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Review article

Driving the future: A comprehensive review of automotive battery management system technologies, and future trends

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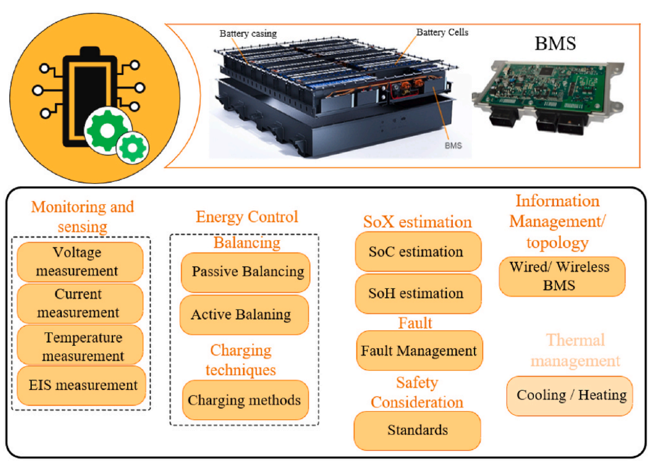
HIGHLIGHTS

- Review of future-proof BMS focusing on hardware, software, safety and performance.
- BMS real-world challenges: modelling, aging, fault tolerance and fast charging.
- Future technologies: V2X, battery swapping, advanced SoX and cyber-secured BMS.

GRAPHICAL ABSTRACT



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ABSTRACT

To date, a variety of Battery Energy Storage Systems (BESS) have been utilized in the EV industry, with lithium-ion (Li-ion) batteries emerging as a dominant choice. Li-ion batteries have not only captured the automotive market but have also exponentially been used in stationary energy storage sectors, thanks to their extended service life, high power, and volumetric density. The surge in Li-ion battery demand, increasing by approximately 65 % from 330 GWh in 2021 to 550 GWh in 2022, is primarily attributed to the exponential growth in electric vehicles sales. However, despite extensive research in academia and industry on Battery Management Systems (BMS), several gaps persist. Challenges include optimizing battery utilization within real-world

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operational limits, adapting BMS concerning chemical changes within batteries, e.g., aging, addressing the complexities of cell balancing in future battery packs, restricting fast charging below room temperature, limitations in fault tolerance capabilities, and the tendency to oversize for safety margins. Furthermore, the integration of efficient models (i.e., physics/data) with cutting-edge sensing technology remains a challenge as current BMS are often isolated and disconnected, narrowing the operational limits of battery systems for EV and stationary energy storage applications. This paper conducts a comprehensive review covering all possible aspects of BMS soft- and hardware solutions for EV applications, focusing on technical performance, safety, and reliability. Topics covered physics- and data-based modelling approaches for edge and cloud, state-of-X (SoX) estimation methods, charging strategies, balancing techniques, fault diagnostics, safety considerations, warranty management, and Vehicle-to-Everything (V2X) capabilities. Additionally, the paper sheds light on emerging technologies and future opportunities in this related field.

1. Introduction

Due to the energy crisis and environmental concerns, the need for renewable energy and electric vehicles, which can provide a zero-carbon world, has increased worldwide. Based on the International Energy Agency (IEA) reports, electric vehicle sales are projected to reach approximately 17 million units in 2024, constituting over 20 % of global car sales. The adoption of electric vehicles as a mass-market product is accelerating across an increasing number of countries. To be more specific, in 2023, global electric vehicle sales reached nearly 14 million units, accounting for 18 % of all cars sold, up from 14 % in 2022. This represents a significant increase of 3.5 million units, or 35 %, compared to the previous year. This upward trend underscores a growing global shift towards sustainable transportation solutions in response to environmental concerns and the ongoing energy crisis. However, despite the increasing popularity of EVs, their widespread adoption on a larger scale faces critical challenges: the performance and safety concerns associated with lithium-ion (Li-ion) batteries.

Batteries are one of the most critical components in EV applications. Li-ion battery cells typically provide a voltage level of 3.6 V–4.2 V. However, electric vehicle (EV) applications necessitate higher voltage levels, with the battery systems of passenger cars and Light Commercial Vehicles (LCVs) typically operating within a range of 48 V to over 800 V [1]. This voltage requirement increases further (i.e., ranging from 600 V to 1.2 kV) for medium- and heavy-duty EVs [2]. To achieve these voltage requirements, multiple cells are connected in series within the battery system of EVs [3]. Despite a lot of efforts, there are still manufacturing-related cell-to-cell variations. These differences, along with the complex chemical reactions and degradation that happen in various types of lithium-ion batteries and the fact that cells are connected in series, pose significant challenges to cell monitoring, balancing, and diagnostics. Consequently, several degradation-related phenomena cannot be detected early enough to prevent intensified degradation, which might lead to hazardous events, for example, the occurrence of thermal runaways and explosions. It is therefore of utmost importance to adequately monitor and observe internal states and useable windows of batteries to diagnose specific battery health and safety critical phenomena with an advanced combination of sensors, physics- and data-based models for a more accurate, reliable, and efficient BMS. The European Commission also recognizes this need through the research project called for 2ZERO – BATT4EU, leading to the initiation of several European Horizons calls Horizon-CL5-2022-D2-01-09, HORIZON-CL5-2022-D2-01-05, Horizon-CL5-2023-D5-01-02, HORIZON-CL5-2025-04-D2-05 on Innovative Battery Management Systems for Next-Generation Vehicles as part of the 2ZERO & Batteries Partnership.

In addition to advanced modelling, monitoring and diagnosing systems, an efficient warning system is essential to ensure the safety and reliable operation of the BMS. Successful and efficient operation of EVs is inextricably connected to the operation of BMS. BMS encompasses hardware (i.e., sensors, balancing circuits, actuators, etc.) and software (i.e., real-time data monitoring, computational algorithms, and control of the BMS) that equips the battery pack in BEVs and is responsible for enhancing its performance and safety, increasing its range, protecting the individual cell from damage, and prolonging its lifespan [4]. Generally, battery management systems have undergone three main generations. Fig. 1 Shows the evolution of BMS over time.

The first generation of battery systems, termed "no management," is suitable for early battery energy storage systems focused solely on monitoring battery terminal voltage for charge and discharge control. However, this generation is characterized by a time-consuming maintenance process and suffers from low efficiency. The development of a "Simple management" battery system represents an improvement, offering enhanced measurement accuracy and reliability compared to the "no management" approach. This system can monitor the external characteristics of each cell in the battery pack, including voltage, current, and temperature. Nevertheless, due to the lack of online monitoring of internal parameters, this version of BMS requires complicated maintenance procedures. Hence, an "advanced battery management system" has been evolved that comprises an advanced SoX estimator, aging, and safety functions. In spite of considerable improvements in the current in-use BMSs, there are still shortcomings. Therefore, future-proof BMS requirements include improving measurement accuracy and reliability, monitoring external characteristics of each cell, enabling online monitoring of internal parameters, implementing a connected solution for continuous data recording similar to a flight-black-box, integrating a SoX digital twin, providing V2X capabilities, and offering warranty coverage for preemptive failure detection on hardware and cell levels. These advancements rely heavily on advanced sensing technologies, e.g., Electrochemical Impedance Spectroscopy (EIS), and higher spatial sensor measurements of temperature, pressure, and stress within the battery hardware. In addition, these advanced sensors inherently generate more data, which, in addition to the raised awareness on the usefulness of the historical data, inevitably leads to the need to handle big data both in edge and cloud. Besides, battery models should also evolve to match this increased level of higher fidelity information and the need to provide a deeper insight into intra-cell phenomena, which calls for advanced battery modeling, in particular, the implementation of the electrochemical models, which also include degradation models. Such models namely feature a higher level of physico-chemical consistency compared to currently used models, which increases their prediction capability and also their applicability as virtual sensors of intra-cell phenomena. Moreover, such models are, in general, capable of virtually replicating the dynamic behavior of the battery with higher fidelity, while their application in real-time systems represents a high challenge on the model structure and complexity as well as on the applied hardware. To handle the computational burden of more complex models, big data processing as well as big data storage, distribution of computational and storage resources between BMS, edge device and distributed computing unit, as for example cloud [5–7], is envisaged and exploited. Based on our thorough literature search, it appears that the existing published papers lack a comprehensive overview of both model-driven and data-driven battery modeling methods, particularly in terms of covering all aspects of electro-thermal, electro-mechanical and electrochemical-thermal models. Consequently, the primary aim of this article is to conduct a thorough analysis of industry and academic research on modeling techniques for LIBs.

Furthermore, in Refs. [8–12] the State of Charge (SoC) estimation, State of Health (SoH) estimation [13–16], State of Energy (SoE) [17,18], and State of Power (SoP) [19,20] of LiBs have been reviewed. This paper have included comparative analyses of both model-driven and data-driven SoC estimation methods, discussing the accuracy, metrics, and limitations of each technique. In Refs. [21–23] charging strategies and in Refs. [24–28] balancing topologies have been reviewed. These functions can also be optimized to boost battery performance while respecting health and safety-relevant constraints while optimizing the selection of cells, size, and structure of the battery pack, as well as its thermal management and costs. Furthermore, integration of the latest technology in Power Electronic (PE) is still a challenging topic. As a result, there are many aspects that need to be enhanced to tackle/alleviate the aforementioned issues. Therefore, this paper extensively reviews previous and state-of-the-art BMS characteristics and features covering a broad range of aspects from topology to fault diagnostics while upgrading these topics with envisaged future functionalities of the BMSs and indicating technology gaps as well as identifying potential future research needs in the emerging areas. Table 1 Illustrates a synthesis of recent review papers on Battery Management Systems (BMS), highlighting their advancements and limitations and identifying areas for further development through the proposed paper.

Table 1
A brief summary of the recently published review paper in BMS and related topics.

Ref. No.	Achievements and limitation
[29]	✓ In-depth and comprehensive review of key aspects of advanced battery management system ➢ excluding fault diagnosis, safety considerations, and BMS topologies
[30]	✓ Review of intelligent algorithms for state estimation ➢ Charging and safety aspects are not covered
[31]	✓ This review explores key technologies of Battery Management System, including battery modeling, state estimation, and battery charging ➢ Fault diagnosis and battery modeling aspects of the BMS are not fully reviewed.
[4]	✓ This review discussed four main areas of (1) BMS construction, (2) Operation Parameters, (3) BMS Integration, and (4) Installation for improvement of BMS safety and performance are identified, and detailed recommendations ➢ In-depth review of all aspects of the battery management system
[32]	✓ Mostly focus on the battery technologies for EVs application ➢ Some aspects of the BMS are not covered, including battery modeling, charging strategies
[33]	✓ The arrangement of the battery cell in EV application ➢ This discussion will not cover the detailed explanation of BMS functionalities in EVs
Proposed paper	✓ Comprehensive review of future proof BMS, from architectures to the advanced functionalities (including BMS modelling, SoX estimation, charging and balancing strategy), streamlined fault diagnosis and future trends including detailed battery passport initiative.

