, nominal voltage and age as well. This would require large computing power that the traditional battery management systems are not allocated for, for example, portable electronics. Cloud computing [58] allows one to outsource intense computing to external sources; that is, by combining information fusion with cloud computing, a greater deal of universality can be achieved in battery management systems, paving the way for optimal battery reuse (see Section 2.5) and reduced electronic clutter in households and work places.

2.7. Self Evaluation

Battery management system evaluation is a very challenging research problem since there are no proven mathematical models to represent the complex features of a Li-ion battery, these features include power fade (PF), capacity fade (CF), temperature effects on parameters, aging, hysteresis and relaxation effects.

There is little literature focusing on BFG algorithm evaluation under realistic usage conditions. The importance of BMS evaluation is discussed in Reference [59]; in Reference [60], the need to minimize power dissipation and extend battery run-time for portable devices is discussed; the advantages of hardware-in-the-loop (HIL) testing to validate a BMS under various failure conditions was motivated in Reference [61]; and a HIL test to validate the BFG using a multi-cell battery pack was proposed in References [62,63].

Evaluating BMS algorithms is a time consuming task [16] that requires research to find efficient solutions. Particularly, the following aspects needs to be studied further:

- The state of the art BMS evaluation is done in a lab setting. Real-time self-evaluation through data driven approaches need to be developed.
- Majority of the existing research experiments are done at a constant temperature. BMS evaluation in the presence of gradual and rapid temperature changes is needed.

3. Solutions Through Model Based Algorithms

Figure 4 shows an overall block diagram of a BMS that consists of three important components [49]: BFG, OCA, and cell-balancing circuitry (CBC). The BFG is considered as the the primary component of a BMS since the BFG output is required in both the OCA and CBC. The BFG estimates the SOC and SOH of the battery-pack based on three measurements: voltage, current, and temperature. The OCA is responsible for regulating the battery charging by generating charging waveforms. The charing waveforms vary in complexity; at the simplest level, a charger applies a constant voltage across the battery terminal; in constant-current constant voltage (CC-CV) charging, the battery SOC (and hence the OCV) rises fast due to the relatively high current; then the charing is switched to CV in order to safeguard the battery from overcharging. Complex charging strategies closely monitor critical battery parameters and adaptively alter the charging pattern. The ultimate goal of an OCA is to charge the battery faster without negatively affecting its SOH [64,65]. When new, individual cells in the battery-packs have similar battery capacity and impedance. However, it is well know that after many charge/discharge cycles these parameters can deviate away from one other causing cell imbalance. Cell-imbalance has many drawbacks from reduced power output, reduced cycle life to catastrophic failures, including fire. The CBC helps to maintain the battery-pack balanced. In addition to this, CBC is also responsible for thermal balancing [66] of the battery-pack. In the remainder of this section, recent contributions to some of the BMS components are described.

The BMS consists of several smaller modules that are critical for improving its safety, efficiency and reliability. Many of todays research is focused on improving these individual modules. In the remainder of this section, we brief the details of the several BMS modules that were developed as improvements to the state of the art.

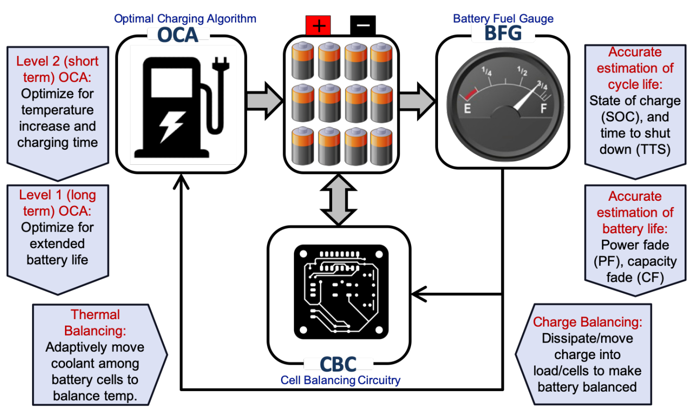


Figure 4. Functional block diagram of a battery management system. Three important components of a BMS are battery fuel gauge, optimal charging algorithm and cell balancing circuitry.

