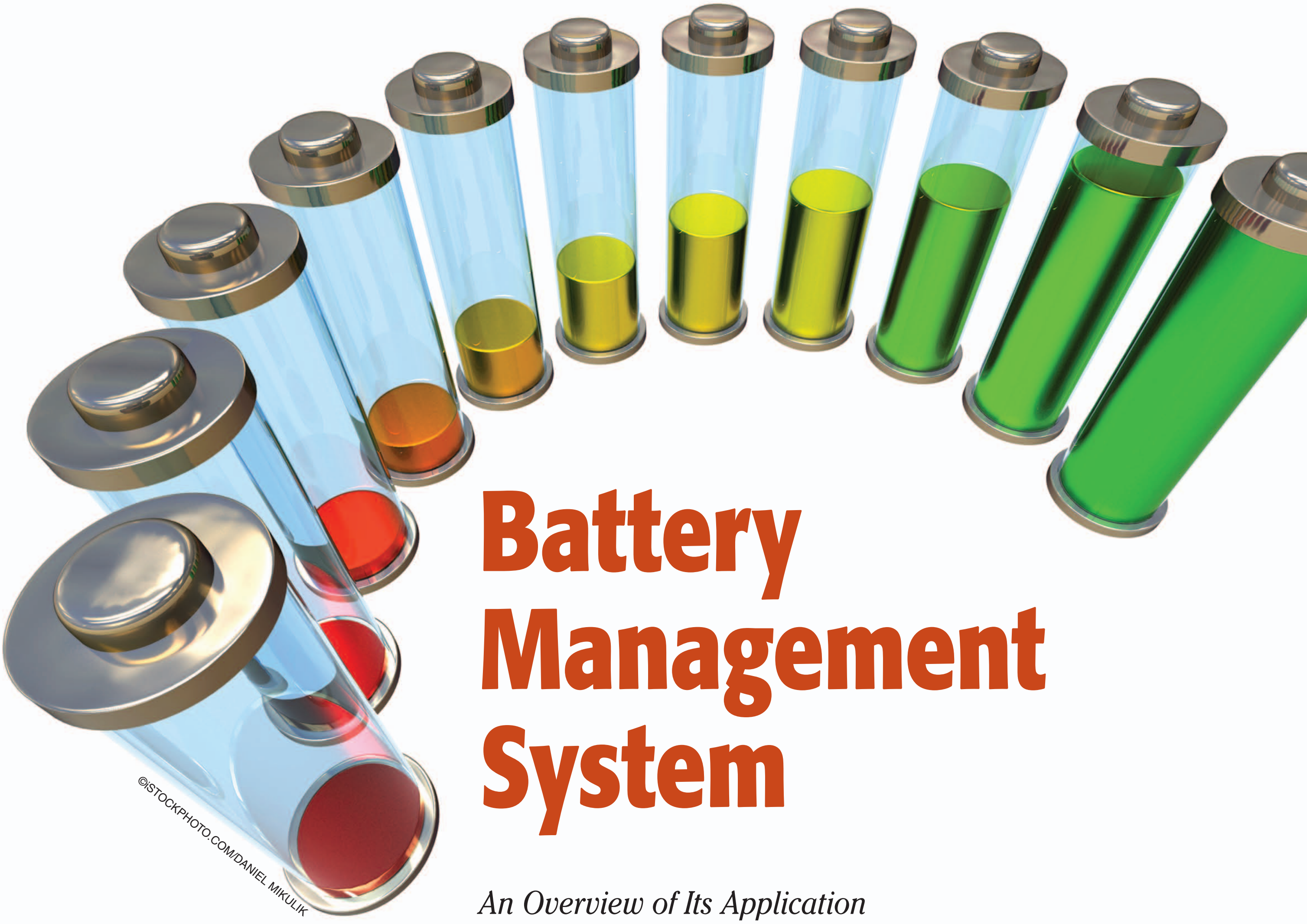

Battery Management System

An Overview of Its Application in the Smart Grid and Electric Vehicles

HABIBALLAH RAHIMI-EICHI, UNNATI OJHA, FEDERICO BARONTI, and MO-YUEN CHOW

With the rapidly evolving technology of the smart grid and electric vehicles (EVs), the battery has emerged as the most prominent energy storage device, attracting a significant amount of attention. The very recent discussions about the performance of lithium-ion (Li-ion) batteries in the Boeing 787 have confirmed so far that, while battery technology is growing very quickly, developing cells with higher power and energy densities, it is equally important to improve the performance of the battery management system (BMS) to make the battery a safe, reliable, and cost-efficient solution. The specific characteristics and needs of the smart grid and EVs, such as deep charge/discharge protection and accurate state-of-charge (SOC) and state-of-health (SOH) estimation, intensify the need for a more efficient BMS. The BMS should contain accurate algorithms to measure and estimate the functional status of the battery and, at the same time, be equipped with state-of-the-art mechanisms to protect the battery from hazardous and inefficient operating conditions.

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The Need for Energy Storage in the Smart Grid and EVs

The smart grid and EVs are two examples of growing technologies that would greatly benefit from the development of advanced infrastructure and components. As one of the major components in the smart grid and EVs, energy storage needs to satisfy several power and energy density criteria based on the characteristics of the application. For different applications, including short-term and long-term power support, various types of energy storage from flywheels to numerous battery chemistries are employed.

In the United States, 29 states have issued the renewable portfolio standards that mandate 15–30% renewable electricity sales by 2025 [1]. Because of this push toward green energy, solar and wind power generation are coming to the forefront as the primary sources of renewable electricity production for the electric utility grid. It is a well-known fact that energy storage is a crucial element in the integration of renewable energy into the grid, especially given the intermittent nature of renewable energy generation. In addition, it is accepted that oil reserves are going to be exhausted in a few decades; 2057 is estimated to be the oil depletion year [2]. This has led to the penetration of battery-powered EVs into the market. Energy storage has thus emerged as a top concern for the future smart grid and EVs. After a brief introduction to these applications, we will discuss the energy storage needs for them.

The smart grid is a concept involving an electricity grid that delivers electric energy using communications, control, and computer technology at a lower cost with higher reliability [3]. The U.S. Department of Energy has defined several features for a smart grid, including active consumer participation, accommodating all generation and storage options, and enabling new products, services, and markets. Depending on the major requirement, the smart grid applications can be categorized into power and energy applications. Power applications such as frequency/area regulation, voltage support, electric service reliability, power quality, etc., require short bursts of high-power output that could last from a few seconds to a few minutes. Energy storage devices such as Flywheel, Li-ion, and advanced lead-acid (Pb-acid) batteries are identified [4] as potential solutions for these applications. Other energy applications, such as energy time-shift, load following, distributed energy storage, and renewable energy integration require a battery that can store a large amount of energy and discharge it over a longer period of time (i.e., from several minutes to several hours). Sodium-sulphur (Na-S), flow battery, and Li-ion have been identified as potential energy storage devices for these energy applications [5].

