

Battery Energy Storage System (BESS) and Battery Management System (BMS) for Grid-Scale Applications

This paper provides a comprehensive review of battery management systems for grid-scale energy storage applications.

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ABSTRACT | The current electric grid is an inefficient system that wastes significant amounts of the electricity it produces because there is a disconnect between the amount of energy consumers require and the amount of energy produced from generation sources. Power plants typically produce more power than necessary to ensure adequate power quality. By taking advantage of energy storage within the grid, many of these inefficiencies can be removed. When using battery energy storage systems (BESS) for grid storage, advanced modeling is required to accurately monitor and control the storage system. A battery management system (BMS) controls how the storage system will be used and a BMS that utilizes advanced physics-based models will offer for much more robust operation of the storage system. The paper outlines the

current state of the art for modeling in BMS and the advanced models required to fully utilize BMS for both lithium-ion batteries and vanadium redox-flow batteries. In addition, system architecture and how it can be useful in monitoring and control is discussed. A pathway for advancing BMS to better utilize BESS for grid-scale applications is outlined.

KEYWORDS | Batteries; battery energy storage systems; battery management systems; control systems; electric grid; energy storage; grid control; grid optimization; grid storage; lithium ion; redox-flow systems; system optimization

I. INTRODUCTION

The electric grid must have the generation capacity to meet the demands of electricity consumers. However, electricity demand varies greatly both daily and seasonally, and operating generators to match loads that have broad peak-to-base spreads is a great challenge [1]. Electricity providers must have enough installed power capacity to match peak demand and must continuously operate enough capacity to meet real-time demand. Meeting these requirements typically means that capacity is operated at 20% over the estimated demand and only an average of 55% of the installed generation capacity is used over the course of one year [2].

Many of these inefficiencies are caused by the perishable nature of energy within the electric grid. Due to the lack of energy storage devices within the grid system, energy must be immediately delivered to and used by the

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consumer [3]. The power capacity for energy storage within the grid currently sits at 125 GW (the majority of which is in the form of pumped hydro plants), which is about 3% of global power capacity [4]. Additional energy storage within the grid would allow many more plants to run closer to full capacity and reduce energy losses during electricity transmission. Energy storage is a key element in diversifying energy sources and adding more renewable energy sources into the energy market.

By utilizing energy storage, generation sources need not be ramped up or down, but can instead be run at optimal efficiency while energy storage accounts for variations in the demand. The applications that could benefit from energy storage within the electric grid have a wide range of requirements. In some isolated regions, seasonal energy storage is required that needs megawatt-hour of capacity stored for months at a time [5]. On the other end, stabilization of the transmission and distribution networks may store energy for only several minutes before releasing it and can have energy capacities on the watt-hour scale [6]. To work across all these time and energy scales, many different forms of energy storage have been developed. Due to the stressful demands on these energy storage systems, an effective management system is required to maintain safe operation and optimal performance.

While many technologies have been developed for large-scale energy storage purposes such as pumped hydro and compressed air energy storage facilities as well as flywheels, capacitors, and superconducting magnetic storage, many are limited in their site dependence, capacity, or response capabilities. Electrochemical energy storage devices offer the flexibility in capacity, siting, and rapid response required to meet application demands over a much wider range of functions than many other types of storage. There is a long history of integrating batteries into grid applications, and while battery energy storage systems (BESSs) currently account for only a small portion of energy storage within the grid, they have seen great growth recently due to their versatility, high energy density, and efficiency [7]. More grid applications have become suitable for BESSs as battery costs have decreased while performance and life have continued to increase [8].

BESSs are able to react to grid demands nearly instantaneously, but also have the capacity to function over longer durations and have a wide range of storage and power capacities. Due to its technological maturity, the lead–acid chemistry has seen the most widespread use among large-scale BESSs [9]. However, significant advancement in newer battery chemistries has allowed for a wide range of battery options for new storage applications and has increased the robustness and functionality of batteries within the electric grid. In the last five years, pilot scale BESS projects have been undertaken for many new chemistries such as: sodium–sulfur; lithium (Li) ion (including Li–titanate and Li–iron–phosphate); nickel–cadmium; sodium–nickel chloride; sodium ion; Li–sulfur;

magnesium ion; metal–air; and several chemistries of flow batteries, which store energy in their electrolyte and pump the electrolyte through the cell to charge or discharge [10]. This work focuses on Li-ion and redox-flow batteries (RFBs) as representative chemistries and the remainder of the paper will discuss the architecture and modeling requirements for BESSs utilizing these chemistries. Regardless of the chemistry, each BESS needs to be controlled properly to ensure safe and efficient functioning while meeting the requirements of different grid applications.

II. BATTERY MANAGEMENT SYSTEMS

BESSs require a battery management system (BMS) to monitor and maintain safe, optimal operation of each battery pack and a system supervisory control (SSC) to monitor the full system. Batteries are dynamic in nature, constantly operating outside the equilibrium state during cycling. In addition, the situation worsens for the case of intercalation-based storage systems (e.g., Li chemistry) which operate as a closed system with very few measurable state variables, making it difficult to properly monitor the states of the battery and maintain safe operation. Furthermore, even under normal operation the battery packs of a BESS will degrade during cycling. This degradation can be accelerated by extreme charging patterns, increased temperature (both ambient and operating), overcharging, or undercharging. A basic BMS controls battery packs only to meet the power demand. However, smarter model-based BMSs can reduce the causes of degradation and improve the performance of the system. Predictive and adaptive BMSs based on models are especially important for large battery packs for applications such as electric vehicles and grid integration [11]–[13]. While there are many possible solutions to the intricate problem of BESS control, Fig. 1 describes a general BESS–BMS structure used for implementation.

The BESS in Fig. 1 can be used for many different objectives, such as:

- matching peak power demand;
- load following to increase generation utilization;
- improving grid stability, power quality, and balancing (e.g., frequency control);
- reducing source intermittency.

The BMS and SSC portion of Fig. 1 can help the BESS provide these services with optimal performance by:

- minimizing temperature gradients across the system;
- protecting the cells from internal degradation and capacity fade;
- providing optimal charging patterns;
- balancing cells throughout the stack.

While these systems work in tandem, unfortunately the internal states of the cells are not accessible to the BMS and SSC. The only battery states that can be measured are:

- voltage;
- current;

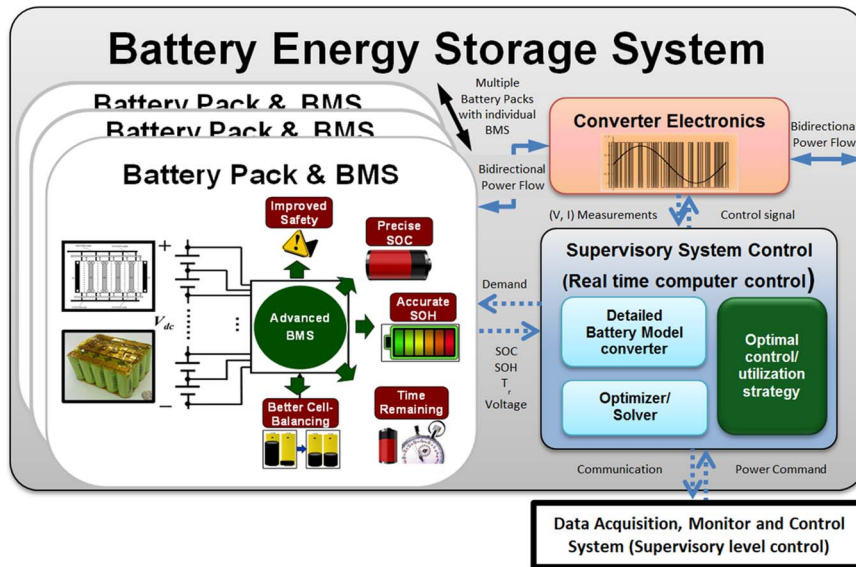


Fig. 1. Schematic for the implementation of a battery pack and BMS into a BESS.

