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REVIEW ARTICLE

Review of state-of-the-art battery state estimation technologies for battery management systems of stationary energy storage systems

Seongyun Park[1] · Jeongho Ahn[1] · Taewoo Kang[1] · Sungbeak Park[2] · Youngmi Kim[2] · Inho Cho[3] · Jonghoon Kim[1]

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Abstract
Lithium-ion batteries have recently been in the spotlight as the main energy source for the energy storage devices used in the renewable energy industry. The main issues in the use of lithium-ion batteries are satisfaction with the design life and safe operation. Therefore, battery management has been required in practice. In accordance with this demand, battery state indicators such as the state-of-charge (SOC), state-of-health (SOH), state-of-function (SOF), and state-of-temperature (SOT) have been widely applied. The use of these indicators ensures safe operation without overcharging and over-discharging. In addition, it can also help satisfy the design life. This paper presents a literature review of battery state indicators over the last three years and proposes the requirement of state-of-the-art battery state indicators. It also suggests future developments for battery management system (BMS) in stationary energy storage systems (ESSs).

Keywords Rechargeable battery · Lithium-ion battery · Battery management system · State indicator · Stationary energy storage system

1 Introduction

Recently, CO_2 emission have been limited to constrain global warming under the Paris Climate Agreement of 2015. Therefore, the use of internal combustion engines has been decreasing, and the use of eco-friendly energy sources, especially batteries, has been rapidly increasing as a replacement [1]. Among eco-friendly energy sources, lithium-ion batteries have been widely used in the energy industry as a replacement for lead-acid batteries and Ni-MH batteries since they offer the advantages of high energy and power densities, long life expectancy, and low self-discharge rate. Thus, lithium-ion batteries have been adopted in many energy storage systems (ESSs) [2, 3]. However, lithium-ion batteries have an economic disadvantage owing to their need for expensive raw materials such as cobalt, which means these batteries make up a significant portion of the price of applications, as shown in Fig. 1a [4, 5]. Battery-based ESSs can be divided into stationary ESSs and mobile ESSs as shown in Fig. 1b. Stationary ESSs include photovoltaic/wind power generation connected ESSs, uninterruptible power supplies (UPSs), and emergency power supplies (EPSs). Meanwhile, mobile ESSs include electric vehicles (EVs), submarines, and electric railroads. According to Bloomberg New Energy Finance (BNEF), energy storage installation will be increase from 9 GW in 2018 to 1,095 GW in 2040 [6]. In addition, the Korean government has announced its Renewable Energy 3020 Implementation Plan (RE3020). The goal of this policy is for renewable energy to comprise 20% of all power generation by 2030 [7]. Under current energy policies and market trends, the interest in and demand for stationary ESSs are increasing daily. However, the Korea Ministry of Trade, Industry and Energy (MOTIE) announced that stationary ESSs have caught fire or exploded 29 times between 2017 and 2020 in Korea. As the MOTIE pointed out, the cause of fires in stationary ESSs are batteries and their management, which has resulted in an increase in the importance of battery management systems (BMSs) [8]. BMSs should be designed to satisfy safe operation and design life requirements by providing state indicators such

✉ Jonghoon Kim
whdgns0422@cnu.ac.kr

1 Department of Electrical Engineering, Chungnam National University, Daejeon, Republic of Korea

2 Department of Nuclear Safety Research, Korea Institute of Nuclear Safety, Daejeon, Republic of Korea

3 Propulsion System Research Team, Smart Electrical and Signaling Division, Korea Railroad Research Institute, Uiwang, Republic of Korea

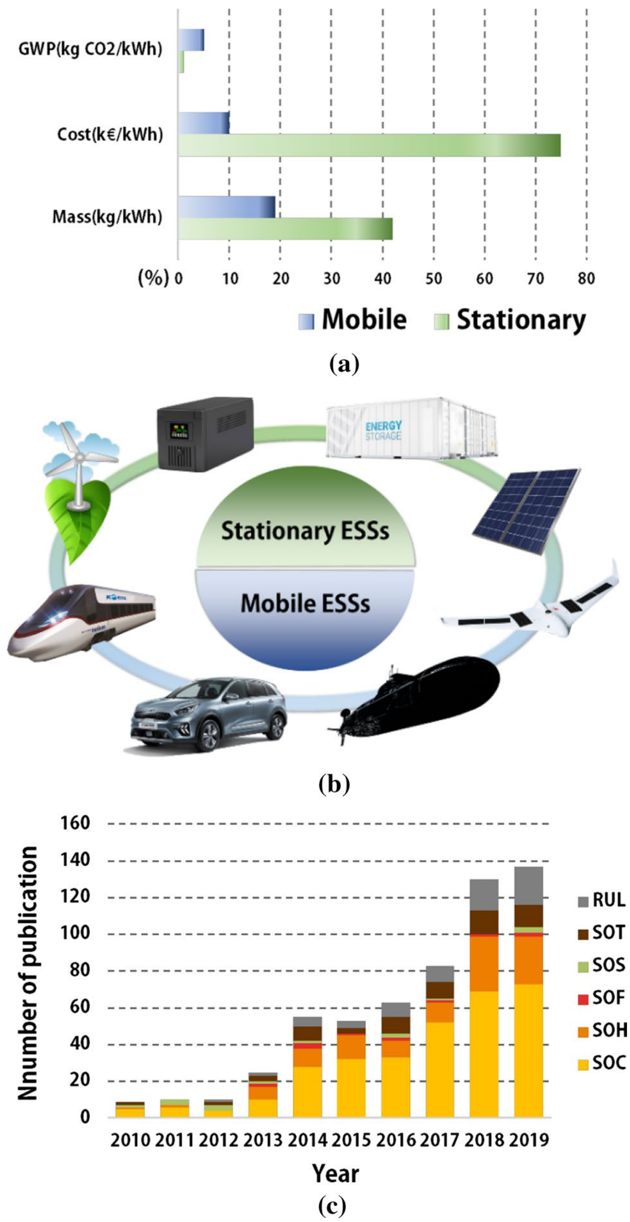

Fig. 1 Overview of ESSs and battery states: **a** energy supplied for different examined systems (normalized per kWh) [5], **b** classification of stationary ESSs and mobile ESSs; **c** number of publications focused on battery states in the last 10 years

