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Review

Battery Management Systems in Electric and Hybrid Vehicles

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Abstract: The battery management system (BMS) is a critical component of electric and hybrid electric vehicles. The purpose of the BMS is to guarantee safe and reliable battery operation. To maintain the safety and reliability of the battery, state monitoring and evaluation, charge control, and cell balancing are functionalities that have been implemented in BMS. As an electrochemical product, a battery acts differently under different operational and environmental conditions. The uncertainty of a battery's performance poses a challenge to the implementation of these functions. This paper addresses concerns for current BMSs. State evaluation of a battery, including state of charge, state of health, and state of life, is a critical task for a BMS. Through reviewing the latest methodologies for the state evaluation of batteries, the future challenges for BMSs are presented and possible solutions are proposed as well.

Keywords: battery management system; lithium-ion battery; state of charge; state of health; state of life

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1. Introduction

From portable electronics to electric vehicles (EVs), batteries are widely used as a main energy source in many applications. Interest in batteries for EVs can be traced back to the mid-19th century when the first EV came into existence [1]. Today, since EVs can reduce gasoline consumption up to 75% [2], EV batteries have gained renewed attention in the vehicle market. Boston Consulting Group [3] has reported that, by 2020, the global market for advanced batteries for electric vehicles is expected to reach US $25 billion, which is three times the size of today's entire lithium-ion battery market for consumer electronics. The U.S. Council for Automotive Research (USCAR) and the U.S. Advanced Battery Consortium (USABC) have set minimum goals for battery characteristics for the long-term commercialization of advanced batteries in EVs and hybrid electric vehicles (HEVs) [4]. To enlarge the market share of EVs and HEVs, safety and reliability are the top concerns of users. However, both of them are subject to not only the battery technology but also the management system for the battery. Therefore, a battery management system (BMS), as the connector between the battery and the vehicle, plays a vital role in improving battery performance and optimizing vehicle operation in a safe and reliable manner. In view of the rapid growth of the EV and HEV market, it is urgent to develop a comprehensive and mature BMS.

Similar to the engine management system in a gasoline car, a gauge meter should be provided by the BMS in EVs and HEVs. BMS indicators should show the state of the safety, usage, performance, and longevity of the battery. Due to volatility, flammability and entropy changes, a lithium-ion battery could ignite if overcharged. This is a serious problem, especially in EV and HEV applications, because an explosion could cause a fatal accident [5]. Moreover, over-discharge causes reduced cell capacity due to irreversible chemical reactions. Therefore, a BMS needs to monitor and control the battery based on the safety circuitry incorporated within the battery packs. Whenever any abnormal conditions, such as over-voltage or overheating, are detected, the BMS should notify the user and execute the preset correction procedure. In addition to these functions, the BMS also monitors the system temperature to provide a better power consumption scheme, and communicates with individual components and operators. In other words, a comprehensive BMS should include the following functions:

- Data acquisition
- Safety protection
- Ability to determine and predict the state of the battery
- Ability to control battery charging and discharging
- Cell balancing
- Thermal management
- Delivery of battery status and authentication to a user interface
- Communication with all battery components
- Prolonged battery life

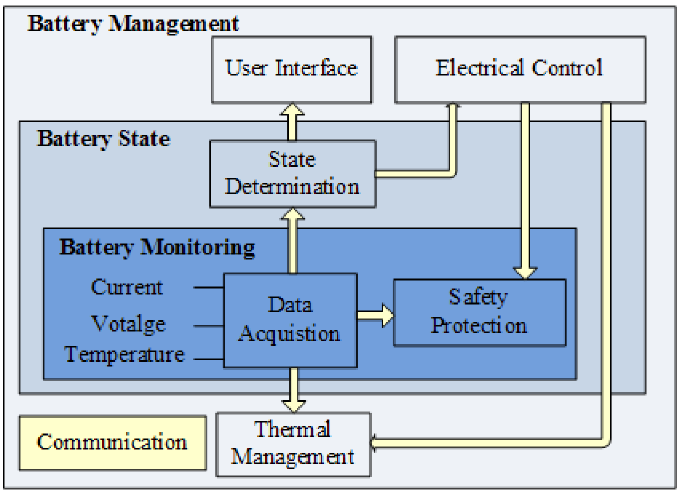
The current BMSs in both academic research and commercialized products are described in Section 2. Major concerns for current vehicles' BMSs are analyzed in Section 3. Section 4 explains the techniques, algorithms, and methods applied for solving the key concerns with BMSs, while Section 5 proposes and analyzes a BMS with multiple functions. In Section 6, the existing challenges and possible solution schemes are put forward. Finally, conclusions are drawn in Section 7.