- temperature;
- electrolyte ion concentrations (in flow batteries only).

And, the BMS and SSC can only control the BESS by manipulating:

- current;
- electrolyte flow (in flow batteries only);
- ambient temperature (when cooling or heating is available).

However, by utilizing physics-based models, the BMS can accurately estimate many internal variables that allow it to gain a thorough understanding of battery state of charge (SOC) and state of health (SOH). More details about these types of models will be outlined in Section IV.

A BESS will incorporate a BMS that is responsible for managing the operations of the battery. The BMS' relationship within the BESS system can be seen in Fig. 1. The BMS is responsible for: safe operations (thermal management, operating between safe current and voltage limits, shutdown on detection of fault, etc.), state estimation (SOC determination), parameter estimation (SOH determination), time remaining (tr) (depending on the applied load profile), and other miscellaneous functions. In addition, for Li-ion and other closed-cell systems, the BMS must also perform intercell charge balancing. For an RFB, the BMS must control the electrolyte flow rate in accordance with the power demand.

In large systems, many battery packs with individual BMS will be combined to create a large capacity BESS. The SSC of the BESS is the interface between the grid and the BMS. The information about battery packs is conveyed from the BMS to the SSC. When the grid demands power to be supplied from the batteries, the SSC

chooses the optimal protocol for releasing charge while accounting for both the current state of the batteries and the grid's demand request. This SSC protocol will call power from individual packs in order to meet the final power demand.

During certain periods, the required power profiles of batteries will be more flexible and the BESS can have more control over the charging pattern. For example, in a peak-shaving application, the discharge power is heavily constrained but the charging power can be chosen based on the needs of the BESS. Here the individual BMS can run optimization routines to come up with the best charging profiles. These charging profiles can be communicated to the SSC which can control the power input from the grid. When determining the performance of a storage system, in addition to the BMS and the SSC, power electronics, which connect these systems to each other, and the grid must be taken into account. These power electronics allow for the bidirectional flow of power to and from the grid [14]. The way these individual pieces are structured creating a hierarchical system architecture will influence the efficiency and operation of the entire system and can aid in control.

A. BMS Architecture

Detailed modeling is extremely useful for predicting accurate SOC and SOH, but to implement the advanced BMSs into a grid-scale application requires an advanced architecture and mix of power electronics to connect the battery and the BMS within the larger grid. In addition, the algorithms implemented in the BMS have to be efficient to handle the model's nonlinearity, constraints, and objectives in real time. BESSs using a tiered architecture comprising

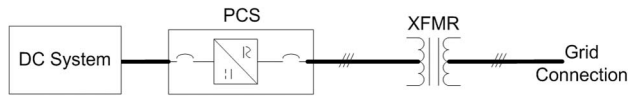


Fig. 2. Simplified illustration of GSS architecture, with a battery-based dc system, a power conversion system (PCS), and a grid connection.

monitoring and control at several interconnected levels can be beneficial for implementing BMSs [15]. This architecture allows for targeted monitoring as well as system-level control through the use of the SSC.

A typical grid storage solution (GSS) comprises a direct current (dc) system, a power conversion system (PCS), a BMS, an SSC, and a grid connection. In the dc system, individual cells are assembled into modules which in turn are assembled into systems of sufficient capacity to support the application requirements of the GSS. Cells are connected in electrical series and parallel configurations to power a high voltage bus, which interfaces with the PCS. The PCS is a four-quadrant direct current/alternating current (dc/ac) converter connecting the dc system to the grid via a transformer. This architecture is shown in Fig. 2.

Physically, the system may consist of several independent dc subsystem, PCS, and transformer combinations, referred to as power blocks, as shown in Fig. 3. The power blocks may be effectively identical or they may include hybrid battery units of different sizes or types. The operation of individual power blocks is coordinated by a BMS and the operation of all the power blocks is coordinated by the SSC, which manages the total system power and the allotment of that power among the power blocks.

In its role as controller of the whole GSS, the BMS must monitor the dc system, receive signals from external controllers and meters, while the SSC calculates the required power responses, and sends power commands to each power block. This control cycle is conceptually illustrated in Fig. 4. The monitoring action of the BMS is performed by a hierarchical hardware structure [15]. In this architecture, data processors are situated at multiple levels of the dc system. At the lowest level, a processor is assigned to monitor and balance individual cells in a single battery module. A single GSS facility may include hundreds of thousands of individual cells and hundreds of intermediate modules. Another processor is assigned to monitor and manage the data and activities of the lower level processors, and so on. The top level processor of the BMS communicates with the SSC which handles the demands from both the intermediate monitoring processors and the external equipment, delegating battery resources to perform the grid functions. By distributing intelligence to lower level monitoring systems, only essential information is regularly passed up to the main site controller, reducing information traffic and comprising a scalable system architecture. In addition to having

large standalone BESSs, it is also possible to distribute energy storage in a nodal system with multiple devices storing energy at the consumer level with supervisory control still acting across the system [16].

An ideal BMS must have a precise knowledge of battery states including SOC and SOH. It also requires exact knowledge of the action required by the grid. Such an ideal BMS would then process both the grid requirements relayed through the SSC and the battery capability to generate the best commands for the battery. The GSS action then affects the new sensor information which helps create the next estimate of battery states.

B. Monitoring the Stack

Regardless of the exterior architecture, during operation, the BMS reads data such as current, voltage, and temperature (and concentration in the case of a flow cell) from the battery as well as any applicable monitoring data or commands from the SSC. The BMS then estimates battery SOC and SOH, records system history, and makes decisions about system commands which can affect the performance and service life of the battery. A BMS can improve the battery performance and prolong the battery life only if it has access to reliable information about battery states, especially SOC and SOH. If this information is not available, the BMS must have internal algorithms that accurately predict these states. These variables represent how much charge is left in a battery over a single cycle (SOC) and how much battery capacity remains for the present cycle compared to the original battery capacity (SOH).

Unfortunately, SOC cannot be reliably estimated by tracking the flow of charge into and out of the battery (Coulomb counting) because of the inaccuracies of current meters; slow, variable losses inside the battery; and side reactions occurring in the system. Estimation of SOC based on current tracking must account for all the physical realities of the battery and measurement system including natural cell self-discharge and series string charge balancing among others.

Many BMSs use other ways to determine SOC in addition to tracking the charge transferred in and out of their terminals. Most commonly, open-circuit terminal voltage is used as an indicator of SOC. As the battery's SOC decreases, the terminal voltage generally decreases, indicating how much charge remains. This method is more accurate for some chemistries than for others, but in all cases, complex nonlinear models need to be created that relate the terminal voltage and the SOC [17]. This approach is risky for any chemistry as the battery degrades and loses capacity leading to potential overcharging or overdischarging.