as state-of-charge (SOC) [9], state-of-health (SOH) [10, 11], state-of-function (SOF) [12], and state-of-temperature (SOT) [13–15]. In addition, BMSs should be designed considering the operating characteristics of the intended applications and their environmental conditions since the performance of lithium-ion batteries varies with different operational conditions such as the magnitude of the current and the depth of discharge (DOD), as well as environmental conditions such as lower or higher temperatures [16–20]. As a result of these battery characteristics, it is very difficult to estimate the battery state accurately. Thus, many researchers have developed battery state estimation methods. Figure 1c shows the trend in terms of the number of papers published on lithium-ion batteries and various battery states from 2010 to 2019 in the Web of Science database (https://apps.webofknowledge.com).

This paper reviews studies published in the last three years on key indicators in BMSs to ensure safe operation and design life. It also suggests future development directions. The organization of this paper is as follows. Section 2 introduces definitions of a number of battery state indicators (SOC/SOH/SOF/SOT). Methodologies for estimating battery state indicators are presented in Sect. 3. Section 4 makes some suggestions for future development of BMSs to guarantee improved accuracy of the state indicators. Finally, some conclusions are presented in Sect. 5.

2 Definitions of state indicators

2.1 State-of-charge (SOC)

SOC is the key battery state indicator to describe how much energy remains in a battery. SOC is similar to the fuel gauge in internal combustion engine vehicles. The SOC provides information to prevent phenomena such as overcharging or over-discharging. It is also used as a performance indicator to determine how much energy can be given to or received from an ESS. In addition, SOC can be the basis of other battery state indicators, such as state-of-function (SOF) and state-of-safety (SOS). Therefore, high SOC estimation accuracy is required to minimize errors for other battery states, to protect against hazardous failures, and to manage the operating conditions of the BMS. However, SOC cannot be measured directly. Thus, SOC should be estimated based on measurable information from the battery, such as current, voltage, and temperature [21–23]. The SOC is generally defined as the ratio of the currently available charge/discharge capacity to the maximum available charge/discharge capacity during operation. SOC can be calculated as follows:

$$\mathrm{SOC}(k) = \mathrm{SOC}(k-1) - \int_{t-1}^{t} \eta \frac{I(\tau)}{Q_n} \mathrm{d}\tau, \tag{1}$$

where τ used as a placeholder for the time variable in the integral, and $SOC(k)$ and $\mathrm{SOC}(k-1)$ are the SOC at time k and time $k-1$, respectively. In addition, η is the Coulombic efficiency, $I(\tau)$ is the current (positive values correspond to discharging and negative values indicate charging), and Q_n is the nominal capacity of the battery. Numerically, the accuracy of SOC depends on the sampling period and the accuracy of the current sensor since SOC is calculated as the integral of the current I and the time between $t-1$ and *t*. Therefore, good accuracy of the current sensor and a short sampling period are required to estimate the SOC accurately. Another reason that SOC estimation is difficult is that the nominal capacity changes under various conditions. Q_n can be changed by battery aging and external and internal conditions such as changes in temperature and mechanical stresses [23]. As mentioned previously, SOC is tightly coupled with other battery states and is affected by environmental conditions. Thus, the design of a highly accurate SOC estimation method is a key issue in BMSs.

2.2 State-of-health (SOH)

As a battery ages, its performance degrades, and the battery will need to be replaced when the maximum available charge/discharge capacity reaches 80% of the nominal capacity. In other words, when the battery has reached its end-of-life (EOL). This means the battery can no longer respond to the demanded peak load.

Widely used parameters for estimating SOH are the maximum available charge/discharge capacity and the internal resistance of the battery during battery aging. SOH can be calculated as follows [24]:

$$\mathrm{SOH_c} = \frac{Q_\mathrm{c}}{Q_\mathrm{n}} \times 100, \tag{2}$$

$$\mathrm{SOH_R} = \left| \frac{R_\mathrm{c} - R_\mathrm{a}}{R_\mathrm{n} - R_\mathrm{a}} \right| \times 100, \tag{3}$$

where $\mathrm{SOH_C}$ and $\mathrm{SOH_R}$ are the SOH based on the capacity and the internal resistance, respectively. In addition, Q_C is the maximum available charge/discharge capacity during battery aging, R_n is the initial internal resistance of the battery, R_C is the current internal resistance, and R_a is the internal resistance of an aged battery at the EOL. However, to estimate SOH based on resistance, a reference value of the resistance that can be determined during aging must be obtained through prior experiments or as a correlation between the capacity and the resistance. The battery internal resistance depends on the electrode material. Thus, it is difficult to determine EOL based on resistance. Nevertheless, resistance is an important parameter for estimating battery health since the available capacity and power of the battery are strongly related to the internal resistance [25].

The battery aging mechanism is very complex due to various aging stress factors. Some studies have investigated the factors that degrade batteries, such as operating time, high/low temperature, high/low SOC, high/low voltage, high current rate, and high pressure. With these aging stress factors, a battery should lose lithium inventory and active material, and exhibit increased impedance [26, 27]. These factors lead to battery capacity degradation. Thus, SOH is decreased by aging stress factors. SOH also affects various battery state indicators. In addition, SOC is affected by changes in SOH. Therefore, inaccurate SOH estimation can compromise battery system safety and reduce the operational efficiency of ESSs. As a result, SOH estimation is a key factor for estimating and predicting various battery state indicators, and is the basis for determining the remaining useful life (RUL) of a battery.