EVs are the main components of the advanced transportation system of the future. The EVs currently in the market are categorized into three types: hybrid EVs (HEVs), plug-in hybrid EVs (PHEVs), and pure or battery EVs (BEVs). While HEVs and PHEVs utilize battery energy storage along with an internal combustion engine, BEVs employ only a rechargeable battery to power the electric motors for propulsion. The two driving forces for the penetration of EVs in the world market are 1) to reduce/eliminate harmful gas emissions (e.g., carbon monoxide and carbon-dioxide) and 2) to reduce energy dependence on oil for transportation [5]. While there are several advantages to using EVs, such as home charging, excellent acceleration, zero emissions, independence from fuel use, etc., electric batteries are heavier than gasoline and take a long time to recharge, making them less attractive than gas-powered conventional vehicles in terms of vehicle range and refueling.

To compete with the existing market, several factors need to be taken into consideration in the design and usage of electric batteries. The United States Advanced Battery Consortium (USABC) has set several medium- and long-term goals for advanced batteries in EVs. Some of the parameters of interest for the USABC are cost (US$/kWh), power density (W/l), specific power (W/kg), specific regenerative power (W/kg), energy density (Wh/l), life (years), cycle life (cycles), operating environment (°C), etc. Some of the batteries that have been used for EVs are nickel-cadmium (NiCad), nickel-metal-hydride (NiMH), lithium-iron phosphate (Li-FePO4), and lithium-polymer (Li-Po). Due to the high energy and power density requirements, the research is also moving toward ultracapacitors [4] and metal air batteries, such as zinc/air (Zn/air), lithium/air (Li/air), etc.

Battery Management System

Besides the growth of the battery technology, the BMS is a key element to make the utilization of the battery in the smart grid and EVs safe, reliable, and efficient. The BMS not only controls the operational conditions of the battery to prolong its life and guarantee its safety but also provides accurate estimation of the SOC and SOH for the energy management modules in the smart grid and EVs. To fulfill these tasks, a BMS has several features to control and monitor the operational state of the battery at different battery cell, battery module, and battery pack levels.

The Need for BMS in Smart Grids and EVs

Although battery technology is growing very fast to provide practical solutions for the EVs and the smart grid industry, the progress in technology and materials alone cannot guarantee a solution that will overcome all the concerns. Some of the concerns regarding the integration of the battery storage into the smart grid are as follows.

- *Cost*—includes manufacturing, labor, maintenance, operation, and replacement costs.
- *Lifetime*—measured by the charge–discharge cycles and calendar life of the battery.
- *Power delivery*—measured in terms of charge–discharge rate, energy storage level, ramp rate, and charge–discharge efficiency.
- *Environmental impact and safety*—measured in terms of the safety/risk factors due to the chemical composition of the battery, operating temperature, etc.

The BMS not only actively controls the functions of the storage device to maximize its life, efficiency, and safety [8] but also provides accurate estimations of the status of the battery to the energy management system (EMS) unit. The EMS [6]–[8] is a unit in the smart grid, and also in EVs, that minimizes the cost involved in energy production, storage, distribution, plant maintenance, and operations, while maximizing lifetime, reliability, and safety. The performance of the EMS is only as accurate as the data provided by the BMS about the battery's SOC, remaining useful life (RUL), round-trip efficiency, etc.

In EVs, specifically, one of the major concerns for battery packs is safety. The battery, as well as the occupants of the vehicles, should be protected against any fire or shock hazard [9]. Accurately predicting the remaining driving distance that the battery can support is equally important since it is the only source of energy for the vehicle. Furthermore, traveling a long distance would involve discharges of up to 80% or more. Thus, it is crucial to have proper battery protection during deep charges and discharges. A battery pack in an EV can contain ten to 100 cells arranged in series and parallel combinations to deliver the required energy and power density [10]. In this scenario, thermal management for maintaining an optimal operating environment (30–40 °C) can also highly increase the efficiency of the battery. Most of the electronic control that is built around these batteries consists of protection circuits [11] from high and low voltages. These simple control units only monitor current and voltage and can be classified as protection units rather than BMS. Thus, we need a thorough and accurate BMS that can predict the SOC, SOH, RUL, etc., to increase the efficiency and the safety of the battery.

Figure 1 shows a block diagram explaining the function of the BMS in

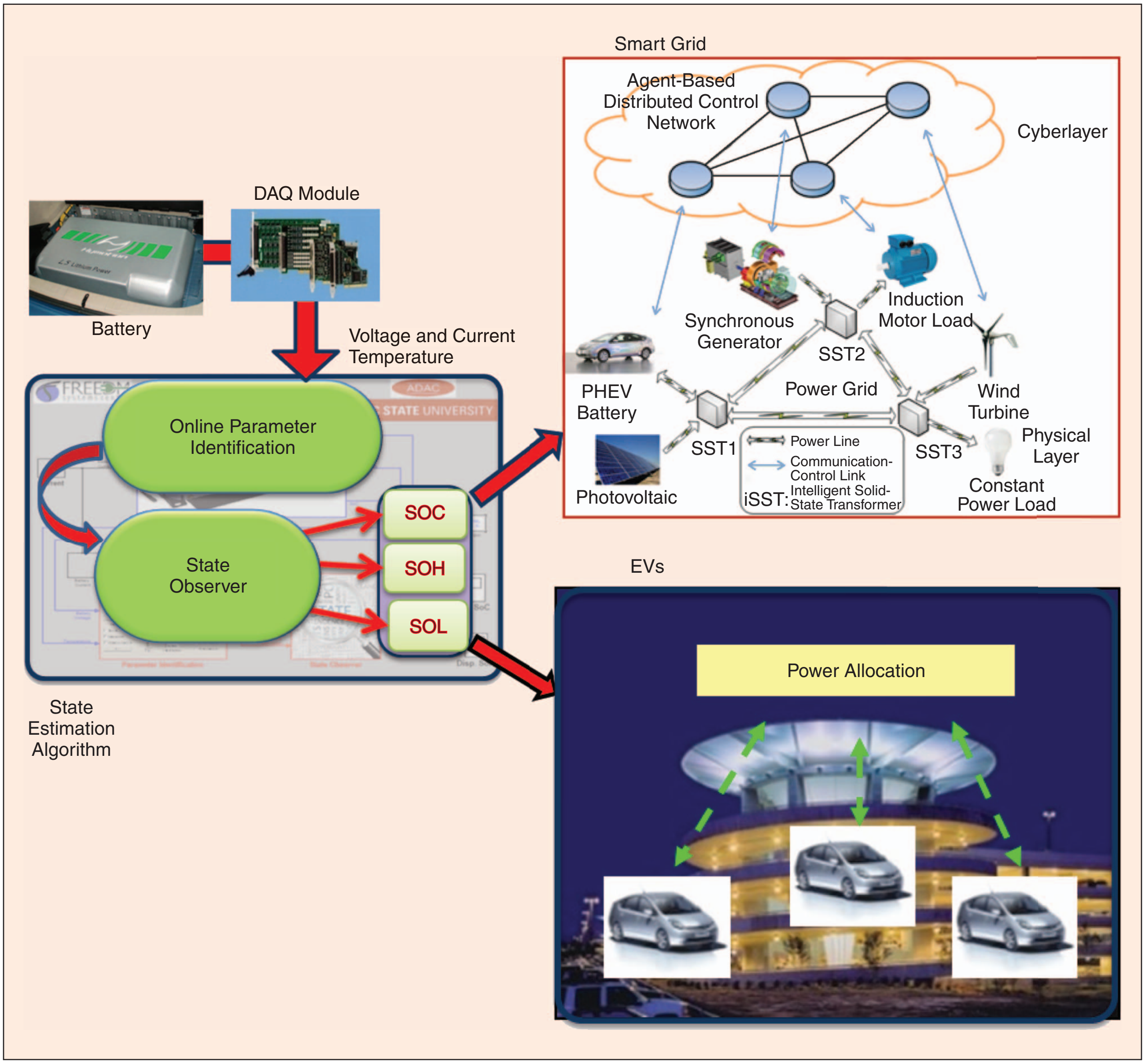

FIGURE 1 – Battery management algorithms function in both the smart grid and EVs.