Some chemistries such as the Nanophosphate battery by A123 Energy Solutions (Westborough, MA, USA) are unusual in that they have a very flat voltage characteristic across their SOC throughout cycling [18]–[20]. An example open-circuit voltage curve versus cell SOC for an A123 Nanophosphate battery is shown in Fig. 5. This

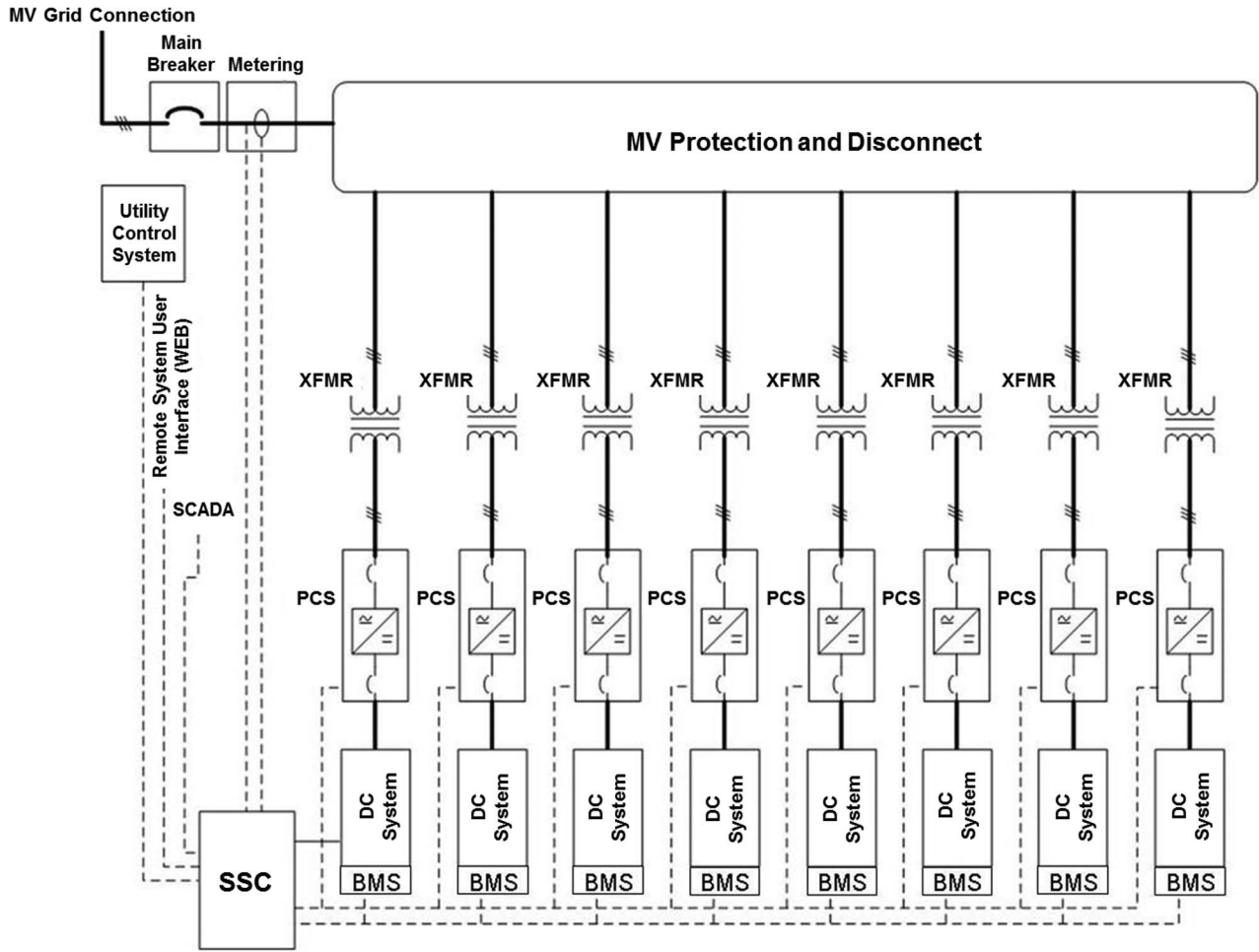


Fig. 3. Simplified illustration of GSS architecture, including several independent modules which all operate under BMS and SSC control.

flat voltage curve is a desirable trait as it enables nearly constant power delivery throughout an entire discharge at any SOC. However, it also makes estimation of SOC for these chemistries much more difficult. This difficulty makes advanced modeling especially valuable for state estimation in these high-performance cells.

Another characteristic which is difficult to estimate in any Li-ion cell is its SOH. The most common method to track SOH is to measure a cell's internal equivalent dc

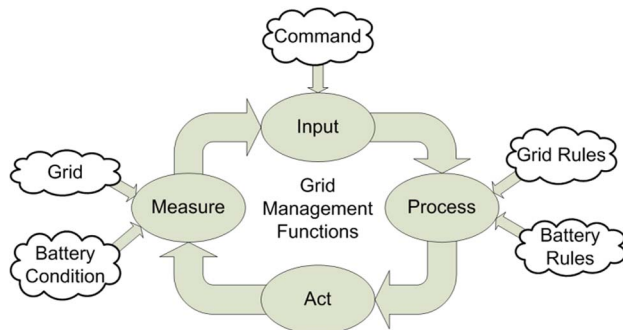


Fig. 4. Conceptual illustration of BMS control cycle.

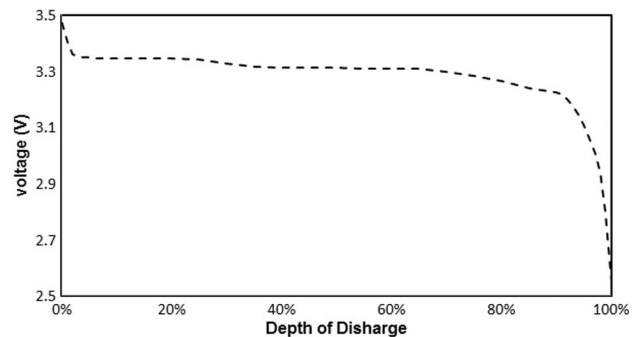


Fig. 5. Open-circuit terminal voltage for an A123 Nanophosphate Li-ion cell across SOC during a discharge cycle at 23 °C. The cell was allowed to relax for three hours between measurements. The very flat voltage characteristic across much of the discharge range makes voltage-based estimation of SOC difficult.