2.3 State-of-function (SOF)

Battery manufacturers generally provide users with limitations such as the battery's upper/lower limit voltage, charge/discharge limit current, and operating temperature range to ensure battery safety. To ensure the safety of a battery, it must operate within the safe operating area (SOA) suggested by the manufacturer [28]. The SOA should be changed due to battery aging and environmental conditions, and battery function degrades as a result of deteriorating feature variables such as resistance and capacity as shown in Fig. 2. In addition, prediction of the maximum instantaneous power capability is required when ESSs increase in response to an increasing demand for higher power. Thus, SOF has been used as a battery state indicator to predict the maximum instantaneous output capability and operation within the SOA [29]. According to the definition of SOF, it can be calculated as follows [30]:

$$P(t) = P_\mathrm{max} \cdot \mathrm{SOC}(t) \cdot \mathrm{SOH}(t), \tag{4}$$

$$\mathrm{SOF}(t) = \frac{P(t) - P_\mathrm{d}(t)}{P_\mathrm{max} - P_\mathrm{d}(t)}, \tag{5}$$

where $P(t)$ and $P_\mathrm{d}(t)$ are the instantaneous output provided by the battery and the power demand at time *t*, respectively.

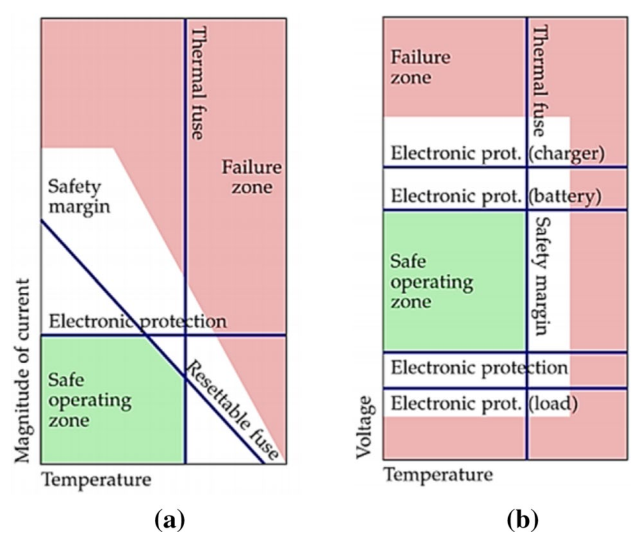

Fig. 2 Example of a SOA zone for protection [31]: **a** current–temperature SOA zone; **b** voltage-temperature SOA zone

In addition, P_{max} is the maximum power that a battery can provide to a load when the battery is fresh [30]. As shown in Eq. (4), SOF is affected by the accuracy of SOC and SOH. Thus, a parallel structure for battery state indicators can experience a large error due to chain reactions.

2.4 State-of-temperature (SOT)

The dynamic characteristics of a battery are very sensitive to and depend on temperature. In addition, increasing demand for high-density battery packs is inevitable since high-energy ESSs are required. As a result, high-density battery packs face thermal management issues due to heat generation during the charging/discharging operation.

When battery cells and packs operate outside the proper temperature range, the decrease in battery capacity and increase in resistance are accelerated. Furthermore, the battery can be induced to thermal runaway due to the occurrence of mechanical, electrical and thermal stresses [32]. Therefore, understanding the characteristics of heat generation and dissipation in lithium-ion battery cells and packs has become very important.

Abada et al. [33] presented a thermal model based on the energy balance between the heat generation and the heat dissipation as follows:

$$\frac{\mathrm{d}}{\mathrm{d}t}Q_{\mathrm{accu}} = \rho C_{\mathrm{p}}\frac{\partial T}{\partial t} = \frac{\mathrm{d}}{\mathrm{d}t}Q_{\mathrm{gen}} - \frac{\mathrm{d}}{\mathrm{d}t}Q_{\mathrm{dis}}, \tag{6}$$

where ρ, C_{p}, T, and t are the cell density, heat capacity, cell temperature, and time, respectively. In addition, Q_{accu}, Q_{gen}, and Q_{dis} are the accumulated heat, generated heat, and dissipated heat, respectively. Q_{gen} includes the reversible heat and irreversible heat generated by chemical reactions. Q_{dis} consists of heat transfer mechanisms such as conduction, convection, and radiation. Based on this thermal model, the electrochemical-thermal model and electro-thermal model were introduced, as summarized in Table 1 [34, 35]. In addition, the symbols and parameters of the electrochemical-thermal model are presented in Table 2. The electrochemical-thermal and electro-thermal models are widely used as heat generation models to analyze battery thermal behavior.

The electrochemical-thermal model presents the heat generated by the chemical reactions of a lithium-ion battery, such as over-potentiation at the reaction surface, ohmic loss in the electrodes, ion transport in the solid electrolyte

Table 1 Comparison of the electro-thermal model and the electrochemical-thermal model

Item	Electrochemical-thermal model [34]	Electro-thermal model [35]
Heat generation	Over-potentiation at the reaction surface: $q_{\mathrm{rxn}} = \frac{V_{\mathrm{ca}}}{V_{\mathrm{batt}}}\frac{RT}{\varepsilon_{\mathrm{ca}}^2 F^2\sqrt{k_{\mathrm{c}}k_{\mathrm{a}}(C_{\mathrm{s,max}}-C_{\mathrm{s}})C_{\mathrm{s}}}}I^2$ Ohmic loss in the electrode: $q_{\mathrm{ohm}} = \frac{\varepsilon_{\mathrm{elec}}V_{\mathrm{elec}}}{V_{\mathrm{batt}}}\frac{1}{A^2\sigma_{\mathrm{eff}}}I^2$ Ion transport in the SEI and electrolyte: $q_{\mathrm{trans}} = \frac{I^2}{\sigma_{\mathrm{SEI}}A^2} + \frac{\varepsilon_{\mathrm{sp}}V_{\mathrm{sp}}}{V_{\mathrm{batt}}}\frac{I^2}{A^2\kappa(2+t^+)}$ Entropy: $q_{\mathrm{rev}} = \frac{V_{\mathrm{ca}}}{V_{\mathrm{batt}}}ai\cdot T\frac{\partial U}{\partial T}$ Irreversible heat: $q_{\mathrm{irrev}} = \frac{I^2}{\sigma_{\mathrm{eq}}A^2} + \frac{I}{\varepsilon_{\mathrm{ca}}V_{\mathrm{batt}}}T\frac{\partial U}{\partial T}$ Total heat generation: $q_{\mathrm{gen}} = q_{\mathrm{rxn}} + q_{\mathrm{ohm}} + q_{\mathrm{tran}} + q_{\mathrm{rev}}$	Reversible heat: $q_{\mathrm{rev}} = IT\frac{\partial U}{\partial T}$ Irreversible heat: $q_{\mathrm{irrev}} = I(U-V) = I^2R$ Total heat generation: $q_{\mathrm{gen}} = I(U-V) - IT\frac{\partial U}{\partial T}$
Heat dissipation	Conduction: $Q_{\mathrm{cond}} = -kA\frac{\mathrm{d}T}{\mathrm{d}x,y,z}$ Convection: $Q_{\mathrm{conv}} = hA(T_{\mathrm{surface}} - T_{\mathrm{environment}})$ Radiation: $Q_{\mathrm{rad}} = \varepsilon A\sigma(T_{\mathrm{hot}}^4 - T_{\mathrm{cold}}^4)$ (neglect in common temperature regions for commercial battery)	