monitoring the battery and providing necessary estimations to the smart grid and EVs. In this figure:

1) The data acquisition (DAQ) module collects the battery data, which includes current, voltage, and temperature at proper sampling frequency and precision.
2) The collected data is sent to the state estimation algorithm module, which includes the online parameters identification module and a state observer. In this module, considering a simple model for the battery dynamics, the parameters of the battery are identified using the input/output data. Afterward, the updated parameters of the battery model are fed to a state observer to estimate the SOC, SOH, and state of life (SOL) of the battery. Since the state observer is designed based on the state-space model of the battery, online identification and updating of the model parameters enhances the accuracy of the estimation. The SOC, SOH, and SOL are the information that the monitoring and management system in the smart grid and the EVs need to know about the battery to perform efficiently.
3) The smart grid diagram in Figure 1 shows a distributed control and energy management among distributed resources, loads, and energy storages in a typical power network in the smart grid. In this network, each component of the grid collaborates with the others to manage the available energy based on the local information and the information from the neighbors.
4) The EVs diagram shows the power allocation of a large-scale EV parking deck to different charging stations based on the state of the batteries and the customer's preference. The EMS module in the parking deck maximizes the satisfaction factor of the customers without exceeding the power constraints. Customer satisfaction is evaluated by the SOC of the vehicle battery at the arrival and departure times and the budget preferences of the customers.

BMS Features

To satisfy the needs mentioned in the section "The Need for BMS in Smart Grids and EVs," and to control and monitor the battery in smart grids and EVs, a BMS usually contains the following features, as shown in Figure 2.

Cell Monitoring

The premise to accomplish the BMS tasks is the acquisition of the current, voltage, and temperature of each cell. Requirements on voltage and current measurements vary according to the type of the battery technology employed. Li–$FePO_4$ chemistry is the most challenging in terms of voltage

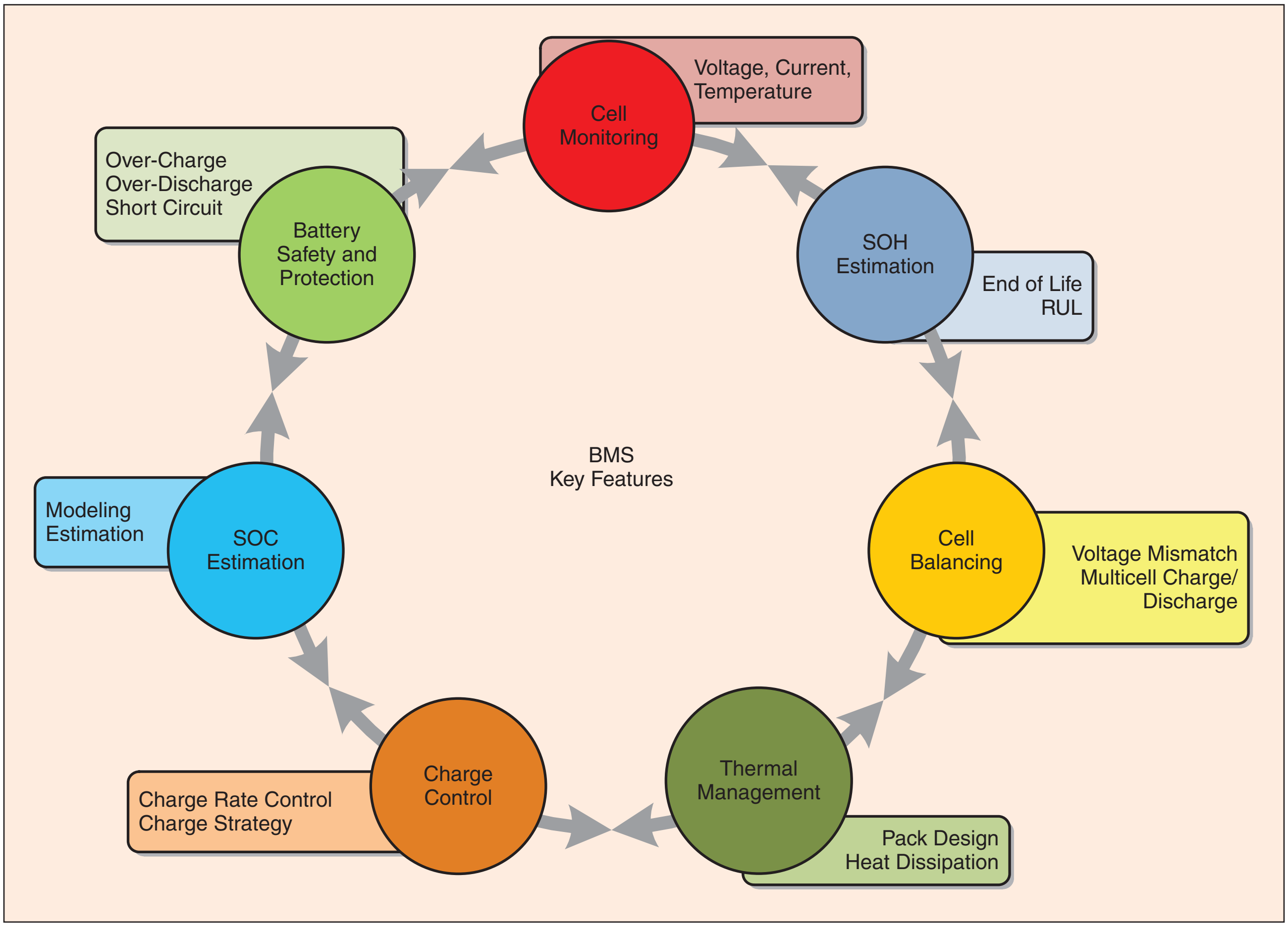

FIGURE 2 – The BMS features.