2. Current BMSs

Comprehensive and mature BMSs are currently found in portable electronics, such as laptop computers and cellular phones, but they have not been fully deployed in EVs and HEVs. This is because the number of cells in a vehicle's battery is hundreds of times greater than that in portable electronics. Moreover, a vehicle's battery is designed not only to be a long-lasting energy system, but also to be a high power system. In other words, batteries for EVs and HEVs have to provide high voltage and high current. These make BMSs for EVs much more complicated than those for portable electronics.

From a hardware structure perspective, three kinds of topologies have been implemented in BMSs, including centralized, distributed and modular structures [6]. However, the functions of the BMSs in each case are similar. Meissner and Richter [7] proposed a layer structure for battery monitoring, battery state, and battery management. Gold [8] categorized the different functions in a BMS. These concepts can be combined into a generic BMS structure with the basic functions as shown in Figure 1. Various sensors are installed in the battery pack for data acquisition at the monitoring layer. The real-time collected data is used to maintain the system's safety and determine the battery state. The battery state determines the charge time, discharge strategy, cell equalization, and thermal management among the cells, while the state will be passed to the user interface as well.

Figure 1. Illustration of a battery management system.



The current commercialized BMSs each perform the basic functions differently. Table 1 shows the main functions of three popular commercial battery management units (BMUs). Drawbacks of the mentioned BMUs include the following:

(1) Limited data logging function. The data logging function plays an important role in database establishment, which stores the driving pattern. This profile can help to build up and update the state of charge (SOC) model.

(2) Lack of state of health (SOH) and state of life (SOL) estimations. SOH and SOL are used to characterize the current health status and the remaining performance of the battery that will guarantee the reliable operation of the vehicle and scheduled maintenance of the battery replacement.
(3) Non-interchangeable among current BMSs. As each BMU has its own cell balancing scheme and communication mechanism, it is impossible to utilize the existing components to form a new BMS.

Table 1. Comparison between different BMS products.

	Maxim DS2726 [9]	**TI BQ78PL114 [10]**	**OZ890 [11]**
Measured Cell Parameters	voltage, current	voltage, current, temperature, impedance	voltage, current
Measured Pack Parameters	N/A	N/A	temperature
Safety Protection	▪ over/under voltage ▪ over current ▪ short circuit current	▪ fail-safe operation of pack protection circuits ▪ three power FETs ▪ one secondary safety output fuse	▪ over/under voltage, ▪ over current, short circuit current ▪ over/under temperature
Data Logging	no	on PC-based GUI only	EEPROM
Communication	unknown	PowerLAN, SMBus	Control Area Network (CAN)
SOC/SOH/SOL Estimation	none	SOC	SOC
Dissipative Cell Balancing	charge shunting	N/A	external equalized resistance
Non-dissipative Cell Balancing	N/A	inductive shuttle charge	N/A

3. Concerns about Vehicle BMSs Today

With the increasing prices of gasoline and continuing breakthroughs in battery technology, EVs and HEVs were reintroduced in the early 1990s and became mainstream in the 2000s. Because of its promising properties, such as high energy density, long life cycle, and low self-discharge, lithium-ion battery technology has been widely developed and applied in the past decade when the development of BMSs for EVs has been slow and insufficient. This lag has been caused by the following difficulties: (a) battery state evaluation; (b) battery modeling; and (c) cell balancing.

3.1. Battery State Evaluation

Knowledge of the battery state not only helps to determine whether the operational environment is safe and reliable, but also provides information about the charge-discharge operation, which is especially important for cell balancing. Usually, the battery state includes SOC and SOH determination. SOC is similar to the fuel usage indication in gasoline cars, but the battery is inaccessible for measuring and experiences aging, varying environmental conditions, and charge-discharge cycles, which will makes it difficult for a BMS to provide an accurate SOC estimation. According to [12], SOH describes the percentage of battery life remaining. However, there is no consensus on the definition of SOH because it does not correspond to the measurement of a specific physical quality. Although the ratio of the current capacity to the maximum capacity that the battery can hold is usually viewed as a health indicator, more parameters referring to the field performance must be considered during SOH evaluation. The actual formula of the SOH for a specific application is often a trade secret.

SOL is referred to in the literature as the time when the battery must be replaced [12]. It is similar to SOH, but quantifies the remaining time until the battery will be unable to perform. Prediction of battery performance helps the engineer to plan maintenance strategies, and handle disposal and replacement issues.

3.2. Battery Modeling

Establishing a battery model is difficult due to the complicated electrochemical mechanisms of batteries. From the perspective of chemical characteristics, Scrosati and Garche [13] presented voltage-to-capacity profiles of several Li/Li+ materials. For example, $LiFePO_4$ has a long flat trend when charging, while the voltage profiles of $LiMn_3O_4$ and $LiCo_{1/3}Mn_{2/3}O_2$ gradually increase without a flat region. They showed that a generic model for a battery family does not work well for general applications.