2. BMS topology

From the implementation perspective, especially communication protocols the BMS market can be classified into two main architectures. 1. Wired BMS,2. Wireless BMS, Fig. 2 Shows both wired and WBMS. In the wired BMS, mainly CAN-bus communication protocol is employed for gathering data and transmitting data between slave and master controller units, while in WBMS, this connection is through wireless channels. As (is shown) depicted in Fig. 2 the architecture of the BMS either in terms of integrated IC or customized model [34] can be categorized into four centralized, modularized, distributed, and decentralized topologies [4,35]. Following the architecture of each category, considering the placement and the number of control units, their implementation and performance can be analyzed/assessed from costs, simplicity, scalability, and reliability perspective [4,35–41].In

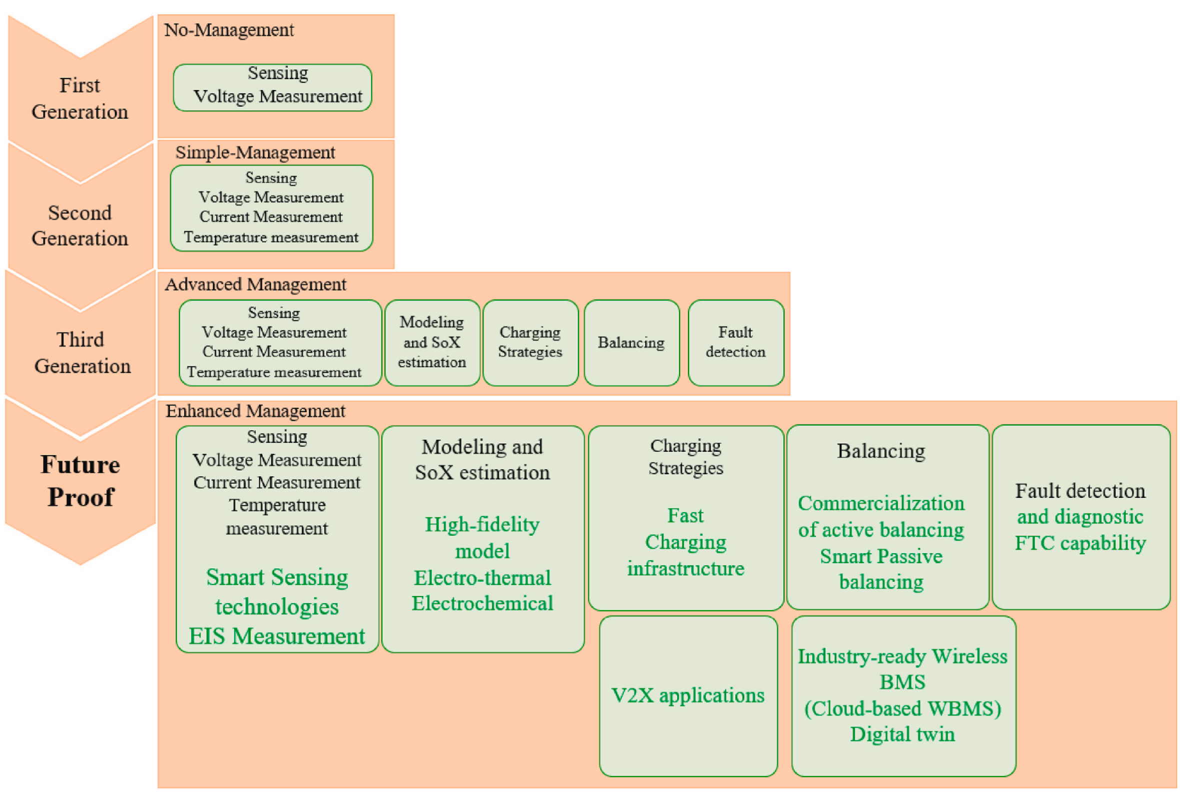


Fig. 1. BMS Evaluation: from no management (first generation) to basic management (second generation), to advanced management (third generation), and ultimately to future-proof enhanced management.

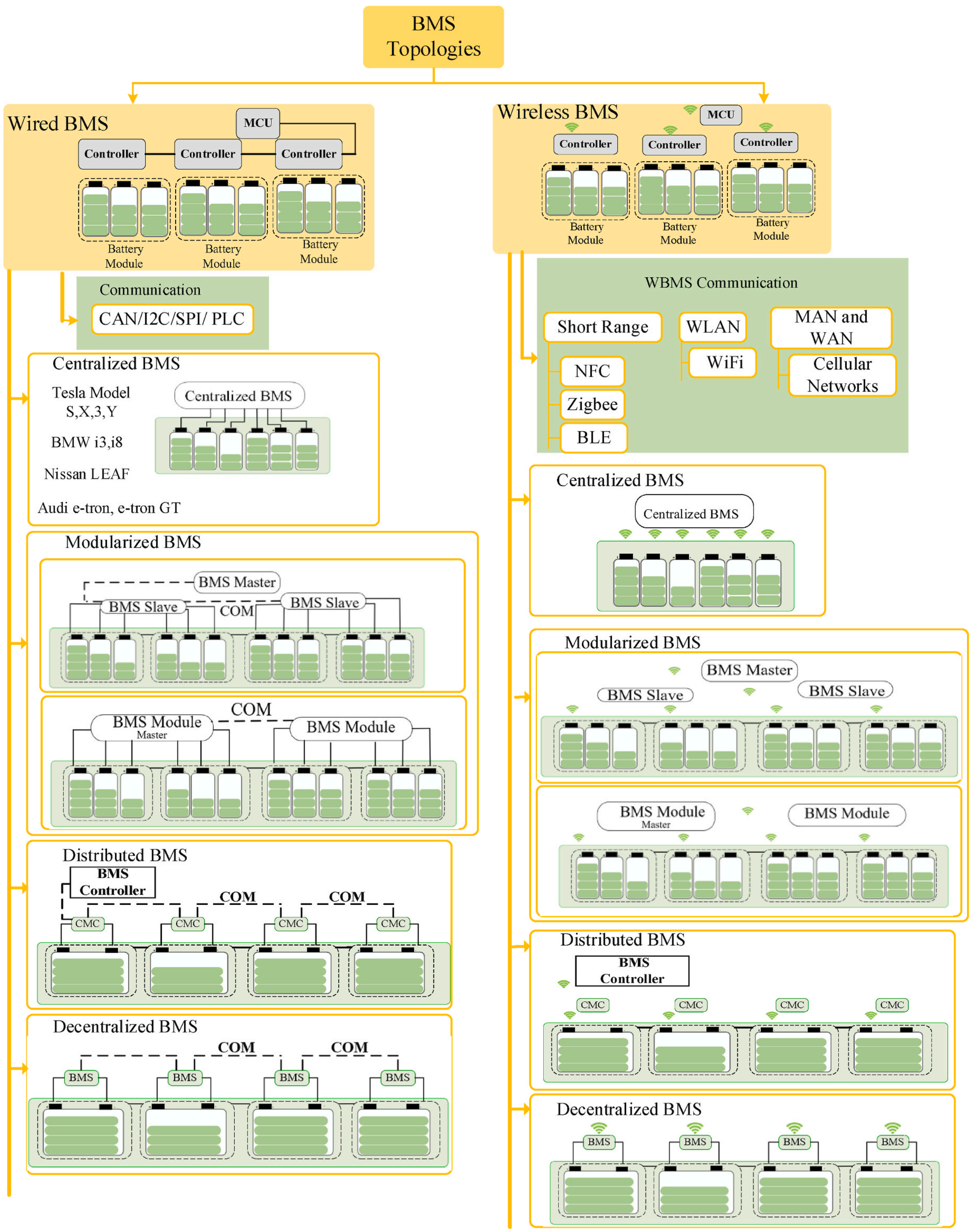


Fig. 2. BMS topologies. Wired and Wireless architecture in terms of integrated IC or customized model and applicable communication protocols and qualitative comparison from cost, reliability, complexity, and scalability aspects. Centralized topology: Cost: low, Complexity: low, Scalability: low, Reliability: low. **Modularized topology**: Cost: high, Complexity: high, Scalability: excellent, Reliability: good. **Distributed topology**: cost: moderate, Complexity: moderate, Scalability: excellent, Reliability: high, **Decentralized topology**: cost: moderate, Complexity: moderate, Scalability: excellent, Reliability: excellent.

centralized BMSs, the batteries or battery cells are connected to a single module which is responsible for all the functionalities. Following the structure of this topology, cost-effective, simplified design, easier maintenance, and troubleshooting are the advantages of this topology. However, this topology suffers from lack of flexibility and scalability, and single-point failure. In modularized BMSs, individual batteries or battery cells are connected to several identical modules, and often one of the modules is assigned as a master or a separate module serves as the master BMS. This topology improves scalability and functional safety, meanwhile the implementation costs increase. In distributed BMSs, each cell string or cell has its own BMS, and all the BMS are in contact with a controller that handles the communication and calculation of the cell

BMSs. These topologies, while improving scalability and reliability, safety and simplifying wiring, increase the complexity and implementation cost. Decentralized topology, which removes the disadvantages of the central control in the distributed topology [35] and provides entire functionality locally and autonomously. Despite increased scalability, safety, and reliability, the challenging characteristic of this topology is the distributed system control based on equal, parallel-operating, and autonomous nodes. Moreover, it has to be ensured that the single point of failure is not only shifted but also eliminated/removed [35]. Although modularized topology [42,43] is the widely used architecture with satisfactory performance in commercialized BMS; the Wired-BMS(WBMS), which mainly utilizes a Controller Area Network (CAN-bus) and I2C/SPI communication protocols, requires a massive mesh of cables for collecting and transmission of data from sensors to the master BMS. This point leads to higher design complexity, higher implementation costs, and the need for galvanic isolation of cells. Moreover, the placement of the master BMS in the desired location can be challenging. Furthermore, due to the vibratory working condition of EVs, the Wired-BMS can encounter physical connection failures, negatively affecting reliability [44,45]. In addition, troubleshooting can be challenging due to massive wiring/cabling. These challenges will aggravate in high-capacity LIBs comprised of a large number of individual cells. Hence, the Wireless BMS topologies have been evolved.

WBMS provides enhanced system reliability, lower cost, and weight by reducing/decreasing the wire's complexity and removing the requirements for galvanic isolation and physical connectors, especially for multicell and high-capacity battery packs [45]. The WBMS, moreover, increases/raises flexibility in the placement of the sensors in the BMS and the placement of the battery modules in the powertrain. The communication technologies in the WBMS can be classified into three main groups [46]: short-range communication, including Zigbee-based (IEEE 802.15.4) [47], Bluetooth-based, and NFC, WLAN technology such as Wi-Fi, MAN and WAN technology such as cellular networks. Zigbee and Bluetooth-based WBMS were the most utilized communication technologies due to low self-power consumption and low implementation cost [48]. The strict requirements for accuracy, reliability, and safety, along with information security and high-resolution sensors, motivate the development of IoT and Wi-Fi-based WBMS. The IoT and Wi-Fi communication techniques enable high-speed and high-volume data transmission. While analyzing and storing a large volume of data in real-time with the limited processing capacity of onboard BMS is highly challenging, in this regard, Cloud-based WBMS, enabled by IoT and Wi-Fi communication for processing a large amount of data, making decisions, and storing the data that are essential for SoH and RUL prediction and fault diagnostic, was developed. Despite conducted research, a large number of challenges in this architecture remain that require further development and research.

- ➢ Practical feasibility with real-time data.
- ➢ Cost, space, and manufacturing limitations for placements and installation of sensors, especially in high-capacity battery packs that can monitor internal and external characteristics of individual battery cells for effective BMS operation.
- ➢ Information Security Commercialization.

3. Battery modelling

An accurate and reliable battery model is the mandatory building block of an advanced BMS. A battery model considering the battery's internal characteristics should be established, which can be of great assistance for intelligent BMS. Battery modeling significantly impacts majority of the BMS functionalities, such as battery equalization, estimation of battery states, and battery fault diagnosis. To date, a large number of battery models have been proposed to reflect battery behavior accurately. All the proposed models mainly can be categorized into two groups: a) model-based methods and b) data-driven approaches. Fig. 3 presents various battery modelling approaches for battery state estimation [49].

3.1. Model-based method

Model-based methods, the widely used approaches, comprise a battery model and a parameter estimation algorithm. According to the input, the model output is measured and compared with the actual data of the battery; by calibrating the model parameters, the error in the model output can be corrected. Based on Fig. 3 the methods in this category include the empirical model, equivalent circuit model, electrochemical model, and reduced-order model.

3.1.1. Empirical model

A simplified model, also called a mathematical model or black box model, utilizes reduced-order polynomial or mathematical equations representing the essential nonlinear characteristic of the battery [50]. Despite limited accuracy, they are easy to configure and provide prompt response. Classical models, zero-state hysteresis model, and enhanced self-correcting model are subcategories of the empirical model.