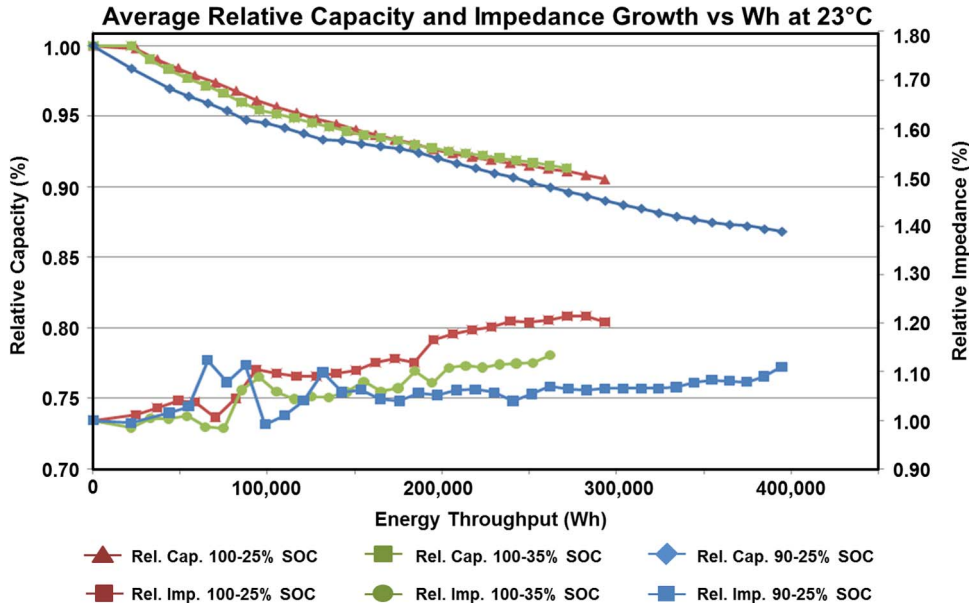


Fig. 6. Equivalent dc resistance of A123 Nanophosphate Li-ion cells exposed to continuous deep discharge over various SOC ranges at a 1 C rate (full cell energy capacity in one hour). The energy throughput is the cumulative discharge plus charge energy over the indicated cycles. Nominal cell capacity is 64 Wh, meaning that 300 kWh is approximately 2400 full depth of discharge (100%–0%) cycles. Note that changes in resistance are a poor indicator of cell remaining life. Rel. Cap. = Relative Capacity; Rel. Imp. = Relative Impedance; 100%–25% SOC represents 75% depth of discharge.

resistance [17], [21], [22]. In general, this resistance rises with capacity loss. However, some battery chemistries do not exhibit trends in resistance that can reliably indicate SOH. For example, the capacity loss versus energy throughput of A123's Nanophosphate Li-ion cells is not well correlated with the rise of cell resistance, as shown in Fig. 6. Alternatively, the BMS can determine the battery SOH by doing a complete charge and discharge cycle under controlled conditions and measuring the effective energy capacity. This method will provide highly accurate estimation of the SOH for any battery type. However, removing a system from service to test for capacity reduces its overall availability to perform its primary function on the grid. When full charges and discharges are not allowed in the normal course of operation, the need for detailed and accurate models becomes more important for providing an estimate of the existing capacity.

Improved estimation of battery states based on advanced cell modeling can lead to improved control decisions which significantly impact runtime performance, overall capacity, and service lifetime. Accurate SOC estimation allows the cells to be maintained at their preferred operating point without risk of drifting too close to an empty or full state during operation. Reliable SOH estimation helps identify particularly harmful operational constraints imposed on the cells and can serve to support preventative maintenance routines by providing advanced notice when battery elements may be nearing the end of their usable life [23].

III. BATTERIES FOR GRID STORAGE

While implementing energy storage within the grid has many benefits, the cost of the storage unit itself must be considered. The inclusion of a BESS will incur the additional cost associated with storage. The price of each kilowatt-hour of energy that passes through storage before being sent to the grid will increase. For example, assuming a generation source that wants to utilize energy storage can generate energy for 10 cent/kWh and chooses a Li-ion battery that costs \$400 per kilowatt-hour to couple to the system. Even if the battery has a life of 4000 cycles (roughly an 11 year operating life at daily cycling), over the life of the battery each storage cycle will add an additional 10 cents to the price of energy, effectively making any energy that goes through storage before being delivered cost twice as much as the original power. To get a true economic impact we would also need to assess the effective cost associated with not storing any energy (essentially the dollar gained from improved efficiency).

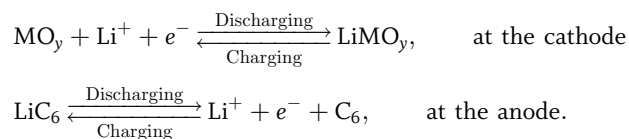
In the past, the high cost of energy storage has made it more economical to build additional generation rather than opt for energy storage, but with energy storage prices continuing to fall while cycle life has increased (and environmental concerns becoming more prevalent), energy storage has become more viable. New technologies have also helped batteries become more feasible. RFBs differ from conventional chemistries in their decoupled power and energy systems, which allow for large energy capacity

and reduced cost per kilowatt-hour compared to conventional cells. Moreover, improvements in fundamental understanding and quantitative predictive modeling approaches for improved cycle life will continue to make redox-flow BESSs more viable. Cost concerns drive the need for advanced modeling that can enhance battery lifetimes and, therefore, decrease the cost per storage cycle.

As previously noted, many different battery chemistries have been employed within BESSs. In general, most intercalation-based rechargeable battery systems including the Li-ion can be simulated using the same types of electrochemical engineering models with proper system parameters to account for the different chemistries and modified solid phase diffusion. Most of the underlying physics of the electrochemical systems remain the same, allowing for cross-development of models among chemistries. However, one battery system that has gained impetus within the storage community recently has been the RFB that uses exterior electrolyte pumped through the typical cathode–separator–anode system. The redox-flow system has significantly different dynamics than the conventional battery and requires a separate modeling approach for obtaining accurate SOC and SOH measurements. So, when designing BMSs for these systems, different models must be implemented according to the system. An example of each type of electrochemical system (conventional and redox flow) are outlined below along with the current methods for BMSs and models currently being applied to BMSs. Although this paper focuses on Li-ion and RFBs, other chemistries including zinc–bromine might be competitive for some applications [24].

A. Li-Ion Chemistry and Modeling

Li-ion batteries transport charge with Li-ions and employ Li storage compounds as the anode and cathode materials. In most commercial Li-ion batteries, the anode is a lithiated graphite or Li–titanate while the cathode can be either a Li metal oxide (MO) or a Li metal phosphate. These electrochemically active materials are typically mixed with a binder to form slurries which coat a metal foil that serves as a current collector. The metals chosen for the current collector foils are typically copper for the anode and aluminum for the cathode. The anode and cathode electrodes are assembled on either side of a microporous polymer separator in the presence of an electrolyte to form a cell. During charging, Li-ions are intercalated into the graphite layers and released from the cathode. The reaction is reversed during discharge. The overall electrochemical reaction for a cell with a graphite anode can be written as



The open-circuit voltage depends on the anode and cathode materials involved, and typically ranges for the cell from 3.2 to 4.3 V for a graphite-based anode [25]–[28].

A number of different Li-ion chemistries are available and many have been commercialized since the early 1990s. These include LiCoO (LCO), LiMnO (LMO), LiFePO (LFP), LiNiMnCoO (NMC), and LiNiCoAlO (NCA). The selection of active materials determines cell capacity, voltage limits, voltage profile, and efficiency, even though the intercalation and deintercalation mechanisms may be similar.

During normal operation, side reactions in Li-ion batteries and electrical isolation of materials due to intercalation/deintercalation-induced stresses reduce the available capacity of the cell. This capacity reduction can be exacerbated when operating under extreme conditions, so one function of the BMS is to minimize the effect of undesired side reactions. Reducing side reactions requires knowledge of the internal states of the battery to predict and prevent conditions leading to capacity fade. Unfortunately, understanding the internal states is difficult due to the limited number of variables in the battery that can be measured online. Typically, only current, voltage, and possibly surface temperatures can be directly observed. From these limited measurements, the BMS must determine internal states of the battery. The BMS will control the battery to meet the operational demands, maintain safety, ensure maximum life, and balance the individual cells in the stack.