Currently, battery modeling for SOC determination is commonly developed from various equivalent circuit (RC network) models, which are distinct for different material characteristics and accuracy requirements [14–16]. Cheng [17] and Tremblay [18] adopted the generic battery model that was integrated in MATLAB [19]. However, the generic model is based on the assumption that the internal resistance is constant during charge and discharge cycles. Thus, the accuracy of this model is subject to challenge. While taking into account SOH estimation, the battery degradation model based on capacity fade was simulated and built [20–22]. These model parameters were predominantly achieved in terms of the physical characteristics of the specific anode and cathode. However, the external factors, such as environment temperature and discharge current load, will make these stationary models inaccurate in a dynamic environment. As a result, model selection is always focused on in a BMS.

3.3. Cell Balancing

In EVs and HEVs, cells are wired in parallel to form a block to satisfy the requirement of high capacity while several blocks (or cells) are connected in series to provide a high voltage [11]. Each cell is distinct due to manufacturing and chemical offset. Thus, the cells in a series have the same current but different voltage. During charging, capacity fade in cells may result in danger if a cell comes to its full charge easily. In other words, it will suffer from overcharging while all the rest of the cells reach their full charge. Similarly, over-discharge may happen on the weakest cell, which will fail before others during the discharging process. When the battery consists of multi-cells in series, it will be subject to a higher failure rate than any single cell due to a series network. To reduce this effect for prolonging the battery life, an effective cell balancing mechanism that would keep the SOC levels of individual cells in a battery pack as close to each other, should be developed.

The mainstream methods of cell balancing can be separated into two kinds: dissipative and non-dissipative. Both of those methods are dedicated to alleviating or even eliminating cell voltage imbalance [23]. However, dissipative equalizers used by resistors facilitate the dissipation of excess energy or current through heat with low efficiency. Non-dissipative equalizers are usually implemented by transformer, inductor or capacitor [6,24]. They are considered more efficient than dissipative equalizers. However, the exchange of charge or energy among cells makes their charge-discharge profile much more complicated than the conventional profiles. These balancing techniques depend on determining the SOC of each individual cell in the battery.

4. Methodologies for Battery Evaluation in BMSs

Based on the analysis above, it can be seen that the evaluation of battery status is one of the weakest links in BMS and yet it has a large impact on BMS performance. The top concern for EV users is the safety and reliability of the power system in a vehicle. The most important question is whether they will run out of battery power on the road. These issues refer to the estimation and prediction of SOC, SOH, and SOL of the EV battery. Thus, an accurate quantification of the battery status has become one of the most critical tasks for BMSs. In this section, the latest methodologies for battery state estimation and prediction are reviewed.

4.1. State of Charge (SOC)

SOC is critical, but it is not measurable given the current onboard sensing technologies. The ratio of the currently available capacity to the maximum capacity can be expressed as SOC [25], which is calculated by Equation (1):

$$SOC = 1 - \frac{\int i dt}{C_n} \tag{1}$$

where i is the current, and C_n is the maximum capacity that the battery can hold.

SOC reflects the amount of remaining charge that is available to the battery. It is used to determine the driving distance remaining in EVs, while it indicates when the internal combustion engine should be switched on or off in HEVs [26]. Due to the inherent chemical reactions of the battery and different external loads, the maximum capacity of the battery gradually decreases over time. Uncertainty regarding these factors will lead to non-linear, non-stationary battery degradation characteristics.

The most straightforward approach for SOC estimation is Coulomb counting, which characterizes the energy in a battery in Coulombs. This method calculates the capacity of a battery by integrating the current flowing in and out of the battery over time. SOC can be obtained by referring to the calibration point at full charge. However, this reference point (*i.e.*, the initial point) will change due to battery aging and coulombic efficiency. Thus, the reference point must be compensated when operating at practice conditions, and the SOC estimation should be updated under different measured voltage.

Building an accurate table between the discharge capacity and open circuit voltage (OCV) is necessary for achieving SOC. However, this process is time-consuming because it requires a large amount of training data to guarantee the accuracy of the table [27].

The extended Kalman filter (EKF) has been successfully applied for the estimation of SOC in HEV BMSs. Plett [28] developed this method on a first-order RC network in a series of papers. The traditional Kalman filter (KF) is used for linear problems, while EKF linearizes the prediction by using partial derivatives and Taylor series expansion. Windarko [14] also adopted the EKF to estimate SOC based on an electrical model with two series RC networks. However, the EKF cannot deal with a highly non-linear system since the first order Taylor series approximation cannot give enough accuracy in highly non-linear characteristics. Salkind *et al*. [29] utilized Electrochemical Impedance Spectroscopy (EIS) data to estimate SOC with fuzzy logic. Kozlowski *et al*. [12] input impedance parameters from EIS data into a neural network to estimate SOC. The time series model, autoregressive moving average (ARMA), was also implemented in his work. However, impedance measurement, which is one of the common points of the three methods, suffers from high cost, size constraints and measurement sensitivity.