- Classical Model

The concept of these models is to define a relation between battery voltage and current, some constant values, internal resistance, and SoC [51]. These methods, also known as typical empirical models, include the Nernst model [52], Unnewehr model, Shepherd model [52], and a combination of all of them. Instead of using higher-order equations, this model reflects the non-linear characteristic of the battery by using a simple set of mathematical and polynomial equations. Table 2 describes the equations for the aforementioned models. Where V_k is the battery output voltage, E_0 denotes the battery OCV, R_0 is the internal ohmic resistance, $K_1 \sim K_4$ constant values for curve fitting and I_k describes the battery current. Note that the battery current is considered positive in the charging process and negative in discharging process, and Z_k is the SoC.

- Zero-state hysteresis model

The hysteresis effect is a form of path dependency, where the battery's voltage behaviour is influenced by the history of its charge and discharge cycles. To be more specific, the voltage response does not follow a consistent path during charging and discharging, thereby leading to significant challenges in State of Charge (SoC) estimation, which can negatively impact the safe and reliable operation of the BMS. Therefore, accounting for voltage hysteresis is crucial for precise SoC estimation [53].

Although voltage hysteresis is a short-term path-dependent phenomenon, it persists even after extended relaxation periods. This effect is strongly dependent on the choice of active material. For example, materials such as graphite, lithium iron phosphate (LFP), and silicon exhibit noticeable/pronounced voltage hysteresis, while lithium-titanate (LTO) shows minimal hysteresis. This path dependency is also related to other battery characteristics, such as cell expansion, rate and power capacity [53].

To enhance the accuracy of SoC estimation and incorporate the hysteresis effect into models, numerous research efforts have been undertaken. Plett in his works [54–56] by adding or subtracting the voltage hysteresis to the OCV equation, describe the dynamic hysteresis behaviour of the Li-ion batteries with a zero states hysteresis. To model the voltage hysteresis of LFP, especially the transition path between charge and discharge curve [57,58], utilized the mathematical model. In Ref. [59] a long short term memory neural network has been applied to model the voltage hysteresis of LPF. Some research provide deeper insight into the internal state of the battery [60–62]. In fact these models

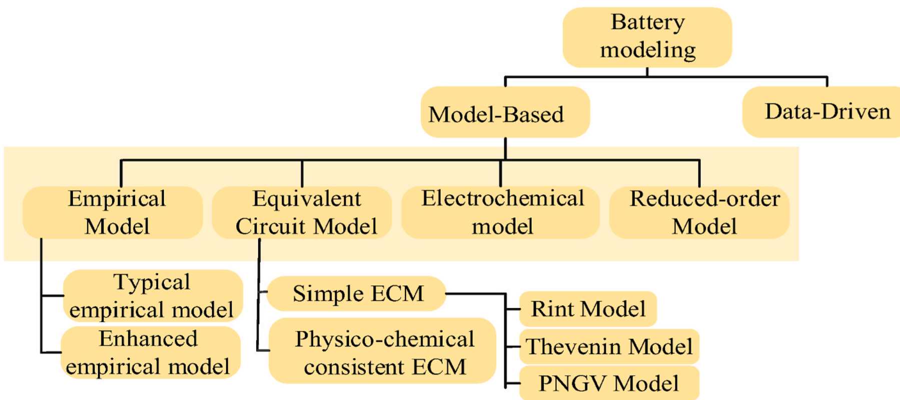


Fig. 3. Battery modelling approaches.

Table 2
The summary of primary models applicable to EV applications and separated color is used show different category of models [50,51].

Model Name and ref.	Governing equation of the model	Features and limitation
Shepherd model [50, 51, 56, 64]	$V_k = E_0 - R_0 I_k - \frac{K_1}{Z_k}$	✓ Accurate in continuous discharging state and linear in the parameters ➢ Thermal, aging, and self of discharge, and hysteresis effects are not included. ➢ Algebraic loop and simulation instability
Unnewehr model [51, 56]	$V_k = E_0 - R_0 I_k - K_2 Z_k$	✓ Simplify model of shepherd model, adding the internal resistance variation with respect to SoC and linear parameters ➢ Does not capture all the complex electrochemical processes inside the battery; thermal, aging, and hysteresis effects are not covered
Nernst model [51, 56]	$V_k = E_0 - R_0 I_k + K_3 \ln(Z_k) + K_4 \ln(1 - Z_k)$	✓ Modification in Shepherd model, adding the exponential function with respect to SoC and being linear in parameters
Combined model [64]	$V_k = E_0 - R_0 I_k - \frac{K_1}{Q_k} - K_2 Z_k + K_3 \ln(Z_k) + K_4 \ln(1 - Z_k)$	✓ Combination of all the aforementioned models for accurate performance ➢ Does not include the hysteresis effect
Zero-State Hysteresis Model [56, 65]	$V_k = V_{oc}(Z_k) - I_k R_0 - M h_k$ $V_k = V_{oc}(Z_k) - I_k R_0 - S_k M - M h_k$	✓ Improve accuracy and enhance prediction capabilities ➢ Limited applicability(applicable in battery chemistry where the hysteresis effect cannot be neglectable) ✓ Complications of the implementation of certain numerical models for state estimation due to non-differentiable hysteresis terms in some model
Enhanced Self-Correcting Model [56]	$y_k = OCV(z_k) f_n(z_k) + h_k f_n(z_k, i_k) + fil(i_k) - R.f_n(i_k)$	✓ Highly accurate in various operating conditions ➢ Extensive data requirements, high computational load, complex implementation
Rint Model [66, 67]	$V_L = V_{OC} - I_L Ro$	✓ Simple and basic equivalent circuits only reflect the ohmic resistance from contact, electrolyte, and electrodes (Steady-State behavior) ➢ The concentration and activation polarization are not covered, so this model is less accurate
Thevenin Model [66-68] (First order and second order 1RC, 2RC)	$V_L = V_{OC} - I_L Ro - V_1$	✓ Relatively simple with considering the ohmic losses and concentration polarization (transient behavior)----- First-order ✓ Better description of the internal ohmic polarization, electrochemical and concentration polarization---- Second-order model ➢ Relatively complex, require more computing energy of existing process---- Second-order model ➢ The accuracy of the SoC decrease by battery aging degree----First order
PNGV Model [66, 67]	$V_L = V_{OC} - I_L Ro - V_1 - V_{cb}$	✓ Reflect the DC response characteristics of the battery
Physico-Chemical consistent ECM	$V_k = V_{CC}^{CAT} + V_{CB,DL,ELY}^{CAT} + V_{ELY}^{SEP} + V_{CB,DL,ELY}^{ANO} + V_{CC}^{ANO}$	✓ Easy transferability of the parameters from the electrochemical model to the ECM ➢ Computationally more demanding than Rint, Thevenin of PNGV models
Electrochemical Model	$V_k = V_{CC/CAT} - V_{ANO/CC}$	✓ Physics-based governing equations and capability of modelling intra-cell phenomena, i.e. electrochemical, transport, thermal and aging Complexity, large number of unknown parameters, computationally heavy
Definition	$V_k$battery output voltage, R_a: ohmic resistance, E_0: OCV of battery,$K_1 \sim K_4$: Constant values, $i(t)$: battery current, Z_k: SoC value, CC/CAT: current collector / cathode interface; ANO/CC: anode / current collector interface; SEP: separator; CB: carbon binder domain; DL: double layer; ELY: electrolyte	

predict not only the hysteresis voltage but also path decency of rate and power capability which are the important parameters in the BMS. In Ref. [53] a modelling approach based on the classical equivalent circuit, applicable to the BMS due to mathematical structure has been proposed. This model provides detailed information on the battery internal states of the voltage hysteresis and rate and power capability, the presented structure in this paper is appropriate for the material that undergone a first-order phase equation. Following model output equation illustrated in Table 2, the hysteresis model represents the instant hysteresis voltage variation, along with dynamic hysteresis variation based on the state of charge, where M acts as a constant coefficient that describes the level of hysteresis, and h_k denotes charging and discharging hysteresis effect, and S_k is the symbol of current based on the charging and discharging state [49].

- Enhanced self-correcting model

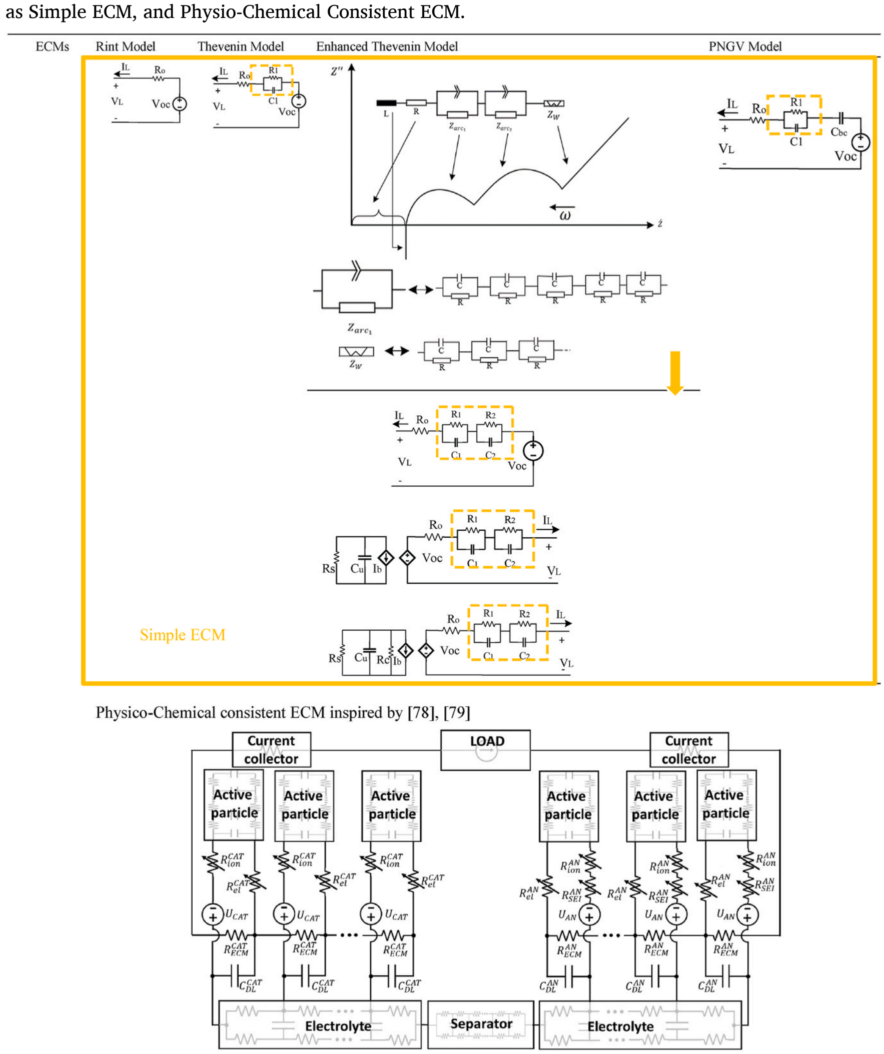
An important element/characteristic which is missing from the aforementioned models (classical and zero state hysteresis) is the characterization of time constants during pulsed current events. When a cell is at rest, it requires time for its voltage to fully stabilize at the rest voltage. Similarly, when a current pulse is applied to the cell, it takes time for the voltage to reach its steady-state level. These time constants, referred to as the relaxation effect, can be represented by a low-pass filter on the input current [55]. Sine the accurate cell model resulting in accurate and precise SoC estimation, it is crucial to take into account the relaxation effects. In this regard, a physics-based model termed as Enhanced self-correcting model incorporating multiple RC networks, hysteresis effect, temperature dependence, and relaxation effects, is proposed [63]. The output equation of this model can be formulated as is shown in Table 2. Where y_k is the estimated voltage; k is index; z represents SoC; h is electro-chemical hysteresis; fil(.) is some dynamic operation filtering its operand; R is the battery resistance; and i is current. Plett in Ref. [55] provides a comparative table of the modelling error for the aforementioned models for one cycle of the UDDS test. In that table he shows that the number of the filtering states up to four can significantly enhance the performance.