In order to predict and control the behavior of Li-ion batteries in any application, a proper model must be chosen based on the specific operational requirements. Mathematical models for Li-ion batteries vary widely in terms of complexity, computational requirements, and reliability of their predictions. An ideal model would be perfectly predictive of battery behavior for all operating conditions and for the entire life of the battery and would provide confident estimates of SOC and SOH. Varying temperature and charging or discharging rates can have a significant impact on output voltage and performance. Ideally, a model would provide good prediction while maintaining minimal computational cost so that it can be solved very quickly with limited computing resources. Unfortunately, there is often a tradeoff between accuracy and computational cost that must be considered during model development.

Empirical models are minimally detailed and provide the highest computational efficiency for Li-ion battery models. Empirical models use polynomial, exponential, power law, logarithmic, and trigonometric function fits with past experimental data to predict the future behavior of Li-ion batteries. However, these models use parameters that lack physical meaning. While these models are very easy to develop from a mathematical standpoint, they are not accurate outside the limited set of conditions from which they were developed. Any change to system parameters, for example, as a result of altered operating

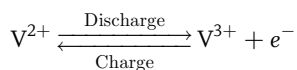
conditions, will decrease the model accuracy. If the response of the battery to aging or temperature changes is not included in the model, these effects can be substantial and unpredictable.

Slightly more accurate than empirical models are equivalent-circuit models, which try to describe the underlying system using a representation that usually employs a combination of capacitors, resistors, voltage sources, and lookup tables [29]. Capacity fade is often represented by a capacitor with a linearly decreasing capacity while temperature dependence can be modeled by a resistor–capacitor combination [30]. Research is being done to continuously update the circuit-based parameters using current and voltage data to improve accuracy [31]. As with empirical models, equivalent circuit models do not account for the physical basis of the system, rather using circuit elements that achieve mathematical similarity to the physical system.

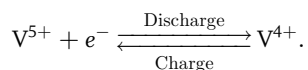
Most current BMS systems utilize either empirical or equivalent circuit-based models because they offer fast simulation of the system and are easy to understand and implement [32]–[37]. In addition, these models can be run on very basic (and cheap) microcontrollers and require very few computational resources. However, their lack of accuracy can lead to inefficient battery operation.

B. Redox-Flow Chemistry and Modeling

The RFB is a technology targeting large-scale energy storage, primarily due to its ambient operating temperature and flexible ratio between available energy and power capability. The vanadium-redox battery was first developed in the late 1980s and, unlike conventional batteries, stores its electrolyte externally in tanks which store the energy through ion concentration. The electrolyte is pumped through the active cell to charge and discharge the battery. The vanadium RFB uses different valence states of vanadium sulfate dissolved in sulfuric acid (H_2SO_4) at the anode and cathode blocks [25], [38]. The half cell reaction at the anode is



and at the cathode, it is



The open-circuit voltage is: $E_{\text{ocv}} = 1.2 \text{ V}$ [39]. The separator for the vanadium RFB is an ion-selective membrane which impedes the cross mixing of the reactants but

enables the migration of protons to maintain system charge neutrality. The vanadium RFB has very low rate of internal discharge and parasitic losses, and the cycle life can be more than 10 000 cycles [38].

Energy storage capability of the system is scaled with increasing electrolyte tank size. However, volumetric energy density of this type of flow battery is relatively low due to limited solubility of vanadium ions. Hence, it requires a sizeable footprint. However, many grid-connected systems can tolerate a large physical battery size, and it is expected that future research in materials and chemistry will improve the energy density of these systems. They are well suited to more energy-intensive applications such as energy shifting and longer acting reserve generation [8].

While RFB research has been active for several decades, the route to commercialization of this technology has been slow with only two chemistries (vanadium and polysulfide–bromide) available in a large-scale commercial format [40]. As such, BMS technology for flow batteries has not been developed to allow for advanced modeling.

As with Li-ion batteries, simplified non-physics-based models, such as equivalent-circuit models or zero-dimensional continuous stirred tank reactor (CSTR) approximation models, have been developed for RFBs. Equivalent-circuit models have been employed in BMSs for RFBs, but do a poor job of representing the actual system [41]. Empirical models for RFBs have been reported in literature. Li and Hikihara developed a transient model for the all-vanadium RFB where the dynamics were governed by chemical reactions, fluid flow, and an electrical circuit representing the system [42]. Li *et al.* reported development of an RFB model based on experimental results [43]. The circuit representation of the system fails to account for many of the internal states of the battery and does not accurately reflect many mechanisms occurring within the battery system, including: parasitic pumping cost for circulating electrolyte; uneven utilization of the membrane and felt electrode; cross contamination; corrosion of the felt electrode; side reactions (including hydrogen and oxygen evolution); and temperature gradients in the stack. These mechanisms can cause a range of problems during operation including capacity fade, cell unbalancing, and safety problems such as thermal runaway. These issues show the limitations of the equivalent-circuit-based model and the need for more detailed physics-based redox-flow models.

While additional model complexity is valuable for its prediction accuracy, it also leads to increased computation time (shown in Fig. 7 for Li-ion battery models and Fig. 8 for redox-flow models). An efficient utilization of these models is required, allowing the models to be solved in real time and, therefore, be useful to an operating BMS. Many detailed models therefore require the use of model reduction, simplification, or reformulation techniques that

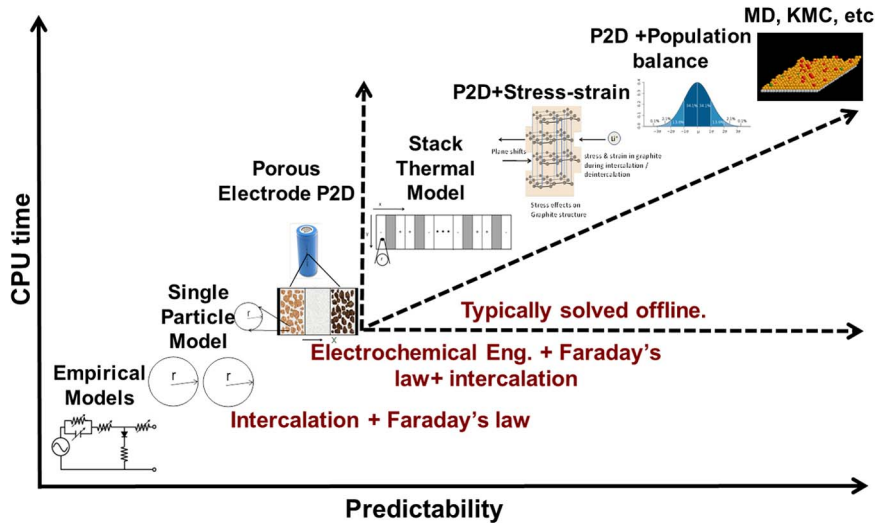


Fig. 7. Model accuracy versus central processing unit (CPU) time for various methods for Li-ion battery simulation. The simulation types are discussed in Section IV-A.

retain the physics of the system while reducing the computational cost.