Hansen and Wang [30] applied a support vector machine (SVM) using both classification and regression to estimate the SOC without establishing a battery circuit model. SVM transforms a low-dimensional nonlinear problem into a high-dimensional linear problem. The kernel function in Equation (2) maps the low-dimensional data into high-dimensional data:

$$f(\boldsymbol{x}) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(\boldsymbol{x}_i, \boldsymbol{x}) \tag{2}$$

where α_i and α_i^* are selected during the training process to minimize the loss function. The input vector $\boldsymbol{x}$ included both current and voltage parameters. The estimation of SOC was evaluated under steady state and dynamic state. However, parameter tuning is a tedious process for obtaining the optimal SVM model [27].

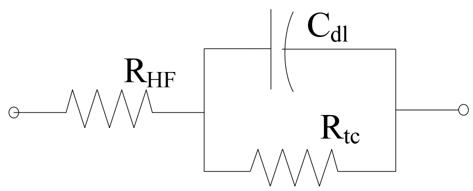
4.2. State of Health (SOH)

SOH describes the physical condition of a battery, ranging from internal behavior, such as loss of rated capacity, to external behavior, such as severe conditions [12]. Unlike SOC, there is no clear-cut definition of SOH. A general definition of SOH is that it reflects the health condition of a battery and its ability to deliver specified performance compared to a fresh battery [26,31]. The SOH in EV applications is used to characterize the ability to drive a specific distance or range. SOH in HEV applications is a characteristic of the specified power, such as the cranking power from regenerative braking. Scholars and manufacturers use the percentage of nominal capacity as the health threshold of the battery [17]. When the capacity reduces to 80% of the beginning of life capacity after charge-discharge cycling, it is defined as battery failure. However, studies have defined different rules or indicators to quantify the SOH in terms of battery characteristics, test equipment, and different applications.

Pattipati *et al*. [31] combined capacity fade and power fade as health characteristics. Capacity fade indicates the decrease in the driving range with a fully charged battery pack, and power fade indicates the reduced acceleration capability. Both of these features were input into an auto-regressive Support Vector Regression (SVR) model to estimate SOH. Here, the power fade was due to an increase in cell impedance during aging. The total resistance ($R = R_{HF} + R_{tc}$) was obtained from EIS data using nonlinear least squares. Figure 2 shows a Randles circuit model of a battery, where R_{HF} and R_{tc} are the high frequency resistance and the transfer resistance.

Widodo *et al*. [32] proposed a new feature, sample entropy (SampEn), as input data to predict SOH for target vectors of an intelligent system. SVM and its Bayesian version, relevance vector machine (RVM) [33], were used to compare the predictive performance.

Figure 2. Randles circuit model for a lithium-ion battery.



$$P = \frac{V^2}{R} \tag{3}$$

$$\text{Power Fade} = 1 - \left(\frac{\text{Power}(k)}{\text{Power}(0)} \right) = 1 - \frac{R(0)}{R(k)} \tag{4}$$

$$\text{Capicity Fade}(\%) = 1 - \left(1 - \frac{\text{Capacity}(k)}{\text{Capacity}(0)} \right) \times 100\% \tag{5}$$

The results also demonstrated that SampEn could serve as an indicator of SOH. SampEn is expressed as Equation (6):

$$\text{SampEn}(m, r, N) = -In \left[\frac{A^m(r)}{B^m(r)} \right] \tag{6}$$

where N is the total number of data points, m is the length of sequences to be compared, r is the tolerance parameters, $B^m(r)$ is the mean value of two similar signal segments that are composed from input vectors with m points, and $A^m(r)$ is similar to $B^m(r)$ and will match for $m+1$ points.

Chao and Chen [34] designed a state of health estimator for lead-acid batteries. Coup de Fouet voltage [35], internal resistance and transient current, were input into a modified extension matter-element model to develop intelligent SOH evaluation [32]. The mathematical formula is expressed as in Equation (7). Here, health is referred to as the "matter", *R*, which is described by three elements: *N* (name), *C* (characteristic), and *V* (value of characteristic). Through training the data, the weight of each characteristic was quantified and estimated based on the test data. The result was validated and compared with the extension neural network method:

$$R = (N, C, V) = \begin{bmatrix} N\, C_1\, V_1 \\ C_2\, V_2 \\ C_3\, V_3 \end{bmatrix} \tag{7}$$

4.3. State of Life (SOL)

SOL is also known as the remaining useful life (RUL) of a battery. Accurate SOL predictions will facilitate failure prevention and maintenance to prolong the service life of batteries. However, in the past, limited work has been done on SOL prediction. The increasing requirements for battery reliability, especially in military products, have promoted the development of state-of-the-art algorithms.