The primary models of the battery system, including their governing equations, features, and limitations, are summarized in Table 2.

3.1.2. Equivalent circuit model (ECM)

ECMs are the widely used models in real-time BMSs in EVs. These models consist of lumped parameters such as resistors, capacitors, and so on. As ECM provides a simple structure with a few components, these

Table 3
Equivalent Circuit Models, including Rint Model, Thevenin model, Enhanced Thevenin model and PNGV as Simple ECM, and Physio-Chemical Consistent ECM.



models attracted considerable attention where the dynamic characteristic of the battery, compared to the electrochemical reaction inside of batteries, is of significance. ECMs frequently include a certain degree of arbitrariness and do not necessarily directly reflect the actual physico-chemical phenomena occurring in the studied battery system [64–70]. Nevertheless, several sources present physico-chemical consistent mapping between processes in batteries and model topology and model parameters, which includes governing physical equations of ECMs with the uniquely defined meaning of each circuit element (resistor, capacitor, etc.) in terms of physical parameters (diffusion coefficient, transport number, conductivity, porosity, etc.) [71–74]. Hence, in general, ECMs can be divided into models, which do and which do not feature physico-chemical consistency; later models will in this paper be termed simple ECMs, while physico-chemical consistent ECMs are indeed models that feature high level of physico-chemical consistency with processes in real batteries Table 3.This missing physico-chemical consistency can be reflected in inconsistent mapping between equivalent circuit topology and underlying processes in real batteries, which results in inconsistency between parameters of specific component characteristics (rates, storage capacities…) and underlying battery phenomena as well as inability to model specific phenomena occurring in batteries including adequate capturing of their non-linearities, e.g. non-linearity of exchange rates of surface reactions. These deficiencies are becoming more critical in the context of current and future applications of ECMs aimed at accurate modelling and diagnostics, with particular emphasis on the state-of-charge (SoC), state-of-health (SoH) and state-of-energy (SoE) as well as state-of-power (SoP) or state-of-function (SoF) observers, which is becoming more important in next-generation BMSs. This lack of physico-chemical consistency can, generally, be associated with an empirical origin of the models, which were postulated with the purpose of elaborating the simplest equivalent circuit topology that enables executing envisaged tasks. Some, but not all, illustrative examples are Rint, Thevenin, and PNVG model elaborated in Refs. [75–78]. In addition to previously listed empirical approaches used to postulate equivalent circuit topologies, there already exist multiple approaches aimed to incorporate physico-chemical phenomena into equivalent circuit models [71,73,74]. Table 3 illustrates the circuit design of the models in the ECM category.

3.1.2.1. Simple ECM. A simple ECM is generally composed of a DC voltage source, resistor-capacitor couples, and an internal resistor linking the input and output parameters. In these models, the resistor denotes the internal resistance of the electrolyte, electrode, separator, etc. The parallel RC networks, considering different time constants, represent the double layer, charge transfer effect, and diffusion process happening inside electrodes and electrolytes. Rint model, Thevenin model, and Partnership for New Generation of Vehicles (PNGV) [27,79], are the main subcategories of the ECMs.

(i) Rint Model

The Rint (resistance internal model) represents the most simplified and basic representation the battery among the ECMs. The model consists of a voltage source representing the open-circuit voltage (OCV) and a single resistor representing the internal resistance of the battery. The resulting output voltage is the difference between the OCV and the voltage drop caused by the internal resistance. The Rint model is ideal for very basic, high-level battery simulations where computational simplicity is highly prioritized. In fact this model reflects only the steady-state characteristic of the battery. This model is not applicable/appropriate in application in which the dynamic behavior of the battery including concentration and activation polarization [80] is required to be taken into account. The governing equation of the Rint model is presented Table 2, where V_L refers to output voltage, V_{oc} represents the open circuit voltage, I_L describes the battery discharge current, and R_0 denotes the battery internal resistance.

(ii) Thevenin Model

As mentioned, the Rint model is not concerned about the battery's dynamic behavior. To overcome this drawback, this model utilized an RC network along with internal resistance, which not only reflects the steady state behavior of the battery but also covers the transient characteristic of the battery. The number of the RC networks varies based on the application, and the values of the RC networks can be determined through the Hybrid Pulse Power Characterization test (HPPC). The more RC pairs, the more accuracy will be achieved. The Rint model, which reflects the static behavior of the cell, is applicable for grid integration.

By adding one more RC network to the Thevenin model, which describes the electrochemical polarization and concentration polarization, respectively, an enhanced Thevenin model will be obtained. Moreover, by taking the aging process into consideration, a comprehensive model can be obtained. In fact, in this model, the self-discharge and capacity fade are considered, as shown in Table 3.This model is composed of two parts. The first part reflects the dynamic behavior of the battery, and the second part captures the battery degradation over cycling. In this model, the capacity and battery run-time are modelled through a controlled current source, and a controlled voltage source represents OCV. Table 3 shows another comprehensive model reflecting the battery aging and remaining useful lifetime of the battery.

Thevenin model with One RC network represents the charge transfer behavior of the battery, and with two RC network covers the diffusion characteristic of the battery as well; both of the aforementioned models can be applied in smart grid integration. The higher RC network, along with the Constant Phase Charge Element (CPE), is applicable for E mobility applications and detection tools. To be more specific, in the case of the enhanced Thevenin model, a deeper look needs to be taken; in fact based on the impedance-based battery model [81], Table 3 the impedance behaviour/characteristic of the battery at high frequency is represented by an ideal inductor and the ohmic resistance by a resistor. For the most accurate and meaningful reproduction of the measured impedance, an approach with Zarc and Warburg elements has been suggested [82]. Zarc elements are a parallel connection of a resistor R and a constant-phase-element (CPE). Buller, in Ref. [83] shows the Zarc elements approximately can be substituted by a variable number of the number of RC-elements as illustrated in Table 3 analogs to the Zarc element, Warburg element on the other hand represents Fourier's transform of the analytical solution for the diffusion equation with the appropriate boundary conditions and can be replaced by a series connection of a resistor and a RC-element.

(iii) PNGV Model

The PNGV model, short for Partnership for a New Generation of Vehicles model, has been developed as part of a broader research initiative to model hybrid electric vehicle (HEV) batteries. This model incorporates more detail, allowing for improved accuracy in dynamic conditions, including transient responses. This model is a combination of the Thevenin model with a capacitor, which represents the changes happening in the electromotive force, as depict in Table 3. This model provides desired accuracy compared to the two models. Although the higher RC network provides more accuracy [84], the complexity of the circuit is increased at the same time.

3.1.2.2. Physico-chemical consistent ECMs. Physico-chemical consistent ECMs strive to virtually replicate processes in real batteries. Therefore, they are frequently inspired by the electrochemical models. As an example, ref. [85] proposes a hybrid like model, where electric field is modelled with a simplified transmission line model (TLM), which does not account for mass transport that is modelled with adding two separate partial differential equations. This means that a final model is not a single fully-coupled equivalent circuit, which limits its applicability, ease of use, and implementation ability on different platforms. Refs. [86,87] have proposed a physics-based equivalent circuit model derived by applying the finite volume method to a pseudo-two-dimensional model of insertion batteries; however, the derived model is also not a single fully-coupled equivalent circuit. The model namely relies on a complex coupling technique between the electric field and mass transfer domains. Ref. [71,88] proposes a single, fully-coupled equivalent circuit model, which also includes a double-layer capacitance, by introducing the so-called triple species element - TSE, which links the electrolyte domain with the domain of the active material.

This TSE interface element was implemented in the model to introduce the non-linear and other effects, which, according to the. statement in Ref. [88], cannot find ready electrical analogs for handling via equivalent circuits themselves. One of the deficiencies of this approach thus arises from the fact that TSE is not an element that could easily be implemented in electrical circuits. Several of the listed deficiencies were resolved in the previous publication of some of the co-authors. In Ref. [73] we have namely presented a derivation which results in the direct construction of a TLM of an electrolyte from the widely used concentrated solution theory (CST) for porous electrodes originally proposed by Newman [89]. In addition, we have recently postulated an electrical analogue of the interface between active material and electrolyte, which is capable of modelling non-linear effects and which enables coupling of the electrolyte and the active material domain within a single fully-coupled network of electrical elements [74], as presented in Table 3.

In Table 3 can clearly be seen that the topology of such a physico-chemical consistent ECMs reflects basic battery components: anode, cathode electrolyte and separator, as well as active material and interfaces. This figure also reflects and inherent merit of such type of models, which is their scalability of such type of models, which can easily be adapted by selecting adequate number of components for resolving resolution of the electrode and of the active particles. Thereby, as exposed, previously, these types of models enable obtaining a deeper insight into intra-cell phenomena due their physico-chemical consistent basis and hence such types of models, similar as electrochemical models, enable advanced SoX diagnostics and open new perspectives in next-generation of BMS.

However, more complex model topology and modelling of non-linear phenomena also increases computational expenses of this type of models, which for a similar level of detail becomes similar to electrochemical models, which is obvious, as models features similar level of detail of modelling of multiple phenomena. These computational expenses might notably exceed the ones of simple ECMs, therefore, use case specific requirements need to be analyzed to select between simple and physico-chemical consistent ECMs as well as level of detail of physico-chemical consistent ECMs.

3.1.3. Electro-chemical model

The electrochemical model, is, similar as physico-chemical consistent ECMs, frequently denoted also as a white box model or physics-based model, which represents a model featuring high level of physico-chemical consistency with real processes in batteries, covers the electrochemical reactions happening inside the battery. Although this model reflects the detailed electrochemical characteristics inside the battery with high accuracy, it is not yet applicable in online practical applications considering CPU and memory constraints of current BMSs, whereas, as exploited in the project EVERLASTING [90] and several ongoing projects in the cluster under EU call HORIZON-CL5-2022-D2-01-09, while similar activities are proposed also in other regions for example [91–93]. Electrochemical models are inspired by the pioneering work of Newman et al., in 1975 [89] in the field of the porous electrode theory.

The main advantage of the electrochemical models is their modelling depth which enables modelling of coupled intra-cell phenomena in much greater detail, for example, the transport of charged species, electric potentials, electrochemical reactions, heat generation, and degradation.

Majority of current state-of-the-art electrochemical models use so-called pseudo-2D approach (P2D) developed by Doyle et al., in 1993 [94] and schematically represented in Fig. 4. Since then, many research papers have been published, e.g. Refs. [95–100] and review papers, e.g. Ref. [100]. The main idea of P2D approach is to model in one dimension transport of charged species (diffusion equation with source/sink term) and electric fields (Ohm's law for solid and electrolyte phase) along the cross section of an elementary electrochemical cell consisting of two porous electrodes (positive cathode and negative anode) and porous separator in-between preventing flow of electrons causing a short circuit, hence these models are frequently named as porous electrode models. The porous structure is filled with electrolyte to enable transport of Li-ions and is assumed to have localised volume averaged physical properties (e.g., diffusion constants or electrical conductivity) according to the porous electrode theory (as shown in Fig. 4).

In classical Newman theory-based models [94], each electrode contains active electrode particles where Li is stored and are typically modelled as a single representative spherical particle in each discretised section of the electrode. Particles are additionally discretised along the radial coordinate, which is the second dimension in the P2D approach and is orthogonal to the coordinate along the electrochemical cell (Fig. 5). Molar flux due to electrochemical reaction on the solid/-electrolyte interface is commonly modelled with the Butler-Volmer equation [95,101,102] and couples partial differential and algebraic equations of the electrochemical model.