3.1. Normalized Open Circuit Voltage Characterization

Open circuit voltage characterization is one of the most important elements of any BMS, as it allows one to estimate the SOC based on a given OCV. Earlier approaches to OCV modelling suggested to store different OCV-SOC parameters at different temperatures. It was shown in Reference [17] that the *normalized approach* to OCV characterization results in a single set of parameters for all temperatures. Further, various models for OCV characterization were evaluated in Reference [17]. Figure 5 shows the results of applying the normalized OCV modelling approach [17] for OCV-SOC characterization. The important advantage of the normalized modelling approach is that the OCV-SOC characterization does not need to be repeated at multiple temperatures. Just one characterization at room temperature is shown to be enough to cover typical operational temperatures experienced by batteries.

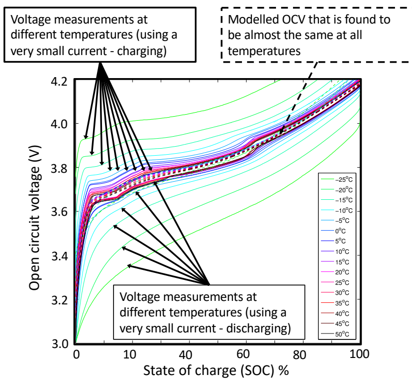


Figure 5. Normalized open-circuit voltage modelling. It is shown that the OCV-SOC parameters obtained through the proposed normalized OCV modelling approach in Reference [17,67] showed little variations with temperature.

The combined model and its variations, such as the combined+3 model [17], remain one of the most used approaches to OCV modelling. Many existing OCV models, including combined model and its variants, suffer from the fact they are not defined at the extreme limits of the SOC, that is, (SOC = 0% and SOC = 100%). For example, let us consider the combined model equation where the OCV ($V_o(s)$ relates to the SOC (s) as follows

$$V_o(s) = \kappa_0 + \frac{\kappa_1}{s} + \kappa_2 s + \kappa_3 \ln(s) + \kappa_4 \ln(1-s) \tag{1}$$

where it can be noticed that the function is undefined when $s = 0$ (SOC = 0%) and when $s = 1$ (SOC = 100%). Existing approaches to the above problem not very optimal. In References [67,68], the effect of not scaling on the performance of SOC estimation is formally quantified and an approach was presented to find the optimal scaling factor; further, it was shown in Reference [67] that the optimal scaling factor remained the same across different battery chemistries and temperatures. Figure 6 summarizes the results of scaling

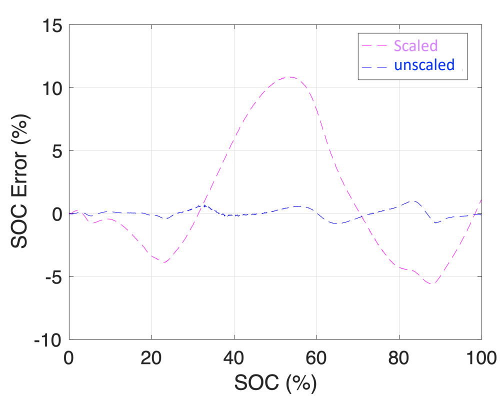


Figure 6. Scaling. The scaling approach [67] reduces the worst case error in OCV modelling.

3.2. Equivalent Circuit Model Identification

Li-ion batteries are powered through chemical reactions. modelling such chemical reactions using physics and chemistry result in very complex models that are challenging to solve. In contrast, ECM provided a simplistic, albeit adequately approximate representation of batteries and battery packs. Figure 7 shows a generalized ECM of a battery.

It was shown in Reference [69] that different approximations of ECM in Figure 8 can be used based on the battery load. Using the appropriate ECM can reduce computation time and complexity and give accurate results. Figure 8a shows the ECM when there is a constant low current load. In this mode the hysteresis can be neglected due to the small effect it has and the capacitors can be ommited due to the constant current. The remaining resistances can be lumped together to form the output resistance (R_0).