The smart grid and EVs are two examples of growing technologies that would greatly benefit from the development of advanced infrastructure and components.

accuracy. As shown in Figure 3(a), the open-circuit voltage (OCV) versus the SOC curve is very flat, between 20 and 80% of the SOC, which is the typical operating range of the battery. A reliable SOC estimation requires a cell voltage measurement as accurate as 1–2 mV [12]. Other flavors of the Li-ion chemistry, such as Li-Po, thiumlithium titanate (Li_2TiO_3), and thiumlithium-mangan (Li-Mn), are less demanding in terms of voltage measurement accuracy. Figure 3(b) shows the OCV–SOC curve for an Li-Po battery that is less flat compared with Li-$FePO_4$ chemistry. A typical accuracy of around 5 mV can be achieved by many commercial multicell battery monitoring ICs.

Current measurements must also be carried out with high accuracy. The battery current represents the major input of any SOC algorithm. The current is usually integrated over time to estimate the charge stored. Ideally, the integration operation (i.e., Coulomb counting) requires the current sensor to be offset free over the working temperature range and time. In other more sophisticated SOC algorithms, the battery current is usually fed to a dynamic cell model along with the measured cell voltage. Therefore, the measurements of the battery current and the voltage of each cell must be performed simultaneously. A typical accuracy target for the current measurement is about 0.5 to 1%, whereas the measuring range depends on the application and can be up to 450 A in an EV.

Battery Safety and Protection

One of the main functions of the BMS is to ensure the safety of the battery and protect it from operating at conditions that are harmful to both the battery and the users. Hazardous conditions are mostly caused by the chemical characteristics of the battery. For example, dangerous situations may occur as a result of deep charging of the battery when the SOC is below a certain percentage, overcharging of the battery when it is fully charged, charging or discharging the battery with a charge rate (C-rate) that is higher than the safe level for the battery chemistry, and going beyond the cutoff voltages of the battery. Operating temperature, which is determined by both the electrochemical reactions inside the battery and the environmental conditions of the application, is an equally important element in the safety of the battery, especially in the case of Li-ion batteries. The BMS sets safety limits to protect the battery from working beyond the safe temperature range, which is, for example, 0–60 °C for charging and 20–60 °C for storage and discharging of an Li-ion battery. Automotive applications also demand compliance with the International Organization for Standardization (ISO) 26262 functional safety standard (i.e., "Road vehicles—Functional safety"). In particular, the BMS design should meet the automotive safety integrity level.

SOC Estimation

SOC is an indicator that represents the available charge stored in the battery compared to the full capacity charge of the battery. An accurate estimation of the SOC is necessary not only for optimal management of the energy in the EVs and smart grid but also to protect the battery from going to the deep discharge or overcharge conditions that degrades battery life

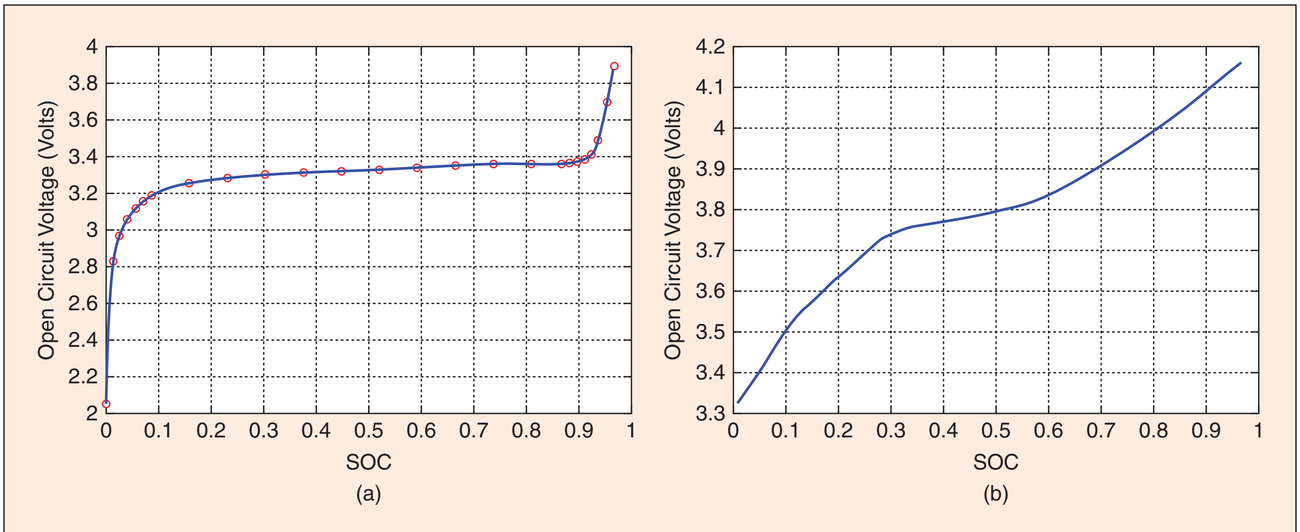

FIGURE 3 – OCV–SOC curves of different battery chemistries. (a) Li-$FePO_4$ battery OCV–SOC. (b) Li-Po battery OCV–SOC.

and may create potentially dangerous situations. Despite the importance of this element, the SOC cannot be measured directly from the battery terminals. This is why algorithms need to be developed to estimate the SOC of the battery pack and the individual cells based on the measured data of each one.

SOH Estimation

SOH is another important indicator of battery functionality that can be observed at the cell or pack level. SOH predicts the number of times the battery can be charged and discharged before its life is terminated. This information is crucial for the EMS in choosing strategies to prolong battery life and simultaneously arrange for substitution of the battery. Again, SOH is not a parameter that can be measured directly from the battery terminals. Furthermore, there is a need to clearly define SOH. Presently, a significant effort is underway to study battery SOH, particularly online estimation of SOH, for EVs and smart grid applications.

Cell Balancing

A multicell battery pack consists of several battery cells in parallel and in series to provide sufficient operating voltage and capacity to support the application. However, if there is a mismatch between the voltage and capacity of the connected battery cells, the entire battery pack cannot operate efficiently. For example, during discharge, as soon as the first cell reaches below cutoff voltage, the discharge stops and the charge in the rest of the cells cannot be utilized. This type of mismatch can occur because of a mismatch in the capacities of the cells or the SOCs of the cells. This is why cell-balancing techniques, which will be explained later in more detail, need to be deployed to optimize the performance of the battery pack.

Thermal Management

As discussed in the safety section, temperature is an important factor in the operation of a battery. In addition to the safety issue that is defined by the temperature range, the efficiency of the battery is also affected by the ambient temperature because of degradation of its capacity and an increase in internal resistance. Therefore, the BMS needs to have the ability to control the temperature of the battery and keep it at the optimal point under different operating conditions. The need to dissipate the heat produced by the battery cells due to electrochemical reactions will be more serious when several cells are compacted in a battery pack. Thermal management uses heat-transfer analysis to determine the distribution of heat inside the battery pack and embed channels to remove the heat using air or a liquid, if necessary.

Charging Control

Although the discharge rate of the battery is predetermined by the application in which the battery is being used, the charging rate depends on the customer's request, which is usually "the faster the better." On the other hand, different batteries have different limitations on the rate at which they can accept the charge because of their chemistries and structures. Those limitations have been considered in the customized charging stations for the particular battery or general-purpose charging device. However, the BMS on the battery pack also needs to have this built-in feature to manage, optimize, and protect the charging regime when the specific charger is not available.