Extensions of the Newman-inspired P2D models were proposed in terms of more consistent representation of the electrode morphology and transport properties [103], especially in the case of phase-separating electrode materials such as LFP Fig. 5, which turned out as very important when modelling specifics of the phase separating materials, for example the memory effect [103,104] and recently revealed phenomena of intra-particle phase-separated state and entrance into the voltage hysteresis, inherent to phase-separating

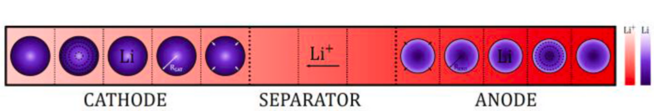


Fig. 4. Schematic representation of the P2D electrochemical model with indicated concentration of Li-ions in electrolyte (red colour) and concentration of Li in particles (purple colour) during a discharge.(For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

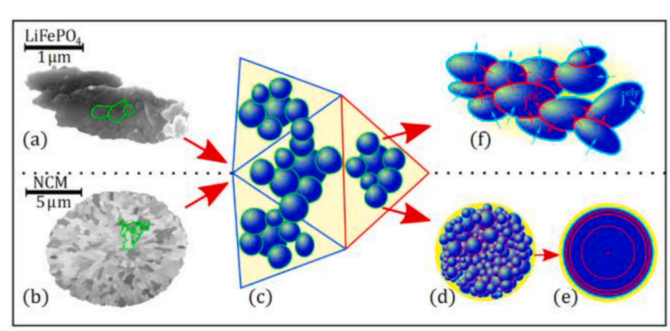


Fig. 5. More consistent approaches in modelling electrode morphology-based transport phenomena demonstrated on the LFP and NCM electrode materials [78].

materials, at finite currents [105].

Porous electrode models can be further extended to model heat generation [106–109] and degradation [109–113].This enables modelling of additional contributions to the overall heat generation on the level of the electrochemical cell which decisively influences the entire chain of mechanisms that can lead to the outbreak of the thermal runaway of the battery [109]. In addition, when integrated in the multidimensional thermal models, such models also enable optimization of thermal regulation concepts and also control strategies to minimize degradation phenomena, also for example resented on the case of Li-plating in Ref. [114].Such detailed models offer a high degree of predictability and applicability, but also high computational complexity which hinders their use in applications where real-time capable models are required, for example in BMSs. Appropriate models with sufficient modelling depth should be tailored to the specific application. High-fidelity physics-based electrochemical models which are computationally more demanding models can run on distributed computing units such as cloud servers for a detailed analysis. These models can be used for advanced modelling-based diagnostics for the most demanding BMS applications. On the other hand, fast and computationally optimized models can run on the embedded hardware (e.g., BMS chip) where various approaches with reduction of dimensionality and/or modelling depth have been proposed in the literature [115], while they are further analyzed in the next section.

Simplified physics-based models running on embedded hardware supported by the detailed electrochemical models running in distributed cloud computing offer an intriguing combination for advanced monitoring of battery states SoX in the future BMSs and consequently increasing the longevity and safety of the battery packs.

3.1.4. Reduced-order model

The term reduced order model is, in general, related to model derivatives of the electrochemical models, which incorporate specific simplifications or reductions of the dimensionality and/or level of detail of modelling specific phenomena with the aim to increase their computational speed, e.g. Refs. [115–117]. Boovaragavan et al. [118] proposed reformulated Newman-based model using advanced mathematical techniques for fast parameter estimation. Coordinate transformation and discretisation using orthogonal collocation approaches were also proposed [93,119] which could retain accuracy with lower number of discretisation points compared to the FVM, FDM or FEM discretisation. Reducing the discretisation of the P2D model leads to the so-called single particle model (SPM) approach [120,121] which considers only one representative particle per electrode ideally immersed in the electrolyte. Such a modelling approach is suited for electrochemical cells with thin electrodes and low applied currents across the cell where no major intra-cell concentration and potential gradients occur. Subramanian et al. [122] further simplified the calculation of the concentration distribution along particle radius by using a three-parameter polynomial. Li et al. [123] proposed a reduced order electrochemical model (ROEM) to describe the electrolyte concentration distribution and combining it with other intra-cell dynamics resulting in complete ROEM as a five-state diagonal system. In Ref. [124] author proposes a ROM which approximates the electrochemical dynamics of LFP batteries. Adopting this technique (POD Galerkin), offers considerable dimensionalities reduction from 169 to 9 state variables and capable of capturing phase transition dynamics and accounts for voltage hysteresis and path dependence dynamics These models are suitable for the control and estimation applications; however, compared to the complete physical model, some of the information is lost.

3.2. Data-driven model

Black-box models or data-driven models are mainly based on the data which are collected in various operation modes of battery. Although the data-driven models have top-of-the-line performances in precision and robustness over their counterparts, especially considering the temperature and aging effects, this model is extremely dependent on the volume of data and the selected training datasets. The more data are collected, the more accurate and reliable model can be achieved [38, 125–127]. Some data-driven models have been identified as more adjustable and effective. They are derived from the external characteristics of batteries and hold a good adherence to the nonlinear electrochemical reactions [40]. However, due to missing physical basis, data-driven models do not feature extrapolation capabilities and their applicability to degraded batteries is also limited, if they were not trained on such datasets. Fig. 6 illustrates the various data-driven and machine learning-based approaches including deep learning [128,129], regression models [130], probabilistic model [131],reinforcement learning models [132], classification methods [133–136], neural networks models [137–139], unsupervised learning models [140–142], prognostic and health management model [143], ensemble models [87, 144,145], and hybrid models [146].

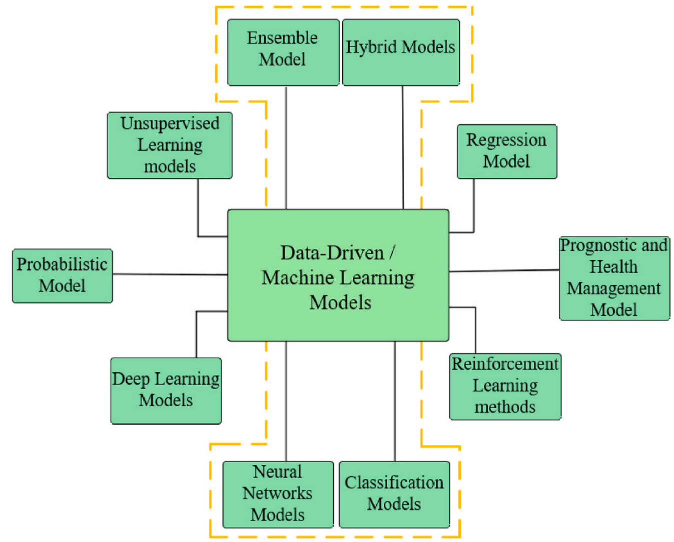


Fig. 6. Data-driven models using in battery modelling system.

In fact ML instead of being a single, specialized tool which is designed for only one specific application, it offers a variety of techniques which can be applied to/employed numerous battery related application such as estimation of the SoC, SoH, prediction RUL, detection anomalies or early fault detection, optimize charging and discharging, and model degradation/aging behavior in different operation condition [147]. Some widely utilized methods according to the literatures are highlighted in orange in Fig. 6 and explained below.

3.2.1. Neural network

Neural network (NN) models are algorithms that follow the functioning of the human brain. This traditional structure, which is fully interconnected, consists of an input layer, one or more hidden layers, and an output layer. The goal of training an NN is to identify a set of optimal weight parameters that minimize the difference between the actual and predicted labels of the training samples [148–150]. Artificial Neural Networks (ANNs) are highly suitable for battery modelling due to their ability to manage complex, non-linear relationships between input and output variables. In Ref. [149], the authors provides a comprehensive review of all the ANN-base algorithms; including CNN (Conventional neural network, DNN (Deep Neural Network),FFNN (Feed Forward Neural Network), RNN (Recurrent Neural Network) with different metric, that are applicable in battery system.

3.2.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm widely used in both academic and industrial fields due to its strengths in handling high-dimensional pattern recognition and approximating non-linear functions effectively due to the usage of the kernel [151,152]. This approach is the widely used techniques for SoH estimation compared to SoC estimation which is due to the well-perform ability for small data sets [151] in fact this approach is appropriate for both classification and regression of complex small datasets [152]. This technique has been used/utilized for the estimation of battery model parameters in the [135,153].

3.2.3. Hybrid models

Mathematical model/physics based model of Li-ion is still a prime challenge in smart battery management system [154]. Hybrid models which integrate the physics-based models and machine learning have been developed that can provide high accuracy and computationally effective model for the battery system [155]. Ref. [156], provides several architectures for integrating physics-based model with data driven models for the battery lifetime prediction. Ref. [157], presents physics-informed neural networks which the capability of forecasting end of discharge considering the battery aging and log-term prediction of battery capacity. In Ref. [158] defines two categories for the combination of physics based and data-driven approach including one data driven assisted physical model and the other one physics guided data driven approaches, analyze the aforementioned categories in the different application.

3.2.4. Ensemble models

Ensemble learning, this approach that recently gain considerable/significate attention/prominence in the literature that integrate multiple learning algorithms including data fusion, data modeling, and data mining into a single unified framework. In this regard, this method enhance the robustness and predictive accuracy in the complex and nonlinear system [147,159–161]. Several methods have been developed for constructing ensemble models, bagging, boosting, and stacking being among the most commonly used techniques. These models have proven to be highly effective in capturing complex nonlinear relationships and are widely applicable across various scientific and engineering domains, especially for identifying battery degradation [162,163].

4. Battery state of X (SoX) estimation

Battery is a nonlinear system with multiple state variables, in this regard the accurate estimation of the states is important/significant for BMS to monitor, and protect and optimize battery lifetime performance. State of Charge (SoC), State of Energy (SoE), State of Health (SoH), and State of Power (SoP) are of crucial importance for BMS. Here, in Fig. 7 estimation methods of SoC and SoH in outer layers, which are fundamental and most practical states in a BMS that influences a host of other functions have been reviewed. The SoC value acts as an input for other calculations such as SoH, cell balancing and power calculations. In essence, accurate estimation of battery SoC would provide a concrete idea to the researchers and manufacturers on the advancement for the future development of EV [164].

4.1. Review of SoC estimation methods

From electrochemical perspective, SoC is positively related to the average concentration of lithium in negative-electrode solid particles and negatively related to the lithium in positive-electrode solid particles. While the cell voltage relies on electrode particle surface concentration, SoC depends on the average particle concentration. Therefore, the capacity of the battery is difficult to measure. Hence, the methods depicted in Fig. 7 are applied for SoC estimation.

4.1.1. Direct estimation

Coulomb counting or Ampere-hour integral is the simplest model-free approach, which estimates the SoC by counting/integrating the instantaneous current over a given time through a full charge and discharge cycle. Due to simple/easy implementation and less/low computational burden/cost, this method is extensively applied in online SoC estimation. However, accumulative error due to unavoidable measured noise and temperature drifting along with initial values of SoC together with the need for high accuracy measurements makes the use of this method challenging in practice [165–169]. To alleviate the mentioned issues, an Enhanced Coulomb Counting approach has been proposed to improve the accuracy of SoC estimation, in fact, based on the numerical iteration and applying a compensation coefficient the accumulative error in CC approach can be reduced, but the error is impossible to remove fundamentally [170].

Open Circuit Voltage(OCV) and AC Impedance methods are known as look-up table methods. In fact, these methods utilized/exploited the mapping relationship between SoC and the external characteristics of the battery, including OCV, impedance, and to name but a few [164]. In the OCV look-up table method, when the battery is in an internal equilibrium state, the exact and precise value of the OCV can be measured. In this case, the OCV-SoC curve reflects the SoC value, while many charge and discharge tests shall be conducted to establish the direct relationship between OCV and SoC needed for estimation. Although currently, the OCV is widely used for calibrating the initial SoC, this method suffers from noticeable demerits, namely/for instance, prolonged relaxation time is required/requested to reach equilibrium. Meanwhile, the actual value of SoC is susceptible to the temperature and aging state [171].