IV. ADVANCED MODEL-BASED BMSs

Managing batteries in real time is paramount for ensuring safety, cell life, and optimal performance. The functionality required (e.g., SOC and SOH estimation) will determine the amount of physics needed in the model. The details of the physics involved, scale involved, time

constants, etc., will determine the numerical challenges and opportunities for faster numerical algorithms and control schemes for improved efficiency. Because grid-connected battery systems are often large and costly, even a small improvement in utilization can result in great economic savings. As a result, the motivation for finding the best possible model, algorithm, and control scheme cannot be overstated. This means that while steady state is normally assumed for flow development, transient flow dynamics must be revisited if a system is to support the

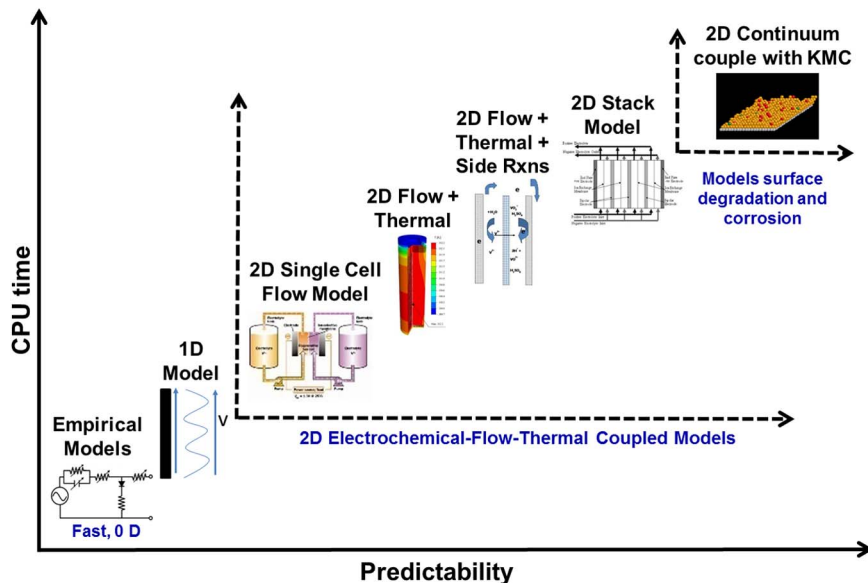


Fig. 8. Model accuracy versus CPU time for various methods for RFB simulation. These simulation types are discussed in Section IV-B.

dynamic power demands of the grid. Advanced models that can utilize efficient simulation techniques and allow the system to react in real time are outlined below for Li-ion batteries and RFBs.

A. Li-Ion Detailed Modeling

The electrochemical engineering field has long employed continuum models that incorporate chemical/electrochemical kinetics and transport phenomena to generate predictions more accurate and meaningful than empirical models [28], [31].

The single-particle model (SPM) is a simple model that represents each electrode as a single particle. The effects of transport phenomena inside the solid phase of a Li-ion cell are considered within the particle, but the concentration and potential effects in the solution phase between the particles are neglected [44]–[46]. This model can be quickly simulated to estimate the SOC and remaining cycle behavior, but is not valid for high rates, thick electrodes, or other conditions where the electrolyte effects and variations across the electrodes are significant [44]. The SPM has also been used to predict capacity fade due to growth of the solid electrolyte interface (SEI) layer [47].

The pseudo-2-D (P2-D) model is a more detailed physics-based model that considers several physically meaningful internal variables during simulation, including the potentials within the solid phase and electrolyte along with Li concentration in both solid and liquid phases [31]. Additionally, nonlinear Butler–Volmer kinetics are used to model the Li reaction. Furthermore, the P2-D model provides a good starting point for adding additional physical phenomena as understanding improves, including thermal and degradation characteristics [45], [48]–[59]. The inclusion of many internal variables allows for improved predictive capability, which has contributed to its popularity among battery researchers, although at a greater computational cost than simpler models.

More detailed models have been developed to accurately describe all of the important phenomena that occur during the operation of Li-ion batteries for future high power/energy applications such as in electric/hybrid vehicles. Thermal effects are important to predict safety and life and thermal properties affect all internal characteristics of the battery [60], [61]. The internal temperature of the cell depends on the surroundings as well as on any heat generation during battery operation and can have a great impact on performance. Higher temperatures allow Li to diffuse more easily, which reduces the internal resistance, but also speeds up reactions and can lead to dangerous thermal runaway, especially for Li oxide cells. High-temperature operation can also lead to increased capacity fade by speeding up side reactions.

Intercalation of Li generally causes an expansion of the active material, such as graphite or manganese oxide, while Li extraction typically leads to contraction (exceptions include Li_xCoO_2) [62], [63]. As Li diffuses within the

particle, the expansion and contraction of the material will not happen uniformly across the particle, causing stress to be induced in the particle which may lead to fracturing and loss of active material [64], [65]. Additionally, during battery cycling, some particles are lost or agglomerate to form larger sized particles, which results in performance degradation. Various models have been developed to examine the volume change and stress induced by Li-ion intercalation for single particles [66]–[68]. A 2-D microstructure model was developed to extend the stress–strain analysis from single particles and was eventually incorporated into the full P2-D model [63], [69].

In order to provide sufficient power for grid-scale applications, battery stacks are employed which have individual cells stacked in parallel or series in a single unit. This configuration allows smaller individual cells to be used, which reduces the internal resistances and ensures that Li-ions do not need to travel large distances, and allows for high total voltages to be achieved. Although the individual cells in a stack are coupled, cell mismatch may occur where some cells are significantly more charged or discharged than others. This can lead to potentially dangerous conditions in which an individual cell or a group of cells is fully charged while the pack as a whole is not. Thus, a poorly designed BMS may continue charging of the stack and overcharging of the individual cells, leading to permanent damage and possibly thermal runaway. A well-designed BMS with tiered architecture will be able to predict such mismatches and take steps to correct it.

The coupled nature of cells in a stack increases the demand of a comprehensive model. The significant increase in computational requirements to simulate a stack model has slowed its development and most examples of stack modeling reported in literature perform some approximation or decoupling to facilitate efficient simulation [60], [70], [71]. Researchers have also published simplified coupled thermal electrochemical models applied to a single particle for stacks in parallel and series configurations [72]. Fully coupled battery stack models for a limited number of cells have been analyzed by using reformulation techniques to improve the efficiency of simulation [73].

B. Redox-Flow Detailed Modeling

The RFB's novel electrochemical storage approach utilizing decoupled electrolyte requires a much different approach for modeling than the more conventional Li-ion battery. The major difference is the inclusion of electrolyte flow within the system. While still maturing as a technology, efforts for accurately simulating the redox-flow system have gained impetus in recent years with renewed interest in large-scale energy storage. The advanced models outlined below enable higher fidelity simulation to be utilized by BMSs [74]. The many available chemistries for redox-flow systems have led to researchers focusing their models around different chemistries. However, the models are applicable across different

chemistries. While models have studied iron–chromium, bromide–polysulfide, and zinc–bromide chemistries, the majority of the modeling efforts have focused around the all-vanadium redox-flow system [75]–[78].