The second mode is shown in Figure 8b. This model is used when there is a high current for extended periods of time. Due to the high current, hysteresis cannot be neglected anymore, and must be incorporated in the model. However, the capacitors can still be omitted due to the constant current. The remaining resistances can still be lumped together in one output resistance (R_0).

Figure 8c shows model 3 that can be used when there is a dynamic load with a constant average load. In this case, the hysteresis cannot be ignored, along with the capacitor/resistor component (C_1/R_1). On the other hand, model 4 is shown in Figure 8d where there is a dynamic current with varying average load. Therefore, a second capacitor/resistor (C_2/R_2) need to be used for accurate battery modelling.

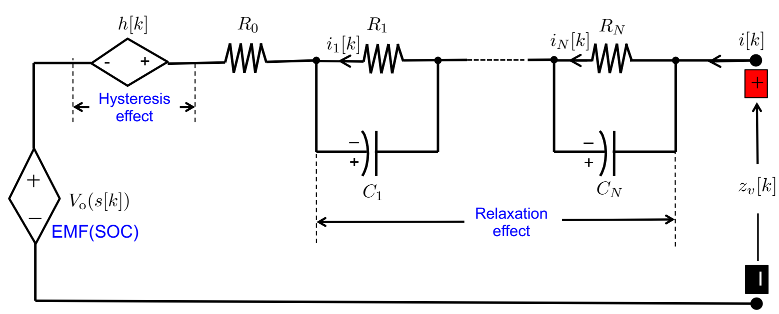
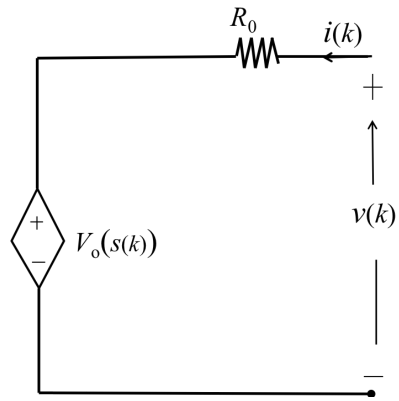
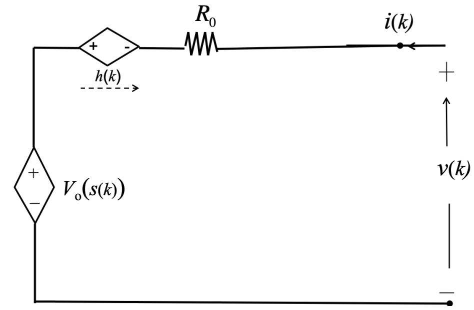


Figure 7. Equivalent circuit model of a battery. Identifying the battery model and estimating its parameters are crucial steps for all aspects of a battery management system, from state of charge estimation to optimal charging to charge and thermal balancing. In practice, reduced models, shown in Figure 8, are employed; In Reference [69] a unified approach to ECM model parameter estimation is developed.

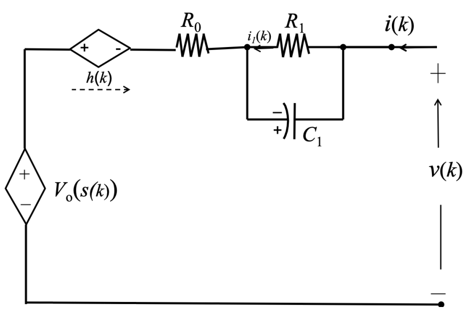
The authors of Reference [69] proposed an approach that is based on weighted least squares method to identify the battery parameters online, which is inexpensive and has high accuracy. This method has the ability to switch between the battery models easily based on the current profile. Furthermore, instead of modelling the hysteresis as a function of the SOC, which can be very complex and inaccurate, the authors proposed a way to model the hysteresis as an error in the OCV, which has the added benefit of fast recovery when the initial SOC is inaccurate.