The Alternative Current (AC) impedance is another method in the look-up table category. The equivalent circuit, in addition to the experimental impedance spectrum and non-linear least squares (NLLS)

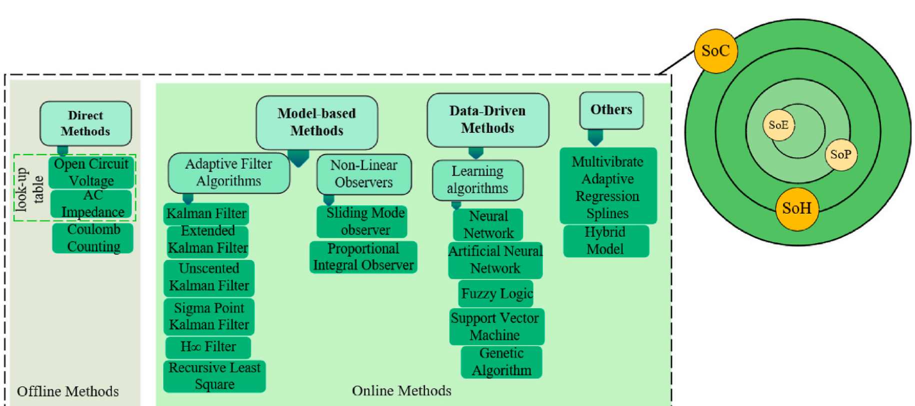


Fig. 7. SoC estimation methods include online: direct methods, offline: model-based methods, data-driven methods, and others.

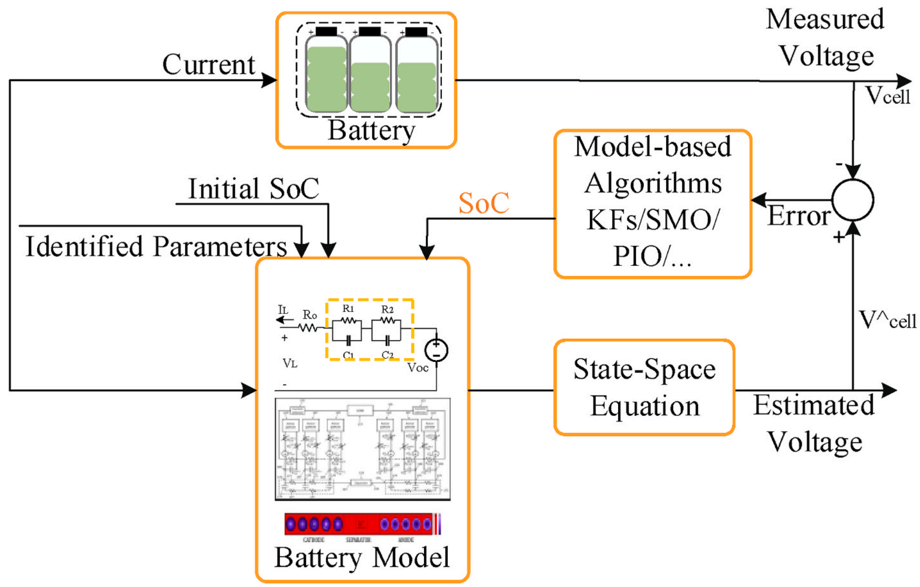


Fig. 8. Block Diagram of the Model-based SoC estimation.

fitting procedure, determines/specifies the impedance parameters in the battery. In order to set up the impedance look-up table, the LIB is charged to a specified SOC value. After that, the LIB is permitted 3 h of rest time [164] before the AC impedance of the LIB is measured through an electrochemical impedance analyzer. The process is repeated at several SOC values to establish a look-up table [164]. The main disadvantage of the methods in the look-up table category is the need for a long time without connecting to a load so that the battery reaches internal equilibrium states. However, in real-world applications and outside of the laboratory environment, the situation is completely different, and the LIB is in operation continuously. Therefore, the use of this approach in real-time estimation is not practical. In addition, expensive equipment is needed to conduct EIS measurements, which are therefore, in general, performed in the laboratory, whereas recently, low-cost EIS chips are emerging as a promising solution to more accurately predict states of LIBs.

4.1.2. Model-based estimation

To deal with the aforementioned disadvantages/limitations of the direct methods, the model-based methods and data-driven approaches have been presented. In model-based approaches, which require prior knowledge of the battery's internal characteristics, the model of batteries is signified as a state space model, and SoC is one of the space variables refer to the diagram shown in Fig. 8 explaining the mobel-based (filter and observer-based) for SoC estimation. To date, a large number of studies have been conducted on model-based SoC estimation. Generally, the methods/the SoC estimation algorithms in this category can be classified into filter-based (including KF family algorithms and other adaptive filter algorithms such as H-infinity, recursive least square, particle swarm optimization algorithm) and observer-based approaches (such as Luenberger, sliding mode, proportional integral observer, and etc.).

4.1.2.1. Filter-based SoC estimation. As in general, SoC estimation is unavoidably subject to current deviation and noise disturbance, filter-based methods, especially the adaptive algorithms, have the ability to adaptively reduce the effect of measurement and sensor noise.

Kalman filter is the widely utilized method for battery state estimation [172]. Due to the nonlinear function of the OCV and battery system in general, the KF cannot be used directly [173]. The principle of Extended Kalman Filter (EKF) is to linearize the nonlinear system and perform Kalman filtering. Ref. [174] used a reduced-order model for the battery system to estimate SoC; in this case, the estimation error is mentioned within 2 %. Ref. [175] propose a dual-time scale EKF to estimate pack SoC; the error is less than 2 %. Improvements either in the battery modeling or in the estimation algorithms can considerably affect the estimation accuracy [119,176,177]. Adaptive Extended Kalman Filter (AEKF) in which the covariance of process noise and measurement noise are adaptive [178]. Ref. [179] proposed a novel one-way transmitted co-estimation based on double AEKF for capacity and SoC estimation. Ref. [180] utilize AEKF for SoC estimation based on the fractional order battery model. In the EKF, the linearization of the OCV_SoC function is near the prior mean, and the nonlinear part is overlooked, thereby leading to considerable estimation error, while the Sigma Point Kalman Filter tackles this problem by a minimal set of sample points and propagating them through the nonlinear system [38,181]. In Ref. [181] a comparative study of nonlinear filters, including AEKF, A-SPKF, and adaptive square root sigma point Kalman filter (ASR-SPKF) for SoC estimation utilizing a reduced-order model, has been conducted that shows the predominant performance of the ASR-SPKF. Unscented Kalman filter (UKF), Improved Unscented Klaman filter (IUKF) [182,183], Cubature Kalman filter (CKF) [184], and Central Difference Kalman Filter (CDKF) are the other algorithms in the KF family, which improve the accuracy in SoC estimation. Ref. [185] provides a comprehensive study of three model-based methods, including EKF, PSO, and RLS, in terms of accuracy, robustness, and adaptability to different operating conditions. Which in result, EKF, compared to the two aforementioned approaches, gives a good performance.

Zhenggang Chen et al. estimate the SoC of lithium-ion batteries using an improved H-infinity observer in which, based on the reverse recursion of historical data updating the inner parameters, the estimation error was kept within 3 % [171]. Datong et al. have developed an online State of Health (SoH) estimator based on an Unscented Particle Filter (UPF), which combines the latest measurement to propose the distribution, which is close posterior distribution, besides representing the uncertainty. In this approach, the maximum estimation error is 5 % [186]. Yigang et al. have proposed a co-estimation algorithm in order to investigate the noise effect on the conventional RLS method. As online battery model identification by RLS has identification biases due to noise in voltage and current measurement, at first, a formula that represents the relationship between the noise and identification biases has been proposed. Moreover, bias compensation RLS and EKF co-estimation algorithms have been proposed to reduce/address the impact of the noises [187].

4.1.2.2. Observer-based SoC estimation. Identical to filter-based methods, observer-based approaches, by minimizing the error between the observed state and the actual state through close-loop feedback, estimate the SoX states. PIO (Proportional Integral Observer) is an effective way to estimate the state of the systems with unknown input disturbance. This method has the capability of simultaneously simulating uncertainties and fast calculation of the SoC estimation [32]. Ref. [188] used this method for SoC estimation. Sliding Mode Observer (SMO) is another approach in this category, which is developed from the sliding mode controller with the capability of compensating the effect of the model uncertainty and environment disturbance by maintaining robust tracking performance [189]. Ref. [190] propose a super-twisting sliding mode observer for SoC estimation and conduct comparison study between the proposed approach, EKF, and conventional SMO.

4.1.3. Data-driven based estimation

Unlike the model-based approaches, data-driven methods require limited knowledge of batteries internal characteristics and features. Data-driven methods perform the estimation process without the need for a battery model. In fact, parameter identification based on data-driven approach, is a black-box identification. These methods consider the battery as a black box and learn the internal dynamics of the battery based on large volumes of measurable data. Although model-based approaches have been introduced as extremely powerful estimation methods, there are two issues regarding the development of accurate and robust models, which can be grouped into practical and theoretical problems. In the practical view, model-based approaches require domain knowledge and longer development time to capture accurate and robust models. From the theoretical perspective, the use of electrochemical reactions, complex equations, and anode and cathode characteristics make the estimation process arduous. However, data-driven methods do not have such issues. In this case, the accuracy of estimation is highly dependent on the quality and quantity of recorded data, so by using a reasonable volume of data, the SoC estimation might be more accurate and faster than model-based approaches. This is because, in model-based, data calculation is executed to linearize a non-linear system, whereas data-driven methods utilize a series of matrix multiplications so as to estimate SoC.

In recent years, a vast number of studies have been carried out in this field, and the development of a new data-driven algorithm has made great improvements toward SoC estimation. Epherm et al., based on recorded data at diverse ambient temperatures, estimate SoC by using a deep neural network [126]. Hicham et al. have proposed an intelligent method in which an input time-delayed neural network estimates SoC [191]. The proposed approach compensates for the battery nonlinearity, electrochemical properties, and battery degradation. Zhongwei et al. have applied Gaussian process regression (GPR) for SoC estimation; in addition, an autoregressive GPR has been proposed in order to improve the accuracy of SoC estimation considering battery chemical properties in different working conditions [192]. Ephrem et al. [193] based on Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) estimate SoC with desired accuracy rate. In Ref. [194] Support Vector Machine (SVM) learning algorithm, which is a cluster of related supervised learning approaches that can universally approximate any multivariate function to any level of accuracy, is applied for SoC estimation.

4.2. Review of SoH estimation methods

SoH, another parameter that indicates the dynamic status of the battery system, is generally defined as the ratio of the useable capacity (or internal resistance) of the aged battery to the nominal capacity (internal resistance) of the new battery. SoH estimation is the basis of predicting the remaining useful life (RUL) or remaining charge and discharge cycles until the SoH value reaches 0 %, which interprets whether the LIB needs to be replaced. The SoH value for a battery at initial condition is 100 %; over time, this value will decrease. In fact, because of irreversible chemical and physical processes inside batteries, defined as an aging process, with time and usage of the battery, SoH will decrease [195]. Considering the used parameters such as voltage, current, temperature, self-discharge rate, stress, and strain, various definitions can be derived from the SoH estimation. Although this parameter is influenced by the mentioned parameters, for simplicity, generally, it has been expressed as a function of capacity fade, considering other parameters unchanged during the moment. Various approaches can be applied for SoH estimation, namely the coulomb counting method, internal resistance and impedance measurement, model-based, and data-driven methods which are demonstrated in Fig. 9.