Analytical-based models can be used to develop a control-oriented dynamic unit cell model that employs mass and charge balances [79]. Assumptions, such as uniform current during charge/discharge and constant velocity flow, allow for analytical solutions to be obtained for specie concentrations. These types of models provide accuracy similar to empirical models and do not offer much help in designing experiments for new materials and changing chemistries.

Isothermal models and 1-D flow models can add detail to simulation of the system [80]–[82]. However, the 2-D, electrochemical flow (2-DE) model provides an accuracy useful for many different BMS tasks [79], [83]–[86]. The 2-DE transient model accounts for charge, mass, and momentum conservation throughout the system and applies Darcy’s Law for describing flow through the porous media [87]. Butler–Volmer kinetics can again be used for the flux at the electrodes, accounting for the charge transfer. The 2-DE model accounts for many more internal states than the previous analytical models. The 2-D nature of the flow model is required to properly understand the changing electrolyte concentration within the electrode and separator region.

Some drawbacks of the 2-DE model include its lack of thermal characteristics within the cell, specifically for the side reaction of evolving hydrogen. High-temperature gradients can dramatically affect the reaction rates and material conductivities, especially for the membranes. Thermal effects can be incorporated into the model by adding equations for conductive and convective heat transport [84]. These thermal effects can influence performance and safety by altering the system over potentials or creating local hotspots.

While the 2-DE model represents the flow system well, additional side reactions must be considered in order to simulate the battery with high fidelity. The evolution of oxygen at the cathode and hydrogen at the anode are the primary side reactions of the system. Inclusion of these side reactions enables the study of gas bubble formations, which can alter electrolyte flow patterns and reduce the overall performance because the reaction consumes a portion of the applied current [77], [78], [86]. Additionally, species crossover at the membranes can cause capacity fade and decrease performance, and these effects can be incorporated in the model [88].

Going beyond 2-D flows, 3-D coupled species/charge/fluid transport models studying pore scale felt electrodes can be employed to obtain a better understanding of the flow on the pore level [89], [90]. The Lattice Boltzmann method can be utilized for the flow across the pore space. For greater understanding of the surface phenomena, including electrode degradation, kinetic Monte Carlo

methods can be employed. These models can be coupled to the continuum scale models to establish very accurate and powerful multiscale models for RFBs. But simulation of these models will be computationally expensive and may not be feasible for real-time control in grid-scale energy storage. However, mathematical reformulation methods can be applied to these systems to reduce the computational cost and make them more feasible for real-time BMS simulation as shown in Section IV-C for Li-ion P2-D model.

C. Reformulating the Battery Models

The wide range of transport and kinetic phenomena that occur in Li-ion batteries can be difficult to model and often necessitate the development of simulation strategies to solve the P2-D model in a reasonable time with limited computational resources. Several reformulation techniques have been used to reduce the computational cost of Li-ion battery simulation, as the direct application of finite difference is computationally expensive. In order to reduce the computational cost of calculating the concentration profiles in the solid particles, the parabolic profile approximation has been developed for low rates [91], while the mixed finite difference approach is valid for higher rates [92]. Order reduction approaches such as proper orthogonal decomposition (POD) and quasi-linearization of the model have been used to reduce the number of equations needed to be solved, though at the cost of reduced accuracy [93], [94]. Orthogonal collocation has been used to compare individual electrode performance to experimental data or to simulate full Li-ion cells with thermal effects [73], [95]. Attempts to decouple the equations so that all dependent variables are not solved simultaneously can be found in the literature, especially for simulation of thermal models in multicell stacks [60], [96], [97]. The method of solving the model can also have significant impact on model performance and work on the subject can also be found in the literature, for example, using Newton–Krylov methods [98] or multigrid strategies. Using efficient simulation schemes combined with model reformulation techniques allows physics-based models to be used for Li-ion batteries in optimization and control and gives better insight on the internal state variables than circuit-based models.

As for Li-ion battery models, the computational burden to solve the detailed 2-D RFB models can be huge. The detailed models required to accurately predict the SOC, capacity fade (cross contamination of species), side reactions (evolution of hydrogen and oxygen for some specific chemistry), electrode utilization efficiency, and temperature distribution create large systems of equations. For the efficient simulation of such sophisticated models in real time for control purposes, it is necessary to perform model reduction, simplification, or reformulation. While the model reduction and simplification ignore some of the physics, reformulation can be used to capture the dynamics

accurately while reducing the computational cost significantly. Although coordinate transformation and spectral methods can be used for the RFB as with the Li-ion battery, since the RFB only has intercalation occurring in the liquid phase, equations for solid phase intercalation do not have to be included, which simplifies the model. However, the presence of a transient flow field necessitates the use of specialized spectral and collocation techniques to capture the moving front accurately.

D. Optimal Model-Based Protocols for Battery-Solar Hybrids

The reformulation approach outlined above allows for more detailed physics-based models to be used when simulating battery cycling and allows for simulations and optimizations to be run in real time, updating the model with changes in system dynamics. For energy storage at grid scale, optimization schemes can be used to produce charging patterns for microgrids or solar tied energy storage systems among other possibilities. An example demonstrating the advantages of a model-based optimization approach is discussed by showing a battery charging protocol optimized for a solar power input.

Starting with a reformulated porous electrode P2-D model explained in Section IV-A, we included equations to model the internal temperature changes during charging and the growth of the SEI layer caused from side reactions at the anode [45], [60], [99]. The passive SEI layer growth causes capacity fade by increasing diffusion resistance and removing Li from the system, and can therefore be used to determine battery cycle life based on the remaining capacity [47], [100]. While SEI growth has been shown to cause fade within Li-ion batteries, many mechanisms which can vary for different chemistries can cause fade to occur.

If the only objective is storing the maximum amount of charge for the system with no time limits or additional constraints, an optimization of the models for batteries leads to a constant-current–constant-voltage (CCCV) charging pattern [101]. However, in order to guarantee long cycle life, the battery should limit the amount of SEI growth during each cycle. By adding a new constraint for the optimization model which sets a maximum allowable SEI layer, the charging pattern will deviate from the typical CCCV charging in order to obtain the greatest amount of charge while ensuring that the SEI layer does not grow significantly. Additionally, constant current charging is not possible when using solar power due to the non-steady-state power from the solar cells.

Applying this approach to an example of a system that combines solar power with battery storage, we can see the effect that optimization can have on a system’s performance and life. Our sample system will be used to help satiate peak demand for a microgrid system by providing as much power as possible between the hours of 4 P.M. and 8 P.M. The solar insolation for the system is approximated by half sine curve over a 12-h period which begins at 6 A.M.

and lasts until 6 P.M. (Assuming full charging of the battery, the system will be able to meet a power demand 141.3% of the peak solar output over the 4-h demand period.) Under basic charging conditions, when power is not demanded from the system, but there is solar insolation, the solar power will go directly to charging the battery. Since some of the solar insolation will occur during the time of demand, this portion of the power will go directly to the microgrid instead of battery charging. The portion of the day for which the battery can be charged will be between 6 A.M. and 4 P.M. and the battery will be sized so that it can capture 80% of the power supplied during that time. This percentage was chosen because many days there will not be perfect solar insolation, which can cause underutilization of the battery. Any power generated once the battery is fully charged will be supplied to the grid at a standard rate.