Pattipati [31] predicted the RUL of a battery using a moving average SVR for different thresholds of capacity fade $C(i)$ and power fade $P(i)$, which are shown in Equations (4) and (5) respectively:

$$RUL(k) = h(\{P(i), C(i)\}_{i=1}^{k}) \tag{8}$$

where k is the kth week. The RUL for an end-of-life criterion is approximately 23% power fade and 30% capacity fade.

RVM can provide the probabilistic interpretation of its outputs. Widodo [32] used RVM regression to predict SOH in capacity fade. The results suggested that RVM produced a more accurate prediction than the SVM model. The likelihood of a data set can be written as Equation (9):

$$p\left(\boldsymbol{t}|\boldsymbol{\omega},\sigma^2\right) = \left(2\pi\sigma^2\right)^{N-2} \exp\left\{-\frac{1}{2\sigma^2}\|\mathbf{t}-\Phi\boldsymbol{\omega}\|^2\right\} \tag{9}$$

where Φ is the $N \times (N+1)$ design matrix with $\Phi_{\mathrm{nm}} = \left\{1, K\left(x_i, x_1\right), K\left(x_i, x_2\right), \cdots, K\left(x_i, x_N\right)\right\}^T$; N is the number of input vectors; $\omega = \{\omega_1, \omega_2, \cdots, \omega_N\}$ is the regression coefficient vector; ω_0 is the bias; and $K\left(x, x_i\right)$ is the kernel function.

Saha [36] also used an RVM regression model, which was built using internal battery parameters from EIS data. This methodology combined the parameters of an offline model with an online state process. RVM regression was used to fit the related parameters of the exponential models with a probabilistic output. The exponential model is:

$$\tilde{x} = C_x \exp(\lambda_x t) \tag{10}$$

where $\tilde{x}$ is the model's predicted value. In this case, x includes charge transfer resistance, R_{CT}, and electrolyte resistance, R_E. The fitted parameters ($\lambda_{R_{CT}}$, λ_{R_E}) were input into the online particle filter (PF) process. Based on the combination of PF and RVM, the end of life point can be determined with a narrower probability density function (pdf). However, this approach still relies on the impedance measurements, which are hard to implement due to cost and space constraints.

He [37] developed a degradation model for lithium-ion batteries according to a new exponential model. This finding suggested a new model of the form:

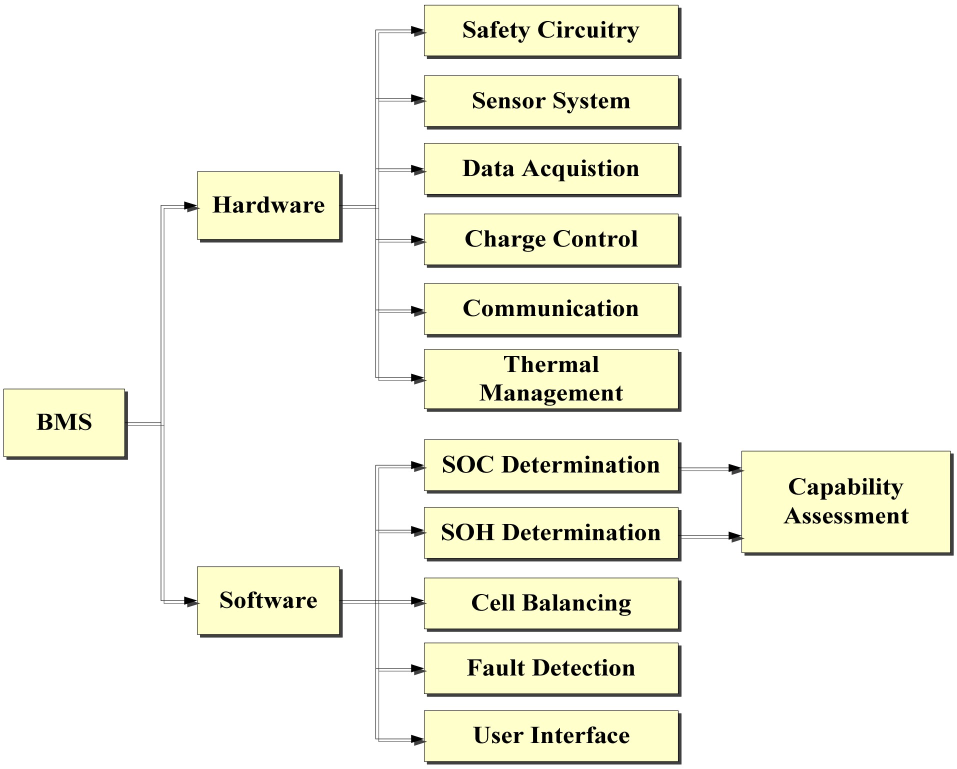
$$Q = a \cdot \exp\left(b \cdot k\right) + c \cdot \exp(d \cdot k) \tag{11}$$

where Q is the capacity of the battery; k is the cycle number; a and b are the electrolyte resistance and transfer resistance respectively; and c and d stand for the aging rates. The virtue of this model is that Bayesian Monte Carlo (BMC) updating is performed by regression analysis. The initial values of a, b, c, and d are defined by the weighted sum of the model parameters obtained from the training data. The Dempster-Shafer model is used to get an initial point for BMC updating. Model parameters are updated by BMC to track the degradation trend of the testing battery.