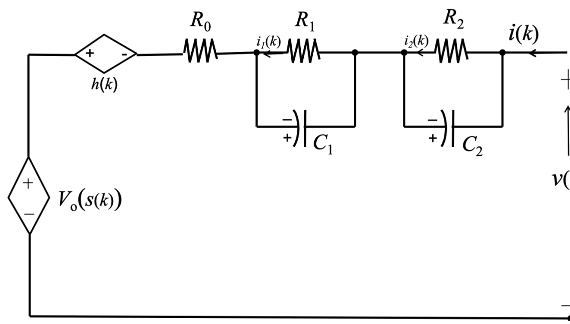
(**a**) Model 1 (OCV moeling)



(**b**) Model 2 (Charging)



(**c**) Model 3 (Stationary load profiles)



(**d**) Model 4 (Time-varying load profiles)

Figure 8. Reduced equivalent circuit models of a battery. Each model is appropriate for different types of loading condition as indicated.

3.3. Real-Time Battery Capacity Estimation

Real-time battery capacity estimation is a very important factor to achieve a universal BMS. It is also one of the ways to improve the accuracy of SOC estimates. The work done in Reference [14] aims to establish an approach that can estimate the battery capacity in real-time. In this paper, two approaches to estimate the battery capacity were investigated; the first approach uses total least squares, while the second approach used the rest states and models the hysteresis as an error in the OCV. Furthermore, both approaches are fused together to estimate the battery capacity with a high accuracy. Finally, HIL approach was used to validate the estimation algorithm; the results showed that it is accurate within 1% of the true value.

3.4. Optimized Charging

Optimal battery charging is one of the most active research areas of BMS. Figure 9 outlines the level-2 and level-1 charging goals.

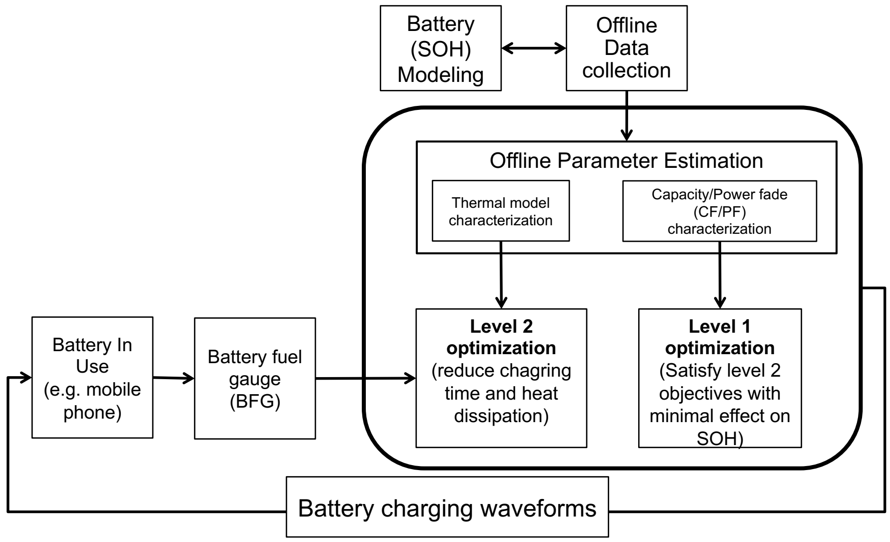


Figure 9. Elements of a smart (optimal) charger.

A closed-form solution to the problem of optimally charging a Li-ion battery was presented in Reference [64] by considering a combination of three cost functions: time-to-charge (TTC), energy losses (EL), and a temperature rise index. It was theoretically shown in Reference [64] that the optimal charging strategy for the simple equivalent model case reduces to the well-known CC-CV policy with the value of the current in the CC stage being a function of the ratio of weighting on TTC and EL and of the resistance of the battery.