Table 2 Electrochemical-thermal model symbols and parameters [34]

Symbol	Parameter	Symbol	Parameter
V_{ca}	Volume of cathode	A	Area
V_{batt}	Volume of battery	σ_{eff}	Effective electrical conductivity
V_{elec}	Volume of anode	σ_{SEI}	Solid phase conductivity
V_{sp}	Volume of separator	σ_{eq}	Equivalent conductivity
$\varepsilon_{\mathrm{ca}}$	Porosity of cathode	C_{s}	Concentration of intercalated Li
$\varepsilon_{\mathrm{elec}}$	Porosity of anode	κ	Ionic conductivity
$\varepsilon_{\mathrm{sp}}$	Porosity of separator	a	Specific area
k_{c}	Kinetic constant of cathode	i	Current density
k_{a}	Kinetic constant of anode	F	Faraday constant

interphase (SEI), and entropy during charging/discharging. The physical meaning of battery operation can be explained by the electrochemical-thermal model. However, the model has a high computational burden due to the large number of equations that are needed to predict battery temperature.

The electro-thermal model was derived through electric parameters replacing electrochemical terms in electrochemical-thermal model for a full-cell [36]. The generated heat in the electro-thermal model depends on irreversible heat since reversible heat is very small when compared to irreversible heat when the battery provides a high current [37].

When compared to the electrochemical-thermal model, the number of required computations is low enough to allow the electro-thermal model to be scaled up to battery module and system levels. Prediction errors can occur due to battery parameters such as the open-circuit voltage (OCV) and resistance.

Although an understanding of the thermal behavior of a battery is very important, the SOT has yet to be defined with a specific meaning. However, efforts to minimize the stress of batteries are being pursued intensively [34–41] by increasing the safety requirements of stationary ESSs over the past 3 years.

3 Methodologies for state indicator estimation

3.1 Research trends of SOC

Many researchers have studied accurate estimation methods for SOC, as shown in Fig. 3. SOC estimation methods can be categorized as conventional methods, model-based methods, and data-driven methods. Conventional methods include the Ah counting method [42], the OCV method [43], and the impedance track method [44]. These methods are easy to understand and have low computational costs for implementation. However, the accuracy of SOC estimation can deteriorate due to error accumulation from the current sensor and the initial value offset, as well as changes in the parameters due to temperature and aging.

Model-based methods are widely used to estimate SOC via a battery equivalent circuit model (ECM). There are two main ECMs: the electrochemical ECM [45] and the electrical ECM [46–49]. The electrochemical ECM can usually guarantee the accuracy of the SOC estimation since it aims to understand the electrochemical reactions between full cell components such as the SEI, the electrolyte, and the electrode [49]. To guarantee its accuracy and representation of kinetics, many partial differential equations are required. In addition, it is difficult to scale up to battery packs and battery systems. Therefore, the electrochemical model is not suitable for the BMSs in large-scale ESSs [50]. On the other hand, the electrical ECM has a simple structure consisting of a voltage source, a resistance, and a capacitor as shown in Fig. 4. The 1st order RC model is widely used in the model-based method to consider the trade-off between accuracy and computation burden. R_{i}, R_{Diff}, C_{Diff}, and V_{Diff} are ohmic resistance, diffusion resistance, diffusion capacitor, and diffusion voltage. The parameters of the electrical ECM can be obtained through electrical characteristics tests such as OCV tests and hybrid pulse power characterization (HPPC) tests, and can be expressed mostly as functions of SOC and temperature. This model is easy to scale up to large battery systems. However, the basis of the employed electrical characteristics test is required to increase the accuracy of SOC estimation.

The accuracy of model-based methods depends on the model accuracy. Model-based methods mostly adopt adaptive filter algorithms such as a Kalman filter (KF) for control with the aim of minimizing errors, where the error is the difference between the measured terminal voltage and the model voltage. Model-based methods can generally achieve good accuracy when compared to other methods [51].

Data-driven methods do not require a battery model or deep knowledge of the battery. Therefore, they are referred to as model-less methods. Many data-driven methods have been studied for battery SOC estimation, such as neural network [52–54], fuzzy logic [55–57], support vector machine

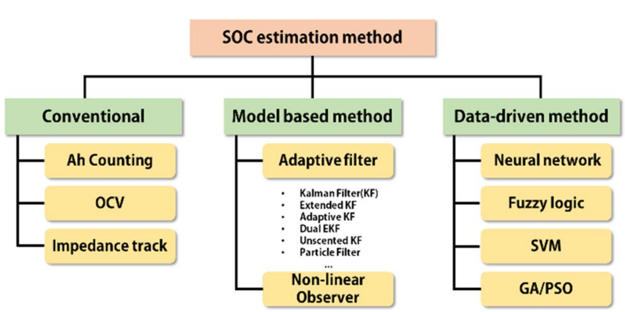

Fig. 3 Classification of SOC estimation methods

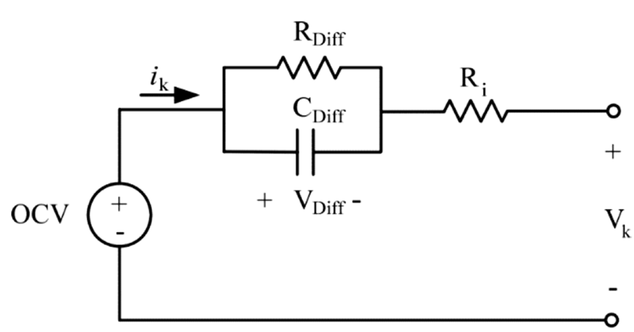

Fig. 4 Electrical equivalent circuit (1st order RC model)

(SVM) [58], genetic algorithm (GA) [59], and particle swarm optimization (PSO) [60] based methods. When a data-driven model is trained using a data set (such as the voltage, current, and temperature) related to the SOC, the result is highly accurate. However, this requires a large number of training data sets and validation sets, and the results can be divergent if the model works under different conditions than those in which the model was trained [61].