5. A Proposed Battery Management System

The weaknesses of current BMSs are identified through a comprehensive review of the existing approaches. To tackle these weaknesses, we suggest that a comprehensive and mature BMS should contain the components shown in Figure 3 as basic functions.

Figure 3. Components of the proposed BMS.



5.1. Hardware

Safety circuitry has long been used in BMSs. However, since more sensors are used in the proposed BMS, improvements in current safety circuitry designs can be implemented, such as the addition of accurate alarms and controls to prevent overcharge, over-discharge, and overheating.

The sensor system consists of different sensors to monitor and measure battery parameters including cell voltage, battery temperature, and battery current [17]. Some researchers have proposed adopting EIS to monitor internal impedance [12,26]. However, both space constraints and device cost hinder the feasibility of these measurements outside laboratory environments. Thus, current, voltage, and temperature should be measured to improve the capability of state tracking in real life applications.

Data acquisition (DAQ) and data storage are critical parts for the software in the BMS to analyze and build a database for system modeling.

Charge control is a subsystem governing the charge-discharge protocol. Batteries are often charged by the constant current/constant voltage method (CC/CV) and will thus need to include a potentiostat and a galvanostat. A variable resistor may be necessary to help balance cells or perform internal resistance measurements. Cell balancing control is still a critical design feature with room for improvement in order to equalize the battery pack and estimate the battery status in an efficient way.

Most subsystems in a BMS are stand-alone modules, and hence, data transfer throughout the BMS is required. Communication through a CAN Bus is a major way to transfer data within the BMS [17,38]. With the development of smart batteries, more data can be collected to communicate with the user and the charger through the microchips incorporated within the battery. In addition, wireless and telecommunication techniques are gradually being incorporated into charging systems that facilitate communication between the battery and the charger.

A module for thermal management is critical because temperature differences have an impact on cell imbalance, reliability and performance. Thus, Pesaran [39] pointed out that it is important to reduce the temperature difference among cells, which must be monitored and operated under proper temperature conditions.

5.2. Software

The software of the BMS is the center of the whole system because it controls all hardware operations and analyses of sensor data for making decisions and state estimations. Switch control, sample rate monitoring in the sensor system, cell balancing control, and even dynamic safety circuit design should be handled by the software of a BMS. Moreover, online data processing and analysis are required for continually updating and controlling battery functions. Reliable and robust automated data analysis is a key factor for success because the analysis determines state estimation and fault detection. This information will be shown to the user through a user-friendly interface with appropriate suggestions. The specific functions of the BMS software are discussed below.

Determination of SOC and SOH will be integrated into a capability assessment, which also presents the life status of the battery and sets the operating limits according to state-of-the-art algorithms, such as fuzzy logic, neural networks, state-space-based models, and so on [17,27,29].

The objective of cell balancing is to maximize battery performance without overcharging or over-discharging. Its nature is to make the SOC levels of cells closer to each other. The controller will control the charge process based on a comprehensive strategy that depends on the SOC of each cell. Thus, the accurate SOC estimation of each cell is basic for improving the balancing.

Most soft faults will be discovered through online data processing. An intelligent data analysis is required in order to provide battery fault warning and indicate out-of-tolerance conditions. Historic data will be recorded and provide the pre-alarm condition before the possible faults.

The user interface should display the essential information of the BMS to the users. The remaining range should be indicated on the dashboard according to the SOC of the battery. Additionally, abnormal alarming and replacement suggestions are needed to inform the users in terms of the estimation and prediction of the battery.

6. Challenges of BMS and Possible Solutions

A literature review has revealed that BMSs are still in a premature stage [40]. Even if state-of-the-art algorithms and monitoring methods were developed and applied in EVs and HEVs, the reliability of BMSs would still make end users suspicious. Thus, the gap between the laboratory tests and the real requirements should be addressed by future research.