In Reference [65], two models were presented for normalized battery capacity: the LAR-$\alpha\eta\gamma$ model and the control variable dependent model. The first model is based on the number of cycles and the latter is a function of the number of cycles as well as two other charge control parameters, viz., maximum terminal voltage of the battery ($v_{\max}$) and maximum charge current ($i_{\max}$). In order to evaluate the accuracy of these models experimental data were gathered from aging experiments performed on Samsung GS4 battery. The results show that these methods are far more superior to the bi-exponential capacity model [70].

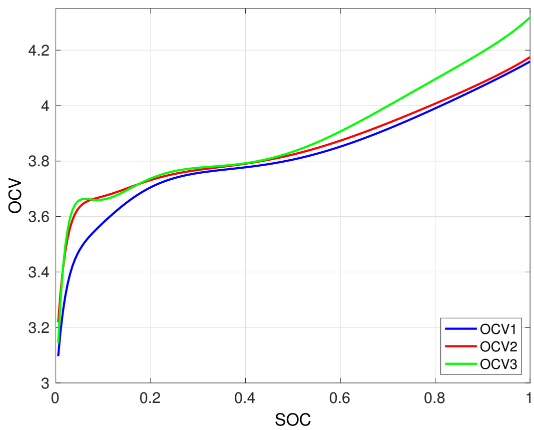
3.5. Adaptive Algorithms for Universality

Developing a generalized BFG that is independent of battery chemistry can be broken down into two categories. The first category is to simply compile a library of all possible OCV parameters and to select the most suitable OCV model for fuel gauging through online deteciton. In other words, this first approach seeks to resolve the association ambiguity between several possible OCV parameters and the battery being monitored in a supervised way (e.g., employing nearest neighbor or any of the machine learning-based classifiers).

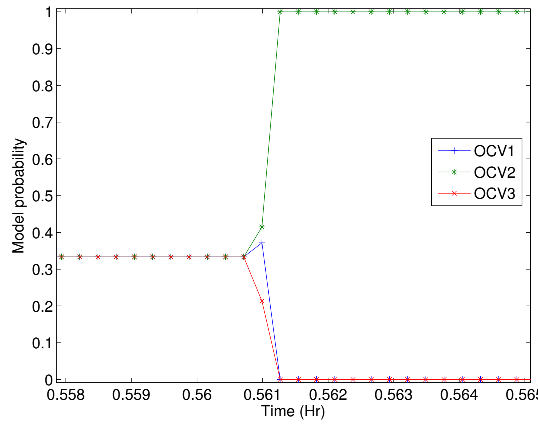
The second category seeks to use online data to estimate the OCV parameters [71–73]; an iterative process is used to keep the OCV parameters and battery capacity up to date. Since users can swap the battery at any time this can cause an issue where the BFG has to be aware of this change and adapt accordingly by restarting the OCV parameter estimation process. Additionally, this routine should only be applied when required. Further, the iterative estimation of SOC, OCV & ECM parameters and the battery capacity can lead to loss of robustness and instability for the BFG algorithm.

One of the first few approaches towards achieving chemistry adaptive BFG was reported in Reference [52] where the probabilistic data association (PDA) methodology was used to achieve this goal.

Here the ultimate goal is to be able to mange an arbitrary battery (present day BMS rely on parameters that are obtained from the same battery type). Figure 10 shows a demonstration of the chemistry adaptivity reported in Reference [52]. Chemistry adaptivity is a desired feature in the secondary applications of used batteries, for example, used EV batteries used in power grid.



(**a**)



(**b**)

Figure 10. Chemistry adaptive BMS. The proposed chemistry probabilistically selects the battery parameters based on the measured data from the battery (voltage and current). In the above demonstration, all three models were initialized with equal probability (1/3); within few samples of measured data, the PDA algorithm was able converge to the correct model. (**a**) OCV curves of different chemistries; (**b**) Model probabilities of the PDA algorithm [52].