BMS Architecture

Architectural choices for implementing a BMS are strictly dependent on the physical structure of the battery. In high-power applications, such as EVs and smart grids, usually ten to more than 100 high-capacity elementary cells are series-connected to build up the required battery voltage. The overall cell string is usually segmented into smaller modules consisting of several series-connected cells. Thus, the battery can be regarded as being made of three nested layers: the elementary cell, the module, and the pack (i.e., the series of modules). Each layer can serve as an intelligent platform for the effective implementation of a subset of the previously outlined BMS. This general view leads to the BMS hierarchical architecture schematically depicted in Figure 4. The innermost layer hosts

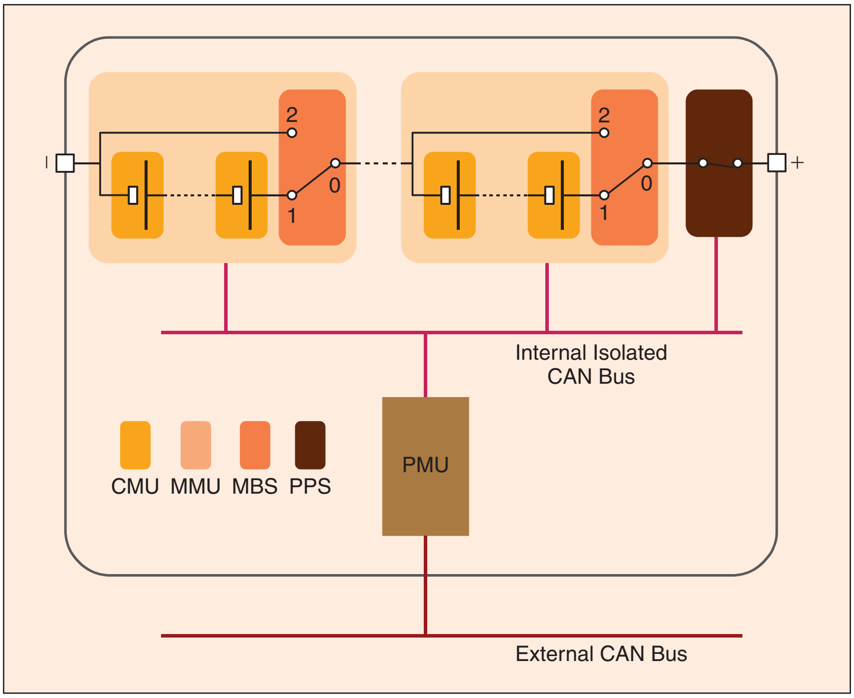

FIGURE 4 – Hierarchical architecture of the BMS.

Designing BMS for the proper integration of energy storage in both smart grid and EVs applications has various challenges as well as opportunities.

the cell monitoring units (CMUs), one for each cell in the string. The middle layer consists of the module management units (MMUs), one for each module in which the string has been partitioned. An MMU uses the basic monitoring functions of the CMUs and provides higher-level services to the pack management unit (PMU), which supervises the entire battery string. A dedicated and ad hoc designed link can be used to connect each CMU to the relevant MMU. A shared galvanic-isolated controller area network (CAN) bus is the preferred choice to implement communication between the MMUs and the PMU. The CAN bus also embeds the interface between the battery and the other control units of the system hosting the battery.

This hierarchical architecture platform is flexible and scalable, as the BMS functions can be freely distributed and, if redundancy is needed, replicated over all three layers of the platform. A simplified instance of the hierarchical platform consists of only the two outer layers. In such a case, the BMS embeds only an MMU for each module and the PMU. This is a relatively common choice, since providing each cell with a dedicated CMU can be expensive. In addition, it may increase the overall self-discharge rate of the battery in a nonnegligible way. However, the actual trend is to build up the battery by series-connecting very-high-capacity cells, instead of groups of parallel connected cells with lower capacity. Consequently, the cost and power consumption of a CMU may seem affordable when compared to the cost and self-discharge rate of a very-high-capacity cell.

The use of the cell layer can be beneficial to the implementation of the BMS monitoring tasks. The CMU can easily act as a gauge measuring the voltage and the temperature of the related cell [13] to provide redundancy to this key BMS function. In addition, the embedded CMU can store valuable information, such as the serial number, the lifetime, and the number of cycles to be evaluated and stored, into the cell itself. This enables easy tracking of the cell history, thus facilitating potential use in a second market application of the smart grid when the progressive degradation of its usable capacity makes the cell no longer suitable for an EV. Along with reducing size and cost, a key point in implementing the CMU is the communication with the MMU. This needs to be isolated because the MMU and the relevant cells belong to different voltage domains. An interesting approach based on a capacitive coupled link among the cells and the MMU is shown in [14] that eliminates the need for a wiring harness with the cells and the MMU.

Challenge and State of the Art of Related Techniques

Extensive research is being conducted to improve the performance of the BMS to meet the required standards in smart grid and EV applications. This research includes developing online algorithms to accurately estimate the SOC and SOH of the battery. Consequently, building a precise model to represent the dynamic and static behavior of the battery is a prerequisite for the state estimation accuracy. The results of the modeling and state estimation at the cell level is necessary information for performing cell balancing and increasing the efficiency of the battery pack.

Designing BMS for the proper integration of energy storage in both smart grid and EVs applications has various challenges as well as opportunities. Several national labs and research institutions are working toward developing better BMSs. The Advanced Diagnosis, Automation and Control (ADAC) Laboratory at North Carolina State University, Raleigh, is working on different aspects and issues of BMSs, especially in the area of SOC and SOH estimation and battery modeling. Figure 5 shows the ADAC Lab experimental platform consisting of a dc–ac converter, an EV simulator, and a LabVIEW-based GUI. In the following sections, some of the challenges and results in SOC and SOH estimation, battery modeling, and cell balancing are briefly described.

SOC Estimation Algorithms

Several algorithms and approaches have been proposed to estimate the SOC from the battery's available measurements. Coulomb counting [15] or Ah counting is one of the most conventional methods in which a time integral of the terminal current determines the amount of charge released from or stored in the battery and is compared to the full charging capacity. Although easy to implement, this method is limited by the unknown initial value of the SOC as well as a current sensor error, which accumulates over time because of the integration process. Measuring the open circuit voltage is another approach to calculate the SOC based on the static relationship between the OCV and the SOC. This method is used independently [16] or in combination with Coulomb counting [17] to increase the accuracy of the SOC estimation. However, due to the long-term battery dynamics (to be explained in more detail later), obtaining the OCV requires the battery to stay at rest (i.e., no charge or discharge) for a long time (sometimes as long as eight hours or more). This requirement voids this method for online applications, such as EVs. Similarly, electrochemical impedance spectroscopy (EIS) [18] is another tool used to estimate the SOC. The internal impedance of the battery is