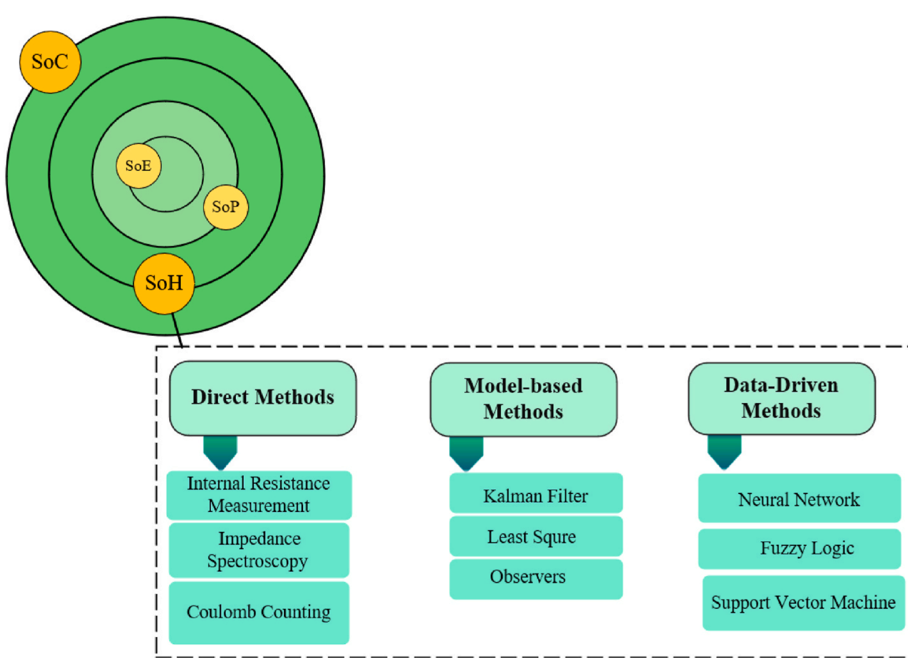


Fig. 9. SoH estimation methods include direct methods, model-based methods and data-driven methods.

4.2.1. Direct methods

In the coulomb counting approach, the most common approach, SoH estimation, is strictly based on the definition of it which is calculated by dividing the measured capacity by the nominal one that is provided by the manufacture. As measured capacity is the integral of current with regard to time, the battery should first be fully charged and then fully discharged so the current will be recorded [196]. In Refs. [197,198] the accuracy of this method mainly relies on the accuracy of the current measurement, ambient temperature, and initial SoC. The main disadvantage/shortcoming of this method is that it requires full charge and discharge for measuring the current, which is a time-consuming process and is not appropriate for the online application. This method is only applicable for calibration of the SoH of an idle battery [198]. Electrochemical Impedance Spectroscopy (EIS) measures the battery impedance over a large spectrum of frequencies. Battery intrinsic impedance is increased by aging. So, this can be an indicator of battery SoH. Refs [199–201] estimate SoH based using EIS. The internal resistance and the Joule effect can also determine the SoH which are covered in refs. [202,203].

4.2.2. Model-based methods

The main idea of the model-based SoH estimation is to estimate aging-related features, such as capacity degradation and resistance, in the three EM, ECM, and EM battery models, which can reflect the SoH [15,204,205]. [195,206–209] estimate the SoH based on the Kalman filters, least squares, and observers. The accuracy of the model-based estimation methods highly depends on the accuracy of the model.

4.2.3. Data-driven methods

In this approach, the battery SoH is predicted based on the processing and analysis of data collected from diverse measuring devices or sensors in the operation condition of the battery. Although data-driven methods circumvent the complex physics-based model, data availability(missing data), quality, and security are some challenges for accurate SoH estimation in this category [210–212].

In summary, the accuracy and robustness of direct estimation methods are not acceptable outside the laboratory. The model-based methods strongly depend on the model's accuracy, computational resources, and sufficient experimental data. Trained by a large amount of data, the data-driven methods have the advantage of insensitivity to the model's accuracy and operating conditions. Its development trends are widely acknowledged to reduce the computational burden and accelerate the processing rate [38]. To develop an efficient battery management system, in recent years, combined estimation or co-estimation has attracted considerable attention. In fact, two or more different states of battery will be predicted at high accuracy and efficient computation [91].

Table 4 and Table 5 provide a quantitative analysis of the different model-based and data-driven approaches, respectively.

5. Battery charging strategies

Optimal charging of Li-ion batteries is still a challenging task among EV manufacturers. Fast charging increases the temperature sharply, which might results in the deteriorating of the battery [110]. Fig. 10 shows that there are a vast number of significant agents in the Li-ion battery charge curve, mainly including the initial state of charge, charge current rate, temperature rise, discharge current rate, charging strategy, overcharge, and over-discharge, and to name but a few.

Many charging algorithms have been utilized so far. Charging algorithms are defined as charging profiles to charge the battery system with regard to current and voltage with time and a situation to terminate the charging process [206].To date, in related research, various classifications have been proposed from diverse perspectives. Based on the internal mathematical model of lithium-ion batteries, a large number of charging algorithms have been developed, which can be categorized into two groups [220]. a. model-free techniques, b. model -based charging methods.

Table 4
Comparative analysis of model-based estimation methods.

References	Methods	Battery Type/profile test	Applied Model/Parameter identification algorithm	Estimated Parameters	State Estimation Accuracy	Achievement
[213]	AEKF	LiMn2O4 urban dynamometer driving schedule (UDDS)/HPPS	Battery Model: Thevenin equivalent circuit model,	SoC	RMSE and MAE< 2 %	Accurate prediction of the terminal voltage and model parameters
[214]	EKF	LiNMC, DST/FUDS	First-order equivalent circuit model / Combined model	SoC	RMSE: 0.72 % / RMSE: 0.6233 %	UKF outperforms EKF in terms of estimation accuracy and convergence rate for each battery model with unknown initial values, Robustness of both methods against current noise, Update parameters corresponding to operating temperature to improve accuracy for both methods
	UKF		First-order equivalent circuit model / Combined model		RMSE: 0.395 % / RMSE: 0.6193 %	
[215]	Sliding Mode Observer (Three terminal sliding-mode observers)	LiNMC DST (Dynamic stress test)/FUDS (federal urban driving schedule)	equivalent circuit model	SoC SoH	Cell A MAE: 3.1 % RMSE: 4.7 % Cell B MAE: 2.09 % RMSE: 3.36 %	Eliminating the low-pass filter in the estimation algorithms/fast speed response and high accuracy
[216]	Sliding-Mode Observer (High-Order sliding model)	Li-NMC Worldwide Harmonized Light Vehicles Test procedures (WLTP)	electric circuit model/ Generalized Super-Twisting	SoC SoH Inner Resistance	Cell A MAE: 2.8 % RMSE: 4.53 % Cell B MAE: 1.99 % RMSE: 3.31 %	This approach ensures SOC estimation using only one observer and estimating the battery parameters without requiring any assumption on the system states
[171]	Improved H∞	$LiNi_{0.5}Co_{0.2}Mn_{0.3}O_2$ DST/ FUDS	equivalent circuit model/ Recursive Least square	SoC	RMSE <3 %	The improved H infinity algorithm proposed in this paper can keep the SoC error within 3 %, and its convergence to the true SOC is faster than the sliding mode observer algorithm.

Table 5
Comparative analysis of data-driven approach.

References	Methods	Battery Type/profile test	Estimated Parameters	SoC Estimation Accuracy	Achievement
[192]	GPR Autoregressive GPR	$LiNi_{0.8}Co_{0.1}Mn_{0.1}O_2$. Four cells in a series FUDS/DST	SoC	GPR FUDS 0/500 Cycles RMSE:0.67/2.19 % MaxAE: 3.61/ 5.64 % DST 0/500 Cycles RMSE:3.38/3.18 % MaxAE: 6.51/ 7.32 % Autoregressive GPR FUDS 0/500 Cycles RMSE:0.12/1.91 % MaxAE: 0.42/ 3.53 % DST 0/500 Cycles RMSE:2.99/2.92 % MaxAE: 5.20/ 4.80 %	Accurate SoC estimation/Approximate the nonlinearity of battery pack Effectiveness of the battery ages compared to operating condition
[217]	DNN	18650 NMC, DST Beijing Dynamic Stress Test (BDST)/FUDS/Supplemental Federal Test	SoC	DST RMSE:3.7 % MSE: 0.15 % BDST: RMSE:7.8 % MSE: 0.61DST % FUDS: RMSE:6.9 % MSE: 0.48 % US06 RMSE:7.5 % MSE: 5.7 %	Increasing the hidden layers (4 layers), resulting in improvement of SoC estimation and decreasing the error estimation/using the Adam optimization algorithm
[218]	LSTM	A123 18650 DST/FUDS/US06	SoC	RMSE ~ 2 % MAE ~ 1 %	a stacked long short-term memory network is proposed to improve the SoC estimation error, comparison with model-based approaches, and Estimation with unknown SoC values, Using various training and testing dataset
[219]	Random Forest Regression	LiNMC, LiNCA HPPC/DST/FUDS	SoC	HPPC RMSE:0.382 % MAE: 0.082 % DST RMSE:0.425 % MAE: 0.193 % FDUS RMSE:0.823 % MAE: 0.346 %	Improved RFR is applied, which enhance the accuracy of the SoC under different drive cycle and at room temperature, comparative analysis with SVM, LSTM, SVM, and analysis of various range of temperature.

5.1. Model-free techniques

Mainly including Constant Trickle Charging (CTC), Constant Current charging (CC), Constant Voltage charging (CV), Constant Power (CP), Constant Temperature (CT), Constant Current Constant Voltage charging (CC/CV), Multistep Constant Current (MSCC), Boost Charring (BC), Pulse Charging (PC), Fig. 10. These methods control the charging process through predefined or prefix values/thresholds irrespective of changing the dynamic characteristic of the battery [109–111].

Although CTC is a simple and inexpensive approach, full charging takes more than 10 h [38,221]. This method is suitable for a short time before the main charging starts or after the charging strategy so that the battery is charged to its full potential. CC can be a solution for reducing charging time. In fact, in this method, the value of the current has been raised to achieve fast charging time. However, the selection of the higher charging current required more control circuits to establish/determine the charging status and termination process. To be more specific, when the battery is fully charged, the increase of the current leads to an increased loss of capacity, thereby declining the battery life cycle [38]. In the CV charging, the charger receives current so that the battery reaches its nominal voltage. After that, it supplies/provides the needed/necessary amount of current so as to hold the voltage at the same point. One of the main merits of CV charging over CC charging is its ability to mitigate the detrimental effects of overcharging, which can lead to a reduction in battery lifespan [112]. So, the precision of setting this voltage is highly important because the battery lifetime will decline when the voltage is over the setting voltage. On the other hand, when the voltage is low, the batter cannot be fully charged, which results in an increased temperature, in fact, because of rapid changes of current to reach the battery to nominal voltage level.

Combining the conventional approaches as CCCV is the highly/widely utilized method. The CC and CV stages complement each other to some extent, with the capacity loss due to the high electrochemical polarization potential in the CC stage effectively compensated by the corresponding large electrochemical polarization potential at the CV stage. Hence, the CC-CV charging method is superior to the sole CC charge alone as well as the sole CV charge and has been chosen to provide a benchmark for the evaluation of the performance of various