3.6. Approaches to BMS Evaluation

In References [15,16], systematic approaches were presented to validate BFG algorithms. Particularly, the following three BFG evaluation metrics were proposed and analyzed in References [15,16]:

- *CC-metric.* The CC-metric is used to evaluate the accuracy of the SOC estimates of a BFG. It was known that the Coulomb counting method is an error prone approach to SOC estimation. However, if the battery capacity and initial SOC are known, the Coulomb counting approach will provide a very accurate estimate of SOC. The CC-metric proposes to use special *BFG validation load profiles* [16] such that the initial SOC and the battery capacity can be accurately estimated in order to evaluate the SOC estimate of a BFG. It must be noted that the CC-metric is a *laboratory based metric*, that is, it cannot be implemented in real-time when the battery is being operated by the end user.
- *OCV-metric:* The OCV-SOC metric proposes to employ the OCV curve [17] in order to find the true SOC which can then be used to validate the SOC estimate given by a BFG. Similar to the CC-metric, the OCV-SOC metric is also a *laboratory based metric* because the battery needs to be rested before the OCV can be directly measured.
- *Time to voltage (TTV) Metric.* The TTV metric [16] is the most rigorous way to test the accuracy of a BFG algorithm. This metric tests several features of a BFG at once. Let us consider an example: the BFG in an EV predicts the remaining milage as 100 miles. The most accurate way to validate this prediction is to actually drive the EV until it reaches end of charge; by subtracting the actual distance travelled from the prediction, the true BFG error can be computed. Now, instead of miles,

consider this in voltage: A BFG can predict the time it takes to reach a certain voltage, given a constant load or constant charging current. Similar to how an EV can be driven to check the accuracy of the mileage prediction, the TTV metric is computed based on the predicted vs. actual time it took for the battery to reach a certain terminal voltage. One drawback of the TTV metric is that it requires a constant current to implement the metric. Most battery chargers employ constant current charging for a certain amount of time—this provides an opportunity to implement the TTV metric in real-time. It must be re-emphasized that the TTV metric is used to quantify the accuracy of the following BFG estimates at once: such as, SOC, battery capacity and ECM parameter estimates

In order to compute the *BFG evaluation metrics* (CC-metric, OCV-metric and TTV-metric), the battery needs to undergo a specific load profile that is named *BFG evaluation profile* in References [15,16]. Figure 11 shows a BFG evaluation profile that is designed to compute the above three metrics for a battery with a nominal capacity of 1.5 Ah. The evaluation profile requires to start the experiment with a fully charged battery and apply various discharge profiles and rest periods until the battery is given a final rest period of about 2 h before constant current profile of moderate to low magnitude is applied until the battery becomes empty; this procedure ensures the total capacity [17] of the battery can be accurately estimated—the estimated total capacity in return ensures the computation of a rigorous CC-metric. The constant current discharge at the end also allows to compute the TTV metric; this is particularly significant because remaining time prediction is crucial when the battery nears it end of charge.