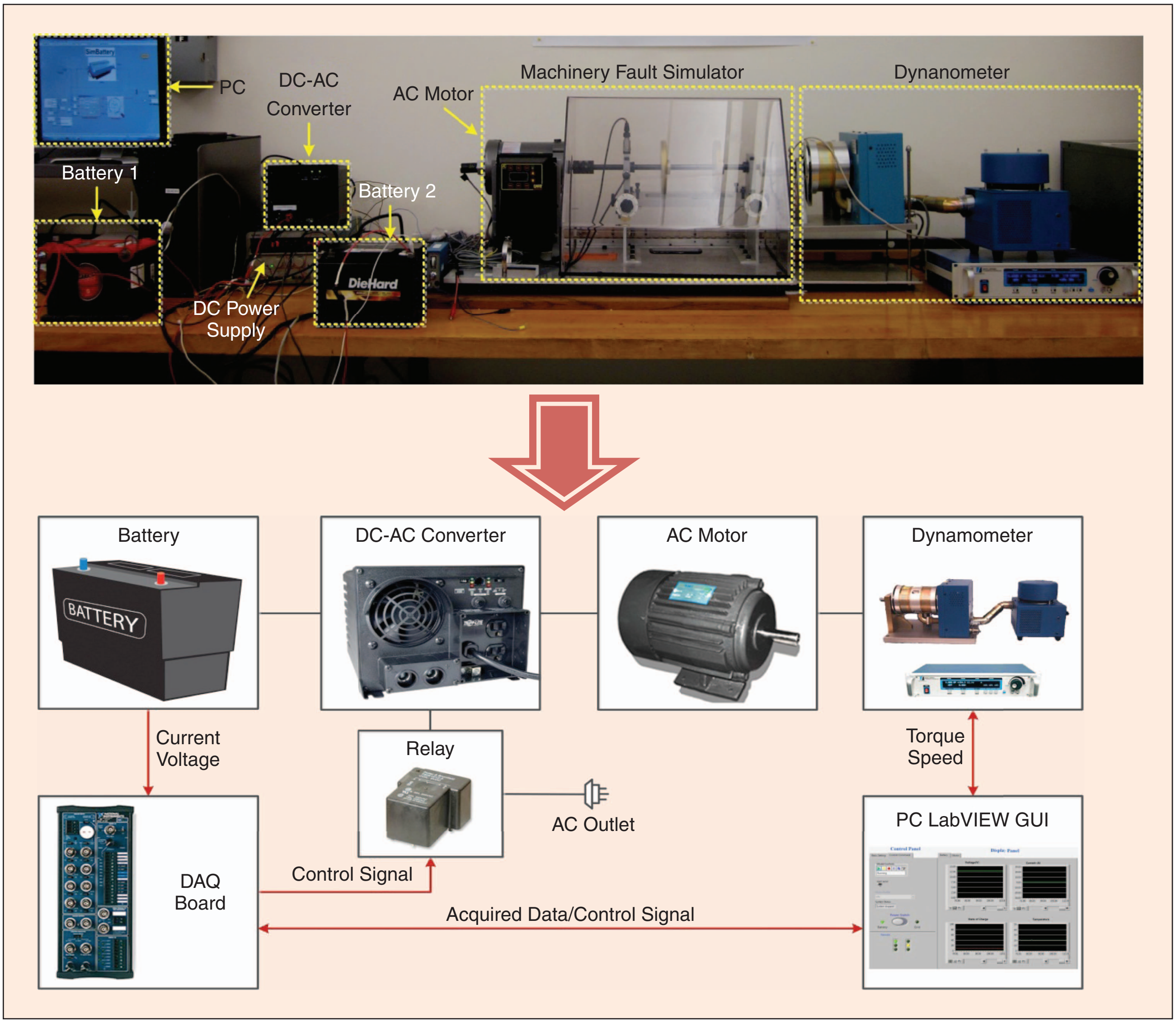

FIGURE 5 – Actual setup and block diagram of a BMS testbed at ADAC Lab, North Carolina State University.

calculated by applying small current signals with different frequencies to the battery and measuring the corresponding voltage using special EIS analyzer equipment. However, this process also takes a long time and, therefore, is only suitable for offline analysis.

Recently, online methods, such as model-based SOC estimation approaches, have been developed and have become popular. The dynamics of the battery are modeled as an intrinsically nonlinear system. Various techniques are employed to design observers to monitor the system's SOC, ranging from simple observers designed by trial and error to advanced robust, optimal [19], and recursive techniques (e.g., Kalman filters [20] and sliding mode observers [21]). Although the latter provides more accurate robust results, these methods are all designed based on offline identification of the battery model parameters. The constant parameters for the battery model identified offline contradict the experimental and analytical results of modeling different batteries at different SOCs and various environmental conditions. As shown in [22], some parameters of the battery model change as much as 800% at the same temperature and discharging current rate when the SOC changes between 0 and 100%.

One of the recently proposed methods by ADAC, called battery parameters/SOC coestimation, depicted in Figure 6 [22], [23], estimates SOC based on a simple battery dynamics model while using an adaptive online parameter-identification algorithm to identify and update the model's parameters. Subsequently, deploying a piecewise linearized mapping of the OCV–SOC curve, the parameters are continuously updated to accurately represent all of the battery's static and dynamic characteristics. Since the SOC is one of the states of the battery model, an observer is designed based on the updating model to estimate the SOC of the battery. Both simulated and experimental data indicate that updating the parameters of the battery model during

While the SOC is a well-defined indicator of the amount of available charge left in the battery, the SOH, which is supposed to indicate the health of the battery, has not been well defined.

SOC estimation is key to increasing the accuracy of the estimation and avoiding unnecessary compensation for uncertainties. Readers interested in quantitative analysis of comparison between SOC estimation algorithms can refer to [23], [24] and the references therein.

SOH Estimation Algorithms

While the SOC is a well-defined indicator of the amount of available charge left in the battery, the SOH, which is supposed to indicate the health of the battery, has not been well defined. Most studies consider the following equation to define the SOH of the battery:

$$\mathrm{SOH}\,(\%) = \frac{Q_{\mathrm{act}}}{Q_{\mathrm{R}}} \times 100, \qquad (1)$$

where Q_R is the rated capacity and Q_{act} is the actual capacity of the battery that is degraded due to the cycling effect. The shortcoming of this SOH definition is that it does not take the application of the battery into account. Let us use a human health analogy to explain this issue. We cannot define a person's health without considering the age, history, and activity of the human being. An ordinary healthy person who can run three to four miles a day may not be healthy enough to take part and finish a marathon race within a desirable time period. The situation is the same for batteries: the definition of the battery's SOH should be strongly tied to the application in which the battery is used, as well as the age and history of its use.

Despite the ambiguity in the definition of SOH, several studies on the microscopic and macroscopic behavior of the battery show that certain physical facts can be used to shed some light on this concept. For example, microscopic analysis detects an aging (i.e., fatigue) phenomenon in the battery that can be caused by various mechanisms [25]. From the application's viewpoint, aging can be related to two major causes: the calendar life of the battery and the cycling life of the battery. Macroscopic representations of aging in the battery are as follows:

- capacity degradation, which is predominantly produced by cycling
- internal resistance, which can also be increased by the storage life of the battery [26].