The research trends in SOC estimation over the last three years are presented in Table 3. They can be seen as comprising six topics: robust design [62, 63], online parameter identification [64–66], development of adaptive filter algorithms [67–70], data-driven methods [71–74], scaling [75, 76], and hardware-in-the-loop [77, 78]. Research trends reveal that the following characteristics are required to accurately estimate the SOC.

1. Robust design under current sensor and model errors.
2. Time-saving and accurate methods for extracting battery model parameters.
3. Improved accuracy and low-computation adaptive filter algorithms.
4. Designs considering inconsistencies between series and parallel-connected batteries.
5. Model-free and formula-free estimations.
6. Reductions in the development cycle and cost.

As mentioned previously, both the current sensor error and the model error affect the accuracy of the current sensor and the ECM. In [63], Xin Lai proposed a credible SOC increment method combined with the Ah counting method and an extended KF for a water tank model, even in the presence of large errors in the current sensor and model. The drift of the current by the sensor was assumed to be within 0.1–1%, and the model error was within 50 mV. Correlations between the measurement error, the model error, and the estimation method were analyzed to establish which factors produce noise to estimate the SOC via incremental methods when compared to a reference value.

Model-based methods are widely used to estimate SOC due to their accuracy and adaptability under various conditions. However, parameter identification and adaptive filter algorithms have numerous burdens for implementation since they require a large number of experiments and have a high computational cost. Reducing the number of experiments to identify battery parameters and the number of computations required are the main issues for model-based methods. Thus, adaptive filters based on least-squares have been used to identify parameters in real-time to reduce the parameter extraction experiments [64, 65]. In addition, adaptive filter algorithms still require a large number of computations, and can diverge as a result of negative covariance. Xuan et al. [67, 68] proposed the sigma point Kalman filter (SPKF) and the square root second-order central difference transform Kalman filter (SRCDKF) to reduce the computational complexity and to guarantee non-negative covariance. The computation cost is significantly decreased by adopting probability density functions instead of a complex non-linear model.

However, model-based methods require expert knowledge to design battery models. Data-driven methods can estimate SOC using measurable variables such as voltage, current, and temperature without the need for a battery model or a precise formula. Furthermore, early learning algorithms such as SVM and neural networks that are widely used to estimate SOC must be designed manually to extract features from raw data and have low accuracy due to their shallow learning structure [71]. Bian et al. [71–74] proposed both stacked bidirectional long short-term memory networks (SBLSTM) and an LSTM-based estimator. SBLSTM adopts a bidirectional structure to capture temporal information in the forward and reverse directions, and increases the number of layers as a multi-layer to improve estimation accuracy.

Hu et al. [75, 76] proposed a series-connected battery pack SOC estimation method based on a fuzzy system. For the SOC estimation of a battery pack, the mean-plus-difference model considering inconsistencies among the cells is used instead of big cell, multi-cell, or $V_{\min} + V_{\max}$ models. A local filter and master filter are used to estimate the SOCs of cells and to fuse these SOCs to estimate the battery pack SOC. In addition, an SOC-based inconsistency adaptive method was proposed using a fuzzy system. In addition, it derives the distribution characteristics between cells SOCs. The accuracies of SOC estimations with online parameter identification and offline parameter identification for battery packs have inconsistencies of less than 0.6% and 1.5%, respectively. To reduce the development cost and time, a realistic battery simulation model is needed. Developers can save development time and cost with a hardware-in-the-loop simulator, which simulates how batteries work using ECMs under various operating and environmental conditions [77, 78].

Table 3 Research trends for SOC estimation over the last 3 years

Research trend	References
Robust design	[62, 63]
Online parameter identification	[64–66]
Development of adaptive filter	[67–70]
Data-driven method	[71–74]
Scaling	[75, 76]
Hardware in the loop	[77, 78]

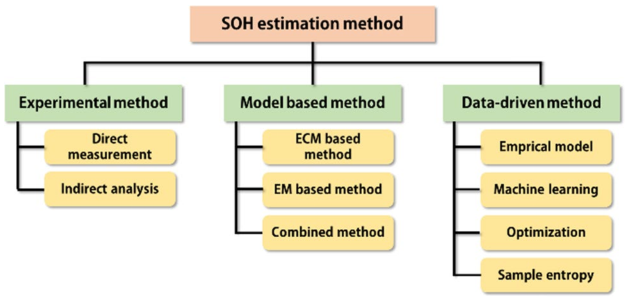

Fig. 5 Classification of SOH estimation methods

3.2 Research trends of SOH

In general, SOH estimation methods can be classified into three categories: (1) experimental methods, (2) model-based methods, and (3) data-driven methods, as shown in Fig. 5. Experimental methods can be classified as direct measurement or indirect analysis methods. For direct measurement methods, the capacity and resistance can be measured directly by the ampere-hour counting method [79] and electrochemical impedance spectroscopy (EIS) [80]. Meanwhile, incremental capacity analysis (ICA) [81], differential voltage analysis (DVA) [82], and health indicators [83–85] are used as indirect analysis methods. Experimental methods require a large amount of experimental data to determine how a given battery ages. These methods can provide good accuracy and information regarding battery aging. However, they are not easy to apply in practical applications since they require low currents (such as a 1/10 C-rate) during experiments for accurate measurement, and the applications should operate with a set routine to measure a certain interval [86].