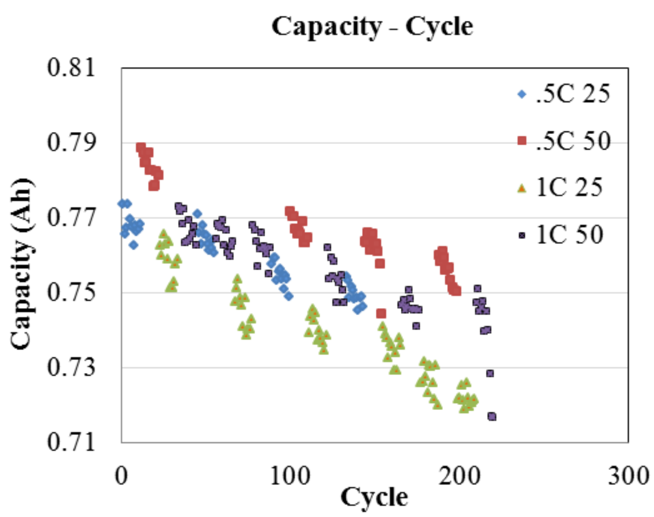
6.1. Challenges

Methodologies to assess battery performance were demonstrated in Section 4 and their characteristics were illustrated as well. Generally, the estimation and prediction methods have unfeasible hardware requirements, such as, impedance measurement, which is costly and not practical in many BMS applications today. Meanwhile, the high computational complexity depends on costly hardware, such as, the central processor. It can be seen that the tradeoff between high performance and feasibility in a BMS is important. Furthermore, most studies are performed in a laboratory environment and are conducted using full charge-discharge cycles. The performance of BMSs under operating conditions, such as vibration from bumpy roads and temperature extremes from snow, rain or summer heat, has rarely been studied. These external loads will be reflected in the battery's available capacity. Thus, it will add un-modeled effects not taken into account in existing algorithms and models. Moreover, with the growth of battery applications, disposal and recycling problems also arise. The problems facing vehicle BMSs are summarized below.

6.1.1. Capacity Estimation under Varying Loads and Environmental Temperatures

Battery degradation models are based on specific materials, environmental conditions, and charge-discharge cycling. Battery status is estimated when discharging at constant current and constant temperature. Ng [25] illustrated the SOC matrix related to the discharge voltage and different discharge rates of lithium-ion batteries (CGR 18650 from Panasonic Co.). However, when it comes to the combined factors, the degradation model based on the single influence factor is subject to query. Figure 4 shows the capacity profile that was tested under two discharge rates and temperatures alternatively.

Figure 4. Discharge capacity alternating at the different discharge rates with different temperatures**.**



The objective of our experiment was to simulate the application under the combined factors. The conditional parameters are listed in Table 2. As Figure 4 shows, the capacity profile moved up with a higher temperature under the same discharge rate, while it went down with a higher discharge rate at the same temperature. Thus, the combined factors increased the complexity of the capacity estimation more than by considering temperature fluctuation or varying discharge current alone.

Table 2. Experiment factors—different discharge rates and temperatures.

Discharge Rate	Temperature
0.5C (350 mA)	25 °C
0.5C (350 mA)	50 °C
1C (700 mA)	25 °C
1C (700 mA)	50 °C

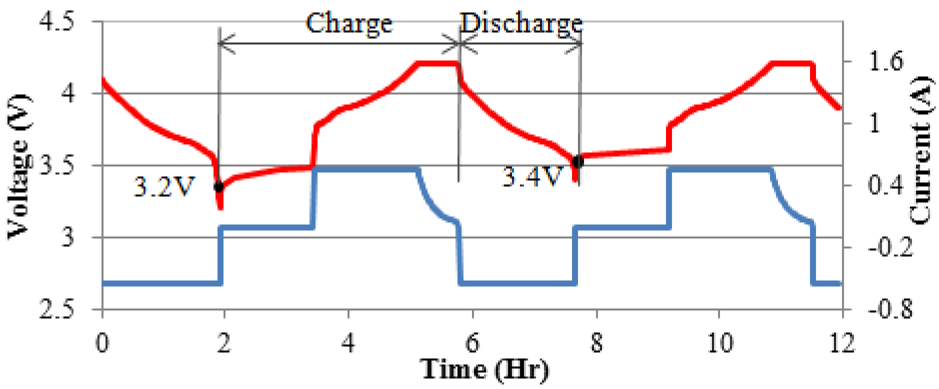
6.1.2. Estimation of Maximum Capacity

The maximum capacity of the battery determines the performance and future life of the battery. The current method for estimation is largely based on the full discharge test. The online capacity is calculated by:

$$\text{Capacity} = \int I dt \tag{11}$$

The longer the integration time, the higher the capacity will be. When the battery is fully discharged at a constant current, the maximum capacity is equal to the result obtained by Equation (11). However, the battery will not be always discharged at a constant discharge current and will not be depleted to the cut-off voltage every time. Figure 5 shows a battery discharged at different depths of discharge. The battery was charged to the full charge, 4.2 V, and stopped discharging at random cut-off voltages. This simulates operation in the real world. Thus, determining how to assess the maximum performance of a battery with partial discharge and variant current loads is a key challenge.

Figure 5. Partial discharge curve.