These variations in the battery's parameters are irreversible and are different from those caused by changes in the operating conditions. Temperature can be used to accelerate the battery life test. Every 10 °C increase in the temperature halves the life of the battery cell [27].

Despite knowing all the factors that affect the battery life, finding an appropriate definition for the SOH is still not an easy task. Most studies in this area consider capacity degradation, internal resistance increase, or a combination of the two as the measure of SOH [28], [29]. The changes in the capacity and the internal resistance are just indicators. They are meaningless without considering the application of the battery. For example, some approaches consider the failure threshold of the battery to be when the capacity is reduced to 80% of its rated value. Some studies have defined more practical indicators, namely the RUL and end of life (EOL) to predict the lifetime of the battery [30], [31]. Although these studies employ statistical analysis to estimate the RUL and EOL of the batteries, they do so mostly in military and aerospace applications and do not consider the requirements and characteristics of the smart grid or EV applications.

An application-dependent definition of SOH in EV and smart grid applications is aimed by ADAC at predicting the RUL and EOL. These applications have different operating power and energy requirements for given time periods, as well as different charging and discharging trends to the battery. It is necessary to take all of the following characteristics into consideration when predicting the EOL and RUL of a battery for a specific application.

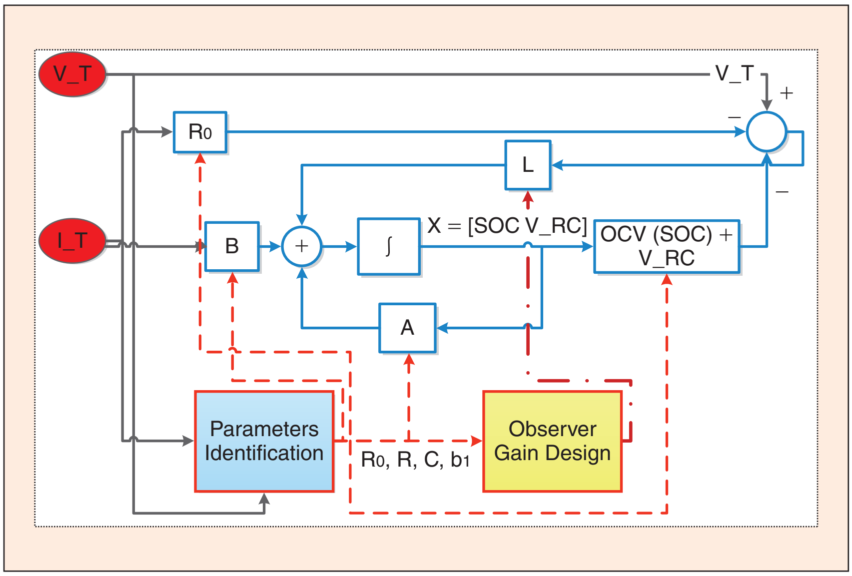

FIGURE 6 – Battery parameters and SOC coestimation block diagram.

- The future behavior of the vehicle and the smart grid is highly dependent on the stochastic behavior of the users as well as the operating conditions. Therefore, statistical analysis is needed to predict the EOL and RUL.
- The current status of the battery needs to be determined online by identifying the corresponding parameters (i.e., capacity and internal resistance).
- Accurate models for the capacity degradation and internal resistance increase regarding cycling need to be developed. Again, statistical analysis is to be used to determine the effect of partial cycling on the battery parameters, compared to the full cycling effect.

Figure 7 shows the steps to be taken to estimate the RUL and EOL in smart grid and EV applications, which are given as follows.

1) Use the online parameters identification algorithm to estimate the capacity and internal resistance of the battery while it is being used in the application.
2) From the capacity degradation and the internal resistance increase models, with the updated online estimations, predict the capacity and the internal resistance of the battery in the future.
3) Estimate the EOL and RUL of the battery using Monte Carlo simulation and Bayesian analysis. This prediction is based on the statistical data about the application and the users' behavior.

Battery Modeling

An accurate model representing the characteristics of the battery is essential to SOC and SOH estimation accuracy. Some researchers have performed rigorous analysis on the modeling of the electrochemical reactions inside the battery [32], [33]. This type of modeling is useful for manufacturers to optimize the design of their batteries, yet it requires a tremendous amount of computational time and memory to solve detailed partial differential equations of the battery model. However, some researchers [34] have modeled the battery as a black box with available experimental current–voltage characteristics with given specific applications. Subsequently, statistical modeling or curve fitting approaches are applied to derive a runtime-based model for the battery. The main shortcoming of these models is that they do not consider the dynamics of the battery.

The drawbacks of the aforementioned models lead researchers interested in the dynamic behavior of the battery to develop electrical models. In these models, the battery is represented by an electric circuit with parameters representing some physical phenomena of the battery. The electrical models are divided into two major categories: impedance-based models and Thévenin-based models. The impedance-based models are derived from the frequency domain analysis of the current–voltage behavior of the battery. The Thévenin-based models were proposed when the impedances were substituted by combinations of resistors, capacitors, and inductors to appear more like electrical circuits. In some of the earlier models, a large capacitor is used to represent the battery's the electromotive force. Most of the recently developed models utilize a controlled voltage source to consider the fact that the OCV–SOC relationship is a static nonlinear characteristic of the battery.

In practice, experimental look-up tables are used to map OCV to SOC with different curves for charging and discharging cycles to represent the hysteresis effect [12]. Moreover, in the Thévenin-based models, the battery's relaxation effect, mainly caused by diffusion and a double-layer charging/discharging effect, is modeled by parallel resistor-capacitor (RC) pairs. The number of RC pairs used is a tradeoff between the accuracy and complexities of the model. It is proposed to use two RC pairs to represent both the long-term and short-term relaxation effects [35], and in many studies, using one RC pair has shown accurate enough performance [28], [36].

Figure 8 presents a Thévenin-based model with two RC pairs: 1) the internal resistance is related to the resistance of the electrolyte to the