Model-based methods for estimating the SOH of batteries are an extension of SOC estimation using model-based methods. Electrochemical ECMs and electrical ECMs have been commonly used to estimate the indicators related to battery health with SOC using adaptive filtering algorithms [87]. The dual extended Kalman filter (DEKF) is widely used to estimate SOH based on models with SOC. However, there is no mathematical formula for the battery capacity or resistance. It simply compensates for the posterior capacity when compared to the prior capacity using the Kalman gain [88]. Thus, the accuracy of SOH estimation with model-based methods still depends on the accuracy of the ECMs and SOC estimation. As mentioned previously, model-based methods have a trade-off. When the model becomes more complex, the computational cost increases.

Data-driven methods estimate SOH through empirical fitting, machine learning, optimization methods, and sample entropy based on the physical correlation between battery health and other feature variables rather than complex principles for batteries. However, SOH estimation with data-driven methods cannot reflect the physical behavior of a battery. Thus, data-driven methods are usually combined with experimental methods such as Ah counting [89], ICA/DVA [90], partial capacity [91], resistance (or impedance) [92] and model-based methods with adaptive filtering algorithms to complement each other [92–94].

Table 4 Research trends for SOH estimation over the last 3 years

Research trend	References
Correlation analysis	[95–98]
Parameter identification	[99, 100]
Real-time estimation	[101, 102]
Data-driven methods	[103–105]
Considering various conditions	[105]

The research trends in SOH estimation over the last three years are presented in Table 4. These trends can be summarized as comprising five topics: correlation analysis between capacity and other variables [95–98], parameter identification via new correlations for SOH [99, 100], implementation in real-time [101, 102], highly accurate data-driven methods [103–105], and various conditions [105]. The research trends in SOH estimation reflect the following development requirements.

1. New feature variables having high correlations with battery capacity.
2. Robust parameter identification for estimating capacity based on battery models and joint estimation with SOC.
3. High-accuracy and non-linear data-driven methods.
4. SOH estimation under various environmental and working conditions.
5. Real-time SOH estimation for updating other battery state indicators.

First, establishing a correlation between capacity and feature variables (which are regarded as having physical meanings related to the battery capacity) is required. Generally, the internal resistance [95, 96] and impedance [97] have been considered to have a high correlation with battery capacity. Thus, the battery capacity can be estimated by regression analysis between capacity and highly correlated parameters.

However, lithium-ion batteries can have different characteristics, even if they are used under the same operating and environmental conditions. Saxena et al. [99] presented a SOH estimation under different C-rates during discharge with a number of cells. The experimental results show that even for the same type of battery, the aging tendencies can differ. It was confirmed that the degradation of capacity gradually increased according to the discharge current magnitude. In addition, the capacity deviation between cells increases.

For model-based methods, SOC-SOH joint estimation methods have been widely used in the past three years by applying adaptive online parameter identification. Kim et al. [99] proposed a model-based SOC-SOH joint estimation method via the 2nd RC ladder ECM. They constructed a smooth variable structure filter (SVSF) for SOC estimation and used an extended Kalman filter (EKF) for SOH estimation. Most adaptive filtering algorithms require the setting of proper tuning parameters to ensure estimation accuracy. This problem was solved using PSO to tune the parameter optimization. According to the correlation between the capacity and the battery parameters in the ECM, the SOH can be obtained when the parameters vary, which is identified through recursive least square (RLS) and optimization algorithms [100].

Chen et al. [101, 102] demonstrated that the capacity and resistance in the initial and aged states can be predicted through the resistance and capacity relationship at any two points using the linear relationship between the capacity and the resistance in real-time. However, there is uncertainty in terms of ambient temperature and aging. Therefore, the battery ECM considered uncertainty has been established by the Bayes Monte Carlo method. The prediction error of the model is 20 mV at 5, 25 and 45 ℃. Accurate battery parameters can be provided to estimate battery capacity via the correlation between the capacity and the resistance through battery modeling. The degradation mechanism for battery capacity has characteristics that are very complex and nonlinear, and depend on DOD, temperature, operation history, and other stress conditions. Therefore, the model-based method cannot estimate SOH under various conditions.

A neural network is considered to be the most powerful method for solving non-linear problems. For instance, stacked-LSTM using past experience data. Qu et al. [103] introduced a combined LSTM and PSO method that can decrease computational burden and increase accuracy for a weight value. Deng et al. [104, 105] proposed a SOH estimation under two different working conditions using a least squares support vector machine (LSSVM). They also determined a new training data set for faster computation and improved accuracy, even if there were some abnormal training points in the training data set. In addition, effective capacitance via ICA/DVA and establishing the relationship via a charge curve such as charging time and charging current with a constant voltage charge step were introduced to avoid uncertainty in the discharge pattern. The degree of battery aging can be obtained from the peak position and magnitude. Results show that the fitting error for $Q=Q(V)$ was 4.4% and that the fitting error for $V=V(Q)$ was 0.9%, where Q and V are the battery capacity and voltage, respectively.

Cui et al. [106] implemented a fast method for determining SOH using SOH diagnosis ECM (SDEM). Generally, OCV variation is neglected during battery aging. However, the OCV recovery time changes due to an increase in the charge transfer impedance. In addition, a relationship is established between the charge transfer impedance and battery capacity. Therefore, the authors proposed a fast diagnosis system during a short relaxation time. Furthermore, partial DV/IC curves have been proposed to quickly estimate SOH with a Gaussian filter to reduce sensing noise [107]. Since SOH is a major factor that can affect various battery state indicators, the accuracy of SOH estimation should be guaranteed for safe operation.

3.3 Research trends of SOF

According to its definition, SOF is the maximum instantaneous power during the charge/discharge of the maximum power at a given capacity [108]. Therefore, SOF can be obtained through the state-of-power (SOP), which is the maximum instantaneous power of the battery. As a result, SOF can be redefined as the power life of a battery, as shown in Eq. (7), instead of using Eq. (5) [108].

$$\mathrm{SOF} = \frac{P_{\mathrm{max,pre}}}{P_{\mathrm{max}}}, \tag{7}$$

where P_{max} and $P_{\mathrm{max,pre}}$ are the maximum available power at a given battery capacity, and the maximum instantaneous power, respectively.