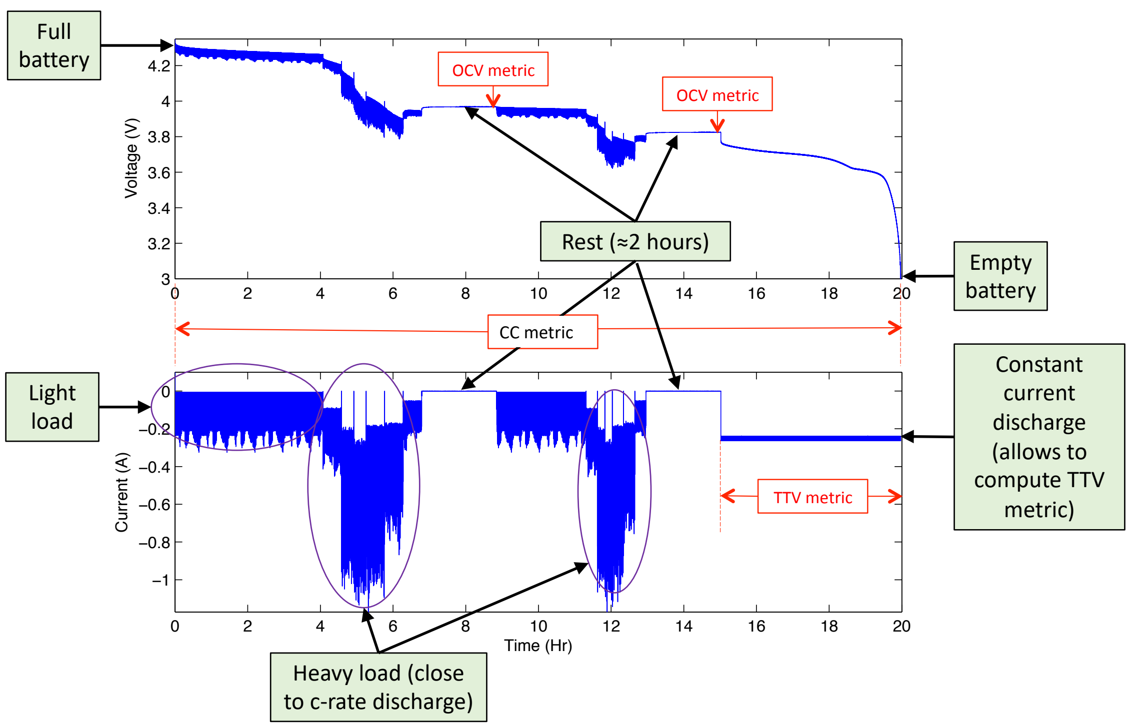


Figure 11. BFG evaluation profile. The battery fuel gauge evaluation profile is a specially designed load current profile that allows to implement all three BFG evaluation metrics: *CC-metric*, *OCV-metric* and the *TTV-metric*. The profile starts with a full battery and ends when the battery becomes empty; this allows to compute the battery capacity accurately. Intermittent rest periods within the profile allows to compute the OCV metric and the constant current load profile allows to compute the TTV metric.

4. Conclusions

In this paper, we detailed the challenges involved in developing a novel battery operating system that is suitable in future applications and described the details of some solutions that we developed. Particularly, details of the following elements of a robust battery management system are described:

- *Open circuit voltage modelling:* It is demonstrated how careful modelling and optimization can result in parameters that are applicable to a wide range of temperatures. The need for careful modelling is demonstrated using *scaling*, a strategy, when ignored, results in up to 90% higher SOC errors.
- *Battery impedance estimation:* Battery impedance changes with temperature and other battery states; real-time impedance estimation is required for effective battery management. In this paper, we summarize a real-time approach to battery impedance estimation.
- *Battery capacity estimation:* Accurate knowledge battery capacity is crucial for all aspects of a battery management system.
- *Adaptive strategies for universal battery management:* Newer versions of batteries come in slightly different chemical compositions. How to develop a battery management system that can stay relevant with ever changing battery types? This paper offers a glimpse into futuristic solutions based on probabilistic data and information fusion.
- *Optimal charging strategies:* Battery chargers have two competing objectives; one seeks to charge fast and the other attempts to minimize capacity fade and temperature rise due to charging. This paper offers high-level summary of 'level-1' and 'level-2' optimal charging algorithms designed to satisfy the above goals.
- *Strategies to evaluate battery management systems:* We describe the challenges involved in evaluating a battery management system and present several guidelines.

Further, we provided insights into the remaining challenges that needs to be addressed in the domain of battery management systems research.

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Abbreviations

The following abbreviations are used in this manuscript:

BFG	Battery fuel gauge
BMS	Battery management system
CBC	Cell-balancing circuitry
CF	Capacity fade
ECG	Electrocardiography
ECM	Equivalent circuit model
EL	Energy loss

EV	Electric vehicle
HIL	Hardware-in-the-loop
Li-ion	Lithium ion
OCA	Optimal charging algorithm
OCV	Open circuit voltage
PF	Power fade
SOC	State of charge
SOH	State of health
TTC	Time to charge
TTV	Time to voltage

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