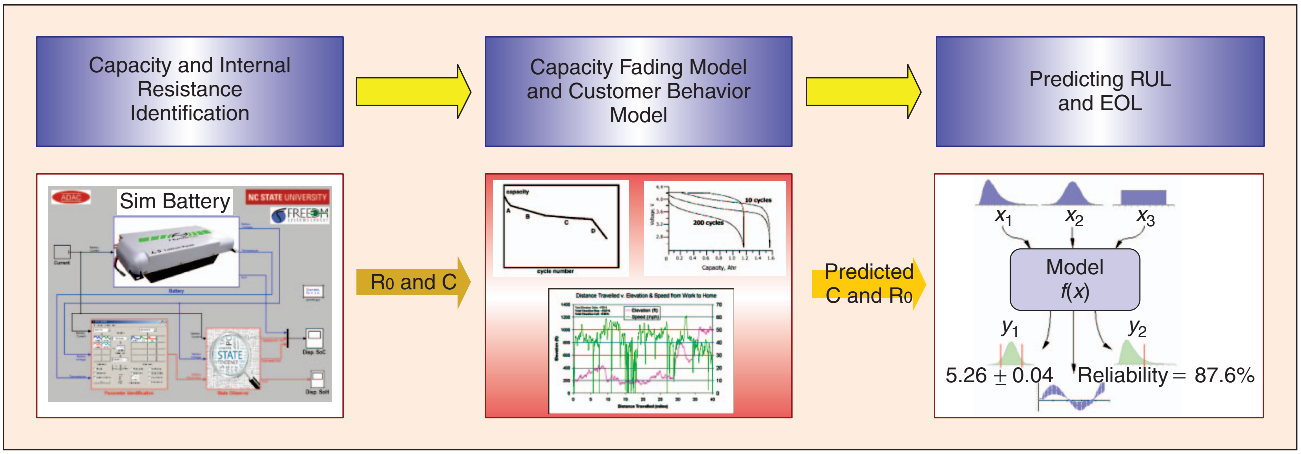

FIGURE 7 – Application-dependent estimation of the SOH.

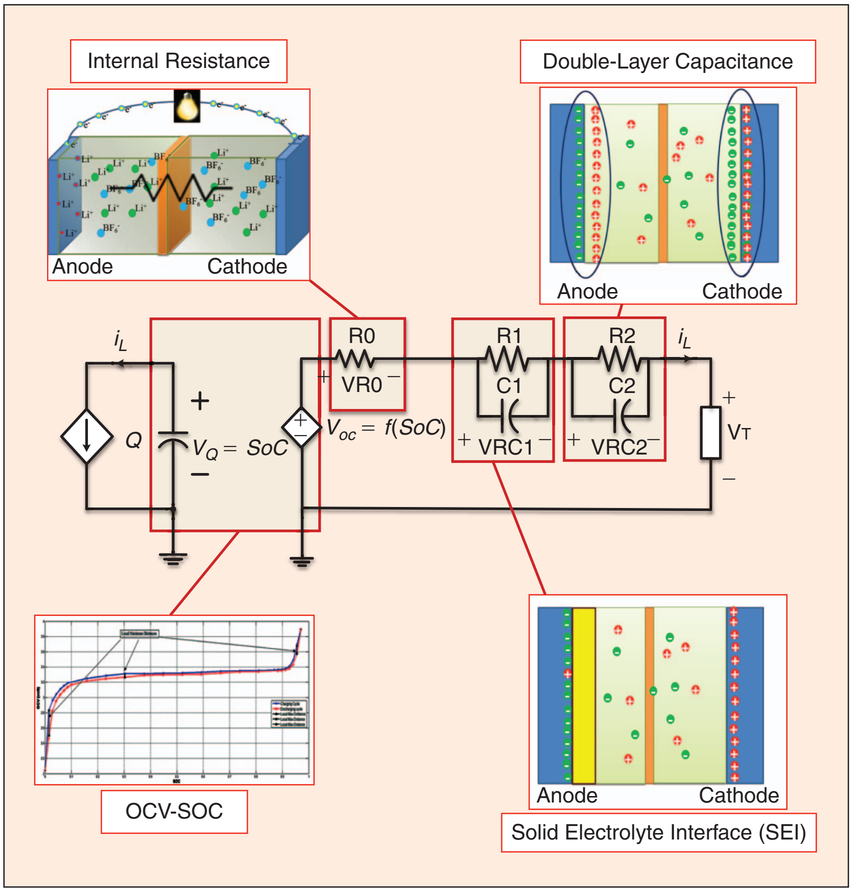

FIGURE 8 – Components of a Thévenin-based battery model with two RC pairs.

propagation of the ions, 2) the short-term relaxation effect is caused by composing the solid electrolyte interface (SEI) at the anode electrode, 3) the long-term relaxation effect is the product of composing double-layer capacitance at both anode and cathode electrodes, and 4) the experimental OCV–SOC curve for a lithium-iron phosphate battery with the hysteresis effect.

All parameters in the model are subject to change with different charging–discharging current rate, SOC, temperature, and aging effect. This is the advantage to using an adaptive model with the same structure as shown in Taure 8 [22], where the parameters are identified and updated online.

Cell Balancing

A good review of various approaches on cell balancing is provided by [37] and summarized in Table 1. The implementation of passive cell balancing is straightforward, requiring only a controlled switch and a bleeding resistor in each cell to dissipate

TABLE 1—COMPARISON OF THE VARIOUS BALANCING TECHNIQUES.

BALANCING TECHNIQUE	BALANCING TECHNIQUE	PROS	CONS	RELATED WORKS
Passive	Cell-to-heat (one bleeding resistor and switch per cell)	Very simple	0% efficiency	[38]
		Very cheap	Slow (limited by the maximum allowable dissipated power on board)	
Active	Module-to-cell (charge transfer from a battery module to a single cell by means of a galvanic isolated dc/dc converter)	Relatively simple	Switch network	[39], [40]
		Good efficiency	High isolation voltage of the dc/dc	
		Fast		
	Cell-to-cell			
Active	Cell-to-cell distributed (charge transfer from adjacent cells)	Moderate efficiency	Bulky	[41]
		Moderately fast	Complex control	
	Cell-to-cell shared (charge transfer from cell A to tank, then from tank to cell B)	High efficiency	Switch network	[42], [43]
		Fast		
Active	Cell/module bypass (a cell/module disconnection from the current path)	High balancing efficiency	High current switches	[44], [45]
		Very fast and flexible	Complex to implement	
			Decrease battery efficiency during operation	

the extra energy stored in the more highly charged cells as heat. The most promising approaches seem to be the module-to-cell and the shared cell-to-cell techniques, in which a single dc/dc converter is used to equalize the charge among the cells of a module. Active cell balancing transfers the extra energy to the less highly charged cells. Different active balancing techniques are possible depending on how the energy is redistributed among the cells. However, a really good tradeoff between the circuital complexity of the active balancing method and achievable efficiency has to be found to make active balancing competitive against passive equalization. The hardware implementation of the charge-equalizer circuit lies in the MMU, while the overall balancing procedure is usually supervised by the PMU, which controls the amount of charge stored in each cell of the package string. Usually, the charge equalizer at the module level can achieve a very high efficiency, up to 90%, compared to the 0% efficiency in passive cell balancing.

Conclusion

A smart BMS is crucial in the realization of the smart grid and the escalation of the EVs industry. The development of battery technology that provides higher energy and power density and reduces cost cannot be fully accomplished without proper BMS circuits and algorithms to monitor and control the battery and guarantee the safety and reliability of the energy storage devices. Although most of the performance requirements for the BMS in laptop and cell phone applications are already provided, there is still much research and development needed to satisfy the standards for EVs and smart grid applications. This field of research includes, but is not limited to, finding an accurate and practical algorithm to estimate SOC, defining proper application-oriented SOH measures to accurately predict RUL and EOL of the battery, and finding methods to actively balance different cells and modules in the battery pack.

A smart BMS is crucial in the realization of the smart grid and the escalation of the EVs industry.

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