Widely used conventional methods consider the relationship between ECMs and the analysis variables correlated with SOF [109]. However, methods based on the analysis variables correlated with SOF [110] require a significant amount of prior work. Thus, recent research trends in SOF estimation have focused on model-based co-estimation with SOC and SOH [109, 110]. In addition, SOF is strongly related to SOC, SOH, and internal resistance, which can be used to calculate SOP more accurately. Therefore, online parameter identification is emphasized under various temperature conditions. Thus, the research trends in SOF

Table 5 Research trends for SOF and SOT estimation over the last 3 years

Research trend		References
SOF	Real-time estimation	[108]
	Parameter identification	[109]
	Co-estimation	[110]
SOT	Core temperature estimation	[113]
	Scaling	[114–116]
	Transient analysis	[117]

estimation over the last 3 years can be summarized as follows and are shown in Table 5.

1. Co-estimation of SOC, SOH, and SOF based on model-based methods.
2. Robust parameter identification under various environmental conditions.
3. Real-time estimation to protect batteries from overcharging and over-discharging.

3.4 Research trends of SOT

The definition of SOT has yet to be precisely established. However, estimating battery temperature has been extensively considered to avoid gas generation and fires resulting from increasing the temperature over 100 ℃. Generally, lithium-ion batteries have been researched using electrochemical-thermal models based on heat generation equations [111, 112]. However, electrochemical-thermal models require a large number of computations to solve heat generation equations. This means that electrochemical-thermal models are not suitable for real-time applications even if they can ensure high accuracy.

The heat generated by electrochemical reactions conduct from the battery core to the battery surface. Therefore, there is a temperature gap between the battery core and surface of over 10 ℃ under high C-rate charging/discharging conditions [42]. Battery core temperature should be measured to prevent battery failures from hazardous heat production. However, only the battery surface temperature is measurable in practice [113]. To overcome these problems, an impedance-based model, a semi-empirical model [114], and a simplified electrical-thermal model has been proposed to estimate the core temperature of battery cells and battery packs. Zhang et al. [115] proposed a monotonic relationship between impedance and battery internal temperature. Unlike prior studies, the internal temperature was estimated using a simplified thermoelectric model. Furthermore, Zhu et al. [116] established a relationship between the impedance phase shift and the battery internal temperature at 10 Hz.

Jeong et al. [117] introduced a heat transfer analysis for a battery module stacking 54 cells. Stacked-cell battery modules exhibit non-uniform thermal behavior. Therefore, heat transfer processes such as conduction and convection must be considered to determine the peak point in the battery module. In addition, the authors proposed an effective thermal model that was successfully scaled up and validated by comparing a detailed thermal model with a 54-cell stacked battery module within a 6% difference.

Li et al. [118] introduced an impedance-based electro-thermal model to analyze overcharging thermal characteristics at 30 °C and 60 °C. The authors proposed an electro-thermal model to diagnose overcharging, and it significantly reduced estimation errors at 0.9 ℃.

According to the references for temperature estimation technologies, the research trends in SOT estimation over the last 3 years can be summarized as follows and as shown in Table 5.

1. Battery core temperature estimation to avoid failures.
2. Large-sized battery pack temperature estimation.
3. Thermal interpretation of the transient phenomena in batteries, such as overcharging and internal /external short-circuits.

4 The future of BMS

In Sect. 3, the research trends in SOx estimation technologies for safe and reliable operation were reviewed and summarized. Through the research trends in SOx estimation technologies, it is possible to gain insight into directions that BMSs should take in the future as shown in Fig. 6 and as follows.

1. *Robust battery design* Most battery state estimation research has focused on model-based methods for SOC, SOH, SOF, and SOT. Therefore, robust battery design can provide good accuracy for controlling battery systems based on such battery state indicators. Thus, considering different working conditions and environmental conditions in ECMs are regarded as main research trends for robust designs. In addition, technologies for parameter identification have been developed to improve the fidelity of battery ECMs using the least squares algo-

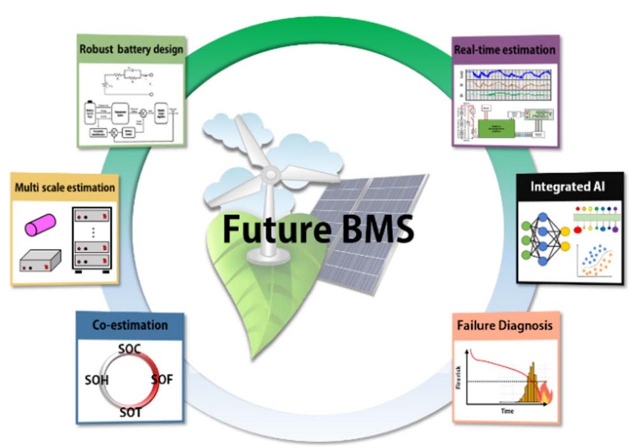

Fig. 6 Future BMS research requirements

rithm and optimization methods such as PSO and GA. These techniques can save a significant amount of time and cost for extracting the parameters in ECMs. However, it is still necessary to establish the relationship between the physical meaning and the result.