A standard charging protocol (labeled “standard charging” in Fig. 9) would charge the battery with power when available. However, using optimization to constrain the passive SEI growth (and, therefore, capacity fade) to the same level as seen in the basic charging, the maximum amount of charge would be stored using the protocol labeled “max stored charge” in Fig. 9. The model-based optimal charging protocol increases the amount of charge stored by 0.5%, and experiences the same amount of capacity fade. To further improve life, we can restrict the total amount of capacity fade which occurs in a single cycle. With the solar insolation pattern, we can limit the SEI layer growth to 90% of the base conditions without losing much stored charge. The “reduced fade” line in Fig. 9 shows the charging pattern with this capacity fade bound in place, which only reduces the charge stored by 0.42%. This small decrease in capacity means we can add

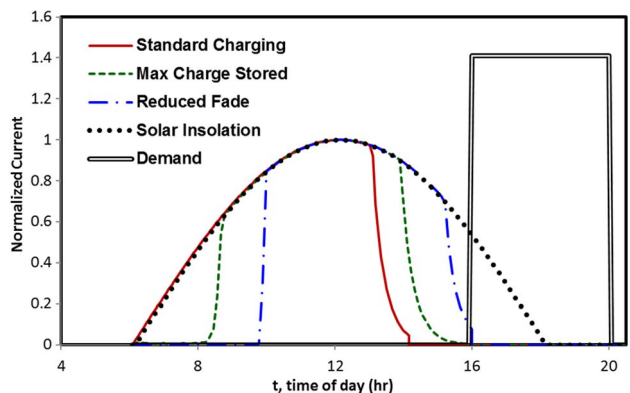


Fig. 9. Different charging patterns for a battery powered from solar cells with different optimization objectives. The solid line shows standard charging and has no optimization constraints; the dashed line attempts to maximize charge stored; and the dashed-dotted line limits capacity fade to 90% of the base case while trying to optimally store charge. The solar insolation and demand for the system are shown as well.

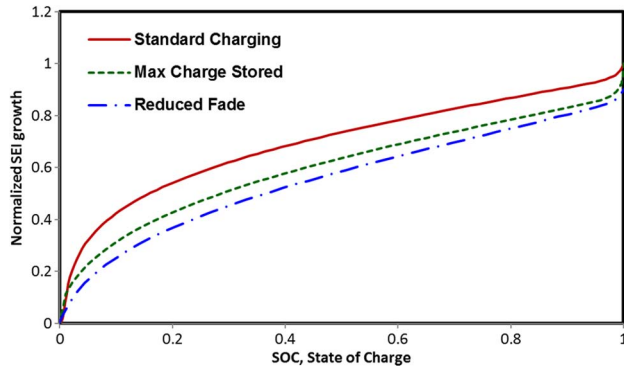


Fig. 10. SEI layer growth normalized to the SOC during the charging cycle for all three charging cases.

many additional cycles to the battery life without sacrificing performance in the short term. This graceful fade regime will continue until just after 10% fade reduction in this case, after which the stored charge begins to decrease significantly and further SEI layer growth reduction is prohibitive (see Fig. 11). When comparing the three cases, Fig. 10 shows the normalized growth of the SEI layer for each charging pattern and Fig. 11 shows the total energy gained over battery lifetime as well as the energy unutilized per cycle due to the SEI layer growth constraint.

Restricting the capacity fade in this example will increase the cycle life by 11.1%. Although each cycle will store slightly less charge, the cumulative amount of storable energy will increase by 9.6% over the lifetime of the battery. The amount of savings will vary depending on the shape and structure of the available charge (e.g., solar insolation) within grid systems, but using adaptive optimal charging protocols gathered from model-based simulation

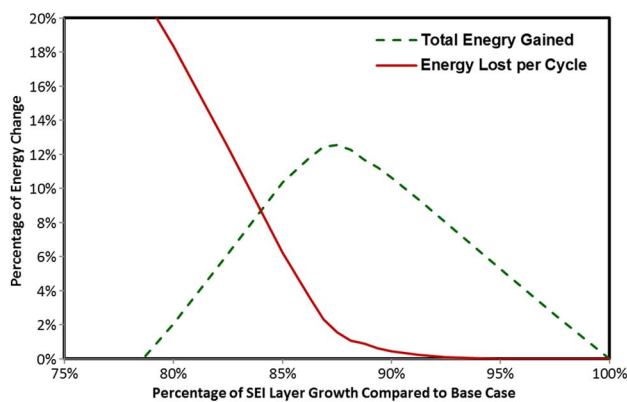


Fig. 11. As SEI layer growth (capacity fade) is restricted per cycle, the solid line shows the amount of charge underutilized per cycle, while the dotted line shows the percentage of total energy gained over the entire life of the battery due to increased cycle life.

that limit degradation effects can lead to significant improvement of energy storage systems over the lifetime of the battery.

The results given here only represent a simple case. Since insolation and demand can change on a daily basis, these types of systems will require continuous real-time optimization based on fast physics-based models. These curves are presented as evidence that modeling and simulation capability for batteries have advanced to a state where one can make real-time predictions and optimize charging protocols [74].¹ The objectives and constraints placed on the battery system can be altered for many different situations, and system sizes can be altered to study the effectiveness of system parameters for various sites. The real-time simulation and optimization was enabled by the advancement in model reformulation and efficient simulation of battery models [73], [91], [92], [102].

V. CONCLUSION AND FUTURE WORK

While batteries continue to take on a more important role as energy storage devices in the electric grid, their internal states remain difficult to quantify. As batteries degrade, it becomes more difficult to estimate the SOC and the SOH through traditional methods and more detailed physics-based modeling is required to make accurate estimates. Battery models for Li-ion systems are well developed, but many higher accuracy models produce heavy computational loads and require long simulation times that are not suitable for control and implementation into real-time BMSs. Although empirical equivalent-circuit models and lookup tables are currently used for SOC and SOH estimation due to their speed and robustness, they lack the desired accuracy for aggressive cycling patterns that are required by many grid-scale applications. A porous electrode P2-D model will deliver a much greater accuracy and when reformulated for fast simulation will also be fast enough to be useful in real-time BMSs.

Modeling for RFBs is in its infancy when compared to other battery systems. RFBs require a different modeling approach from conventional battery systems because the electrolyte is decoupled from the rest of the system. A more thorough understanding and modeling of the redox-flow system will be beneficial to the ultimate utilization of the systems, which offer great promise for grid-scale systems.

When creating BMSs for large grid systems, many battery packs and individual BMSs must be combined in order to reach the desired capacities. The architecture of these battery systems into a larger BESS with SSC is required for efficient operation of energy storage. Additional models that account for multiple stacks are required to perform optimal control of the individual stacks. By implementing these predictive models through

¹The codes shown from the example here are available upon request from V. R. Subramanian and will be posted at www.maple.eece.wustl.edu.

the BMSs and the BESSs, these energy storage devices can be much more aggressively operated while maintaining safe and efficient conditions.

An example of use for physics-based model charging was shown for the case of batteries charged with solar power and provides an example of the efficiency gains made possible through simulation and optimization within the electric grid. Going forward, additional development to

increase the robustness of reformulated and numerical models is required, in particular, for multiphase and transient flows in redox systems. In addition, model validation and testing for the full range of operational interest must be performed. The architecture and design of these large-scale BESSs must also be optimized in order to facilitate fast computation and system response, allowing BMSs and SSC to be useful across the system. ■

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