6.1.3. Communication Mechanisms

In practice, the battery needs to communicate with the internal vehicle modules, the charger and external environments through the BMS. The communication between internal modules is relatively mature through a CAN bus, which is standard in vehicles manufactured today [6]. The system management bus (SMBus) was developed to communicate with the charger with the appearance of a smart battery. This battery is able to transmit battery data, such as, the current condition, usage history, and SOC indication through the SMBus. Currently, it is difficult to make the interaction mechanism with the charger uniform due to the different manufacturers and applications. Furthermore, wireless technology is also being developed not only to gather external environment data, such as, humidity and vibration, but also to communicate between the battery and the charger. In such a process, the reliability and interference of data transmission is essential.

6.1.4. Assessment of Battery Health

Assessment of battery health is a concern for manufacturers. Since battery technology in EVs is not yet mature, a specific reference or standard needs to be built based on a large database system. In addition to capacity and energy, more weight factors may be combined to evaluate the health status, such as, an increase in cell resistance, a decrease in actual capacity, and the number of charge/discharge cycles.

6.1.5. Battery Disposal and Recycling

As the amount of batteries consumed increases exponentially, disposal has become a significant issue. Tesla has implemented a recycling strategy that reuses or recycles over 60% of a battery's materials [41]. Once pack production volumes increase, this recycling percentage will be raised up to 90%. The battery of Tesla's Roadster consists of 6831 cells that are assembled in 11 sheets. It would be a huge waste of resources if there were no recycling. Unfortunately, from the perspective of most manufacturers, the high recycling costs and the complex disposal process are not worth the effort of implementing an environmentally friendly recycling strategy.

6.2. Possible Solutions for BMSs

Prognostics and health management (PHM) is an enabling strategy consisting of technologies and methodologies for BMSs. By monitoring the sensor signals and processing real-time data from a BMS, the battery status, including SOC, SOH, and SOL, can be estimated and predicted to provide end users with an accurate "gauge meter" in an EV or HEV. Based on the data collected, the BMS determines the corresponding maintenance strategies. Meanwhile, abnormality detection can be used to capture signals to update the predictive results and guarantee the safety and reliability of batteries.

In terms of inaccessible internal reactions of the battery and varying external loads, accurate battery modeling should be established that takes into account imposed factors. Regression technology combined with the state-space models are proposed as a competitive approach for battery degradation modeling. The regression approaches use data training to fit degradation trend curves based on specific battery materials. Once the Markov process utilizes the fitted parameters as its initial information, the empirical degradation characteristics can be combined with the real-time state information to achieve accurate predictive results. Our view is to measure and collect current, voltage, and temperature as the main operational parameters in order to improve feasibility and reduce design costs.

Different driving patterns cause different loads on batteries. The battery power profile can be used to determine the effects of driving behavior on the performance and life of an EV battery. The U.S. Advanced Battery Consortium (USABC) calculated a battery power-time profile for an Improved Dual

Shaft Electric Propulsion (IDSEP) minivan and specified it in the USABC Electric Vehicle Battery Test Procedures [42]. The first step was to map the operational parameters onto the battery loads, such as power or discharge current. A reference point for capacity (*i.e.*, initial fully discharged) was then established to calculate the maximum capacity of the battery.

High costs and the time-consuming nature of these processes are obstacles when it comes to the battery recycling. Due to the large number of surviving cells in a failed battery pack, quick screening methods need to be developed to verify the performance of each cell when recycling a battery pack. It is helpful to classify the unknown batteries in terms of the extent of degradation. Meanwhile, the indication test for a cell with high performance and long life is also important. However, since the battery degradation mechanisms vary in different environmental conditions due to electrochemical characteristics, an accelerating life test is difficult to conduct to estimate battery life at normal conditions. Uno [24] studied the influence of high frequency on the life performance of lithium-ion cells. He showed that high frequency testing had little impact on the calendar life of lithium-ion cells. Thus, the high frequency signal should be developed for screening tests on battery calendar life.

7. Conclusions

As batteries are the core energy sources in EVs and HEVs, their performance greatly impacts the salability of EVs. Therefore, manufacturers are seeking for breakthroughs in both battery technology and BMSs. Chemical reactions in the battery are subject to operating conditions, and hence, the degradation of a battery may vary in different environments. Developing a comprehensive and mature BMS is critical for manufacturers who would like to increase the market share of their products. The major concerns of BMSs were discussed in this paper. They include battery state evaluation, modeling, and cell balancing, wherein the evaluation methodologies of battery status were viewed as the crucial issue. Thus, related work on the SOC, SOH, and SOL of batteries were reviewed with comparisons. A BMS framework was proposed to deal with the deficiencies of current BMSs in both research and commercial products. Based on previous work, specific challenges facing BMSs and their possible solutions were presented as a solid foundation for future research. Due to varying situations in real-world applications, a standard solution was not wanted. Based on the specific situation, different strategies should be applied to improve and optimize the performance of BMSs in future EVs and HEVs.

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