2. *Multi-scale estimation* Due to growth in the high-energy ESS market, the requirements for larger batteries have increased. Thus, battery systems can be divided into various levels including cells, modules, packs, racks, and systems. However, most studies have focused on the analysis of battery cells. It has been established that a battery is an electrochemical energy storage unit that has the characteristics of non-linearity and unpredictability due to its complexity. Therefore, analysis results for a cell are not fully extendable to battery packs, racks, or systems. In addition, inconsistencies in series-connected and parallel-connected systems can lead to poor estimation accuracy, and battery performance quickly degrades. Therefore, reliable estimation and management methods are required.
3. *Co-estimation* Reducing the number of computations is required, while maintaining good accuracy. Thus, "simplify" is one of the key words found in the last 3 years of research trends. To overcome this problem, a number of co-estimation methods have been proposed. The advantage of co-estimation is that SOC estimation can be compensated adaptively when the capacity changes via SOH. However, parallel estimation structures can lead to large errors if one of the state indicators is estimated inaccurately. Therefore, it is necessary to establish methods to minimize or detect the effect of abnormal points due to noise and disturbances.
4. *Integrated AI* Battery ECMs are becoming more complex to ensure their estimation accuracy while considering various conditions. Therefore, they require expert knowledge and a large amount of preliminary experimentation. Thus, model-free methods have been proposed including neural networks, SVM, and optimization algorithms. These methods determine the relationships of signals with physical relevance, and estimate the output when a new input occurs. Recently, AI-based BMSs have been studied using measurable values such as voltage, current, and temperature. However, these methods require a large amount of training date for good accuracy. Therefore, reducing the required training data sets is one of the problems to be solved.
5. *Real-time estimation* Many researchers have turned their attention to methods for implementing state estimation algorithms in real-time. The functions of BMSs are becoming increasingly diversified and more technologically advanced. Therefore, to estimate in real-time, a trade-off between hardware performance and software complexity must be considered. In particular, online parameter identification has been extensively researched for implementation in real-time. Adaptive filter algorithms based on least squares and optimization algorithms contribute to the onboard use of model-based methods and data-driven methods under various conditions (e.g., temperature, DOD, and aging). On the other hand, parameter identification methods are becoming more complex due in large part to measurement noise and disturbances. It is necessary that robust and high-fidelity estimation algorithms with low computation cost due to measurement noise be developed for application to large-scale ESSs.
6. *Failure diagnosis* As mentioned previously, a lithium-ion battery can catch fire or explode when it is exposed to stresses or excessive conditions. Most battery research has been conducted to ensure battery safety during operation. Thus, battery safety (or failure) monitoring systems are required. Battery safety monitoring systems based on voltage and temperature have been proposed. The function can be composed of various sub-functions that indicate the safety of the battery. Battery safety should be determined by integrating all of the battery states to protect against hazardous failures.

5 Conclusion

This paper reviews the definitions of battery states in Sect. 2, and discusses recent trends in state indicator estimation technologies (SOC, SOH, SOF, and SOT) in the past three years through a literature survey in Sect. 3. In addition, this paper provides insight into the future of BMSs, which is presented in Sect. 4. It includes the following directions: (1) robust battery design, (2) multi-scale estimation, (3) co-estimation, (4) real-time estimation, (5) integrated AI, and (6) failure diagnosis. Various studies have been conducted to ensure safety and to satisfy the design life of ESSs. In particular, it is expected that research to monitor and manage battery states will be continuously conducted to prevent failures and fires for future BMSs in ESSs.

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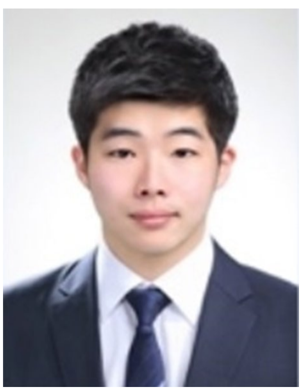

Seongyun Park received his B.S. degree in Mechatronics Engineering from the Korea University of Technology and Education (Koreatech), Cheonan, South Korea, in 2016. He is presently working towards his joint M.S. and Ph.D. degrees in Electrical Engineering at Chungnam National University, Daejeon, South Korea. He worked in the Non-Contact 3D CMM Department at Dukin Co., Ltd., Daejeon, South Korea, in 2018.

Jeongho Ahn received his B.S. degree in Electrical Engineering from Chungnam National University, Daejeon, South Korea, in 2020. He is presently working towards his M.S. degree in Electrical Engineering.

Taewoo Kang is presently working toward his B.S. degree in Electrical Engineering at Chungnam National University, Daejeon, South Korea.

Sungbeak Park received his B.S. degree in Electrical Engineering from Korea University, Seoul, South Korea, in 2007; and his M.S. degree in Electrical Engineering from Chungnam National University, Daejeon, South Korea, in 2019. He was a Researcher at STX Heavy Industries, South Korea, from 2008 to 2011. He was a Senior Researcher at Daelim Co., South Korea, from 2011 to 2013. He is presently working as a Researcher in the Department of Nuclear Safety Research at the Korea Institute of Nuclear Safety, Daejeon, South Korea.

Youngmi Kim received her B.S. degree in Computer Engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 1994; her M.S. degree in Computer Science and Engineering from the Pohang University of Science and Technology, Pohang, South Korea, in 1996; and her Ph.D. degree in Computer Engineering from Chungnam National University, Daejeon, South Korea, in 2012. She was a Development Researcher in the Korea Trade Network, South Korea, from 1994 to 2000. She was a Research Engineer at Daekook I.N.T Co. Ltd., Busan, South Korea, from 2000 to 2002. She is presently working as a Researcher in the Department of Nuclear Safety Research at the Korea Institute of Nuclear Safety, Daejeon, South Korea.

Inho Cho received his B.S. degree in Electrical Engineering from Hanyang University, Seoul, South Korea, in 2007; and his M.S. and Ph.D. degrees in Electrical Engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2009 and 2013, respectively. He was a Researcher at LG Chemicals, South Korea, from 2000 to 2000. He is presently working as a Researcher in the Department of Propulsion System Research at the Korea Railroad Research Institute, Uiwang, South Korea.

Jonghoon Kim received his B.S. degree in Electrical Engineering from Chungnam National University, Daejeon, South Korea, in 2005; and his Ph.D. degree in Electrical Engineering and Computer Science from Seoul National University, Seoul, South Korea, in 2012. He worked for the ESS Development Group, Samsung SDI, South Korea, from 2012 to 2013. He was Assistant Professor in the Department of Electrical Engineering at Chosun University, Gwangju, South Korea, from 2013 to 2016. He is presently working as an Assistant Professor in the Department of Electrical Engineering, Chungnam National University, Daejeon, South Korea.