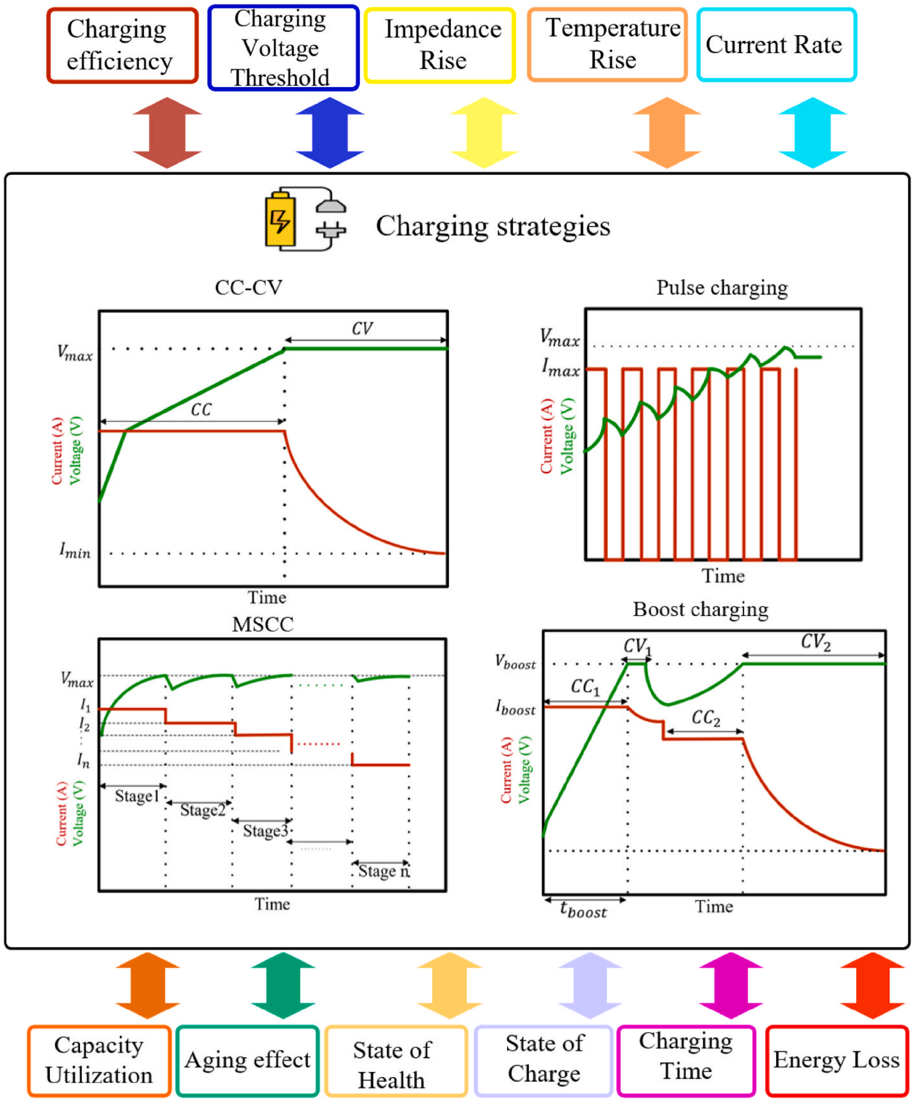


Fig. 10. The impacting factors on battery charging strategies, along with the charging profiles of different methods.

battery charging approaches [222]. The charging time of the battery for this method is determined by the constant current mode (CC mode). The suitable current value provides an equilibrium between charging performance and battery safety. If the current is too high or too low, it can cause negative effects on the battery [223]. For example, in Ref. [224], due to the formation of an electrical double layer, the use of CC at higher C rates is discouraged. The following methods are based on the fast-charging idea that adjusts the current value during charging, which may lead to shorter charging time and reduction in cell degradation. These approaches are designed to reduce heat generation, mechanical stress, and lithium plating [225].

MCC decreases the charging time and handles the temperature rise. However, it can be problematic due to fixing the value of the current for each step. Although different computing algorithms, including Taguchi, ant-colony algorithm, genetic algorithms, and particle swarm optimization method, have been employed for setting optimal value for each step, switching at the diverse value of current results in the decomposition of electrolyte, thereby losing capacity [226]. MCCCV is developed to reduce loss capacity and ensure full charge [22,227,228]. So far, two-step and five-step charging have been applied, and results have shown that the design and implementation of this algorithm is complex and time ineffectual. To date, several research studies have been conducted regarding the optimization of the number of steps and amount of time per step. As this method initially depends on CC charging, a high degradation rate is observed.

Constant Power charging strategy in which the power is held constant across the battery. When the voltage is low, the current is high, and as the voltage rises, the current declines [229]. Kim U et al. [230] have been shown that compared to CC-CV, this method shows better thermal behavior. Mai et al. [231] is referred to as the better performance of the CP-CV in comparison with CC-CV in terms of lithium plating. The result of cycling tests results in lower capacity fade and capacity loss. Despite the aforementioned merits, low energy efficiency makes this approach unsuitable for fast charging. In the Constant Temperature (CT) method, the battery's temperature is kept constant. As in this approach, the thermal characteristic of the battery is controlled; CT outperforms the other charging strategy and has a positive effect on the degradation rate of the battery. Reference [232] employs an easy-to-implement Proportional-Integral-Derivative (PID) controller with a feed-forward term that results in 20 % faster charging compared to CC-CV.

In reference [233] authors have applied a simple PID controller to a closed loop CT-CV charging circuit, which leads to fast charging. In fact, Voltage-mode control (VMC) and average current-mode control (ACM) methods were implemented to keep the battery voltage, current, and temperature at safe limits. As per simulation results, 23 % faster charging is achieved by implementing VMC, and almost 50 % faster charging is attained by employing the ACM technique in the PID controller. The proposed control strategy is validated experimentally, which yields up to 25 % faster charging of a battery than the battery used CC-CV charging technique.

Pulsed Charging (PC) is defined as a fast and effective charging method. In this method, the charging current is transferred to the battery through a pulse-width form. The main disadvantage of it is the difficulty of picking the proper current pulse. Actually, this strategy is aimed at lowering concentration polarization by reducing the risk of anode potential becoming negative at the local scale or by declining mechanical stresses due to uneven extraction and lithium insertion [222,234]. Pulse charging can be done either manually using dedicated chargers or automatically through the battery management systems. The regulation of pulse frequency, duration, and amplitude is typically implemented to ensure optimal outcomes while avoiding any potential harm to the battery [235].

Another approach in fast-charging category is Boost Charging (BC) approach strategy. This method is more analogous to the CC-CV approach. In which, the charger applies a high current to the battery for a short period of time. This high current causes the battery voltage to rise quickly. Once the battery voltage reaches a certain level, the charger switches to a lower current mode to finish charging the battery [222,236,237]. This method is appropriate for completely drained batteries. In fact, this method assures a drained battery can be recharged to

Table 6
Comparison of different charging techniques.

Ref	Methods	Comparison criteria: Charging time/Temperature/SoC %	Battery type	Features
[232]	CT-CV	SoC: 100 % tch CT-CV: 70 min tch-CV: 85 min CT_CV:18 % faster than CC-CV Temperature rise: 7.5 for both methods	Samsung INR18650-25R	improvement in charging time compared to CC-CV, with the same temperature rise as the CC-CV method
[238]	Pulse charging	Pulse Amplitude Method (PAM): Imax = 8A tch = 60~90Min SoC = 97.48 %–98.77 % Pulse Width Method: tch = 70.2 Min SoC = 95.87 % CPC: tch = 48.6 min SoC = 95.12 %		Two improvements in the pulse charging method have been presented and compared with the constant pulse charging technique. Presenting a cost function with two scalar weight coefficient, that considers the effectiveness of amplitude and width of pulse in the charging process.
[239]	TC-MSCC	Charging time: MSCC Max. SoC: 91.14 % TC-MSCC: Max. SoC: 93.68 % Temperature Rise: MSCC: 7 °C TC-MSCC: 5.5 °C	Lead Acid battery	Propose temperature compensated-MSCC, which, compared to CC, CC-CV, and MSCC, provides faster charging time.
[240]	Pulse-CV charging method	for 50 Hz: 17.62 % faster than CC-CV for 100 Hz: 18.59 % faster than CC-CV for 1 kHz: 16.98 % faster than CC-CV	LG 18650 lithium-ion batteries with NMC cathode	Analysis of the effectiveness of different frequency rates (50Hz, 100Hz,1kHz) on the charging time compared to CC-CV at every 25 cycles. The mentioned values are based on the average.
[241]	model-based	Fast Charging, considering charging time High Constant Current/Constant Electrolyte Concentration/Constant Cathode Current tch = 10.31 min temperature rise:19.89 °C energy loss: 0.87 Wh tch- CC-CV = 20.36 min for 6 °C Balanced Charging: Considering charging time, temperature rise, and energy loss tch = 16.23 min temperature rise:12.44 °C energy loss: 0.58 Wh tch- CC-CV = 21.58 min for 4 °C temperature rise: 13.02 °C energy loss: 1.39 Wh	Fast charging Balanced charging commercial LiFePO4/ graphite cell ANR26650	Based on the physics-based battery model, propose a multiobjective optimal control (cost function) that investigates optimal charging techniques considering temperature rise, charging time, and charging loss factors.
[242]	Model-based (Electrothermal-aging model)			This work compares model-based balanced charge protocol and a 5C CCCV charge protocol. In this work, three charging management with the following key findings have been analyzed: Minimum time charge: the protocol is exactly 15C constant-current/constant voltage (CCCV), requiring 5.20 min to replenish the SOC from 25 % to 75 %. Minimum-aging charge: the protocol is pulse-like rather than a slow constant current charge such as C/10 CCCV. The associated SOH decay is 0.0027 %. Balanced charge: the Pareto Frontier demonstrates that a fundamental tradeoff exists between charge time and SOH decay

one-third of its rated capacity without degradation effect. In all of the aforementioned techniques, factors such as current rate and voltage threshold have considerable effects on the charging performance; in this regard, the optimal value of the above-mentioned factors can lead to optimized charging performance. The basis of the model-free charging approach is to modify the current or voltage profiles to enhance the charging performance while reducing the charging time. The model-free charging methods, known as passive charging approaches, lack observation of the internal parameters and states during the charging process; therefore, they cannot modify the charging profile accordingly. Hence, it is hard to find the parameter degradation pattern during the charging process.

5.2. Model-based charging methods

The methods in this category can be divided into empirical model-based methods and electrochemical model-based approaches. The empirical methods include the equivalent circuit and data-driven approaches, which estimate battery states and electrical element data based on past experimental data. Although the methods in this subcategory are simple and computationally fast, they cannot reflect/deliberate/elaborate the battery aging and physic-based parameters. In fact, after working for a given cycle, some dynamic characteristics of the battery may change, thereby negatively affecting the performance of the charging process.

Charging strategies/algorithms based on the electrochemical model, which consider the internal characteristic and dynamic behavior of batteries, namely kinetic and transport equations, are more complicated [237].

The close loop optimization algorithms can minimize the charging time and make up/compensate for uncertainties and noises. Moreover, the temperature variation of the battery can be predicted by considering the thermal-related equations. However, the electrochemical-based charging algorithms, when used as state observers, are closer to actual battery mechanisms, and the intensive and sophisticated partial differential equations restrict/constrain the further application to real-time control charging algorithms [237].

The commonly applied EMs in optimizing charging are the single particle model, pseudo-two dimensional, and reduced order electrochemical model. These models, due to a computationally intensive partial differential equation, currently not yet be utilized at a commercial level and real-time optimization charging strategy, whereas recent initiatives, as the as for example NEXTBMS project in the cluster under EU call HORIZON-CL5-2022-D2-01-09, on development of advanced battery management systems (BMS), aim at pushing boundaries of such applications. On the other hand, ECMs are composed of an ohmic resistor and one or more RC networks that show the behavior of a cell to different inputs. Because of the ECMs simplicity, these models are widely used in charging optimization. In addition to reducing charging time, energy loss, and capacity loss objectives, reducing temperature rise can be set as an optimization goal by embedding thermal effect into ECMs [220].Table 6, provides a quantitative analysis of the various charging algorithms mainly in terms of charging times.

5.3. Fast charging and corresponding adverse effects

Fast charging remains a significant concern in the current electric vehicle (EV) market. Alongside cost and safety issues, fast charging poses substantial practical barriers to the widespread adoption of EVs. The absence of a standardized definition for fast charging has led to varying interpretations by different organizations. For instance, the US Advanced Battery Consortium stipulates that a battery discharged to 60 % depth should attain 40 % State of Charge (SoC) within 15 min. Meanwhile, advancements in the automotive sector have enabled the rapid charging of a fully depleted battery to 80 % SoC within 15 min. In China, the Ministry of Industry and Information Technology mandates that fast charging for mobile telecommunication terminals should replenish 60 % of battery capacity within a 30-min timeframe. Additionally, the US Department of Energy is pursuing plans for Extreme Fast Charging, exceeding 6C, which can extend the vehicle's range by an additional 200 miles with just 10 min of charging [243]. The possibility of fast charging in EVs needs to be analyzed from two perspectives: power capacity and battery capacity. Although, recently, the power capacity of fast charging has been improved, there are still some battery-related challenges for fast charging [244,245]. A large number of studies have shown/demonstrated that the problematic issues of fast charging lie in the battery aspects rather than the power capacity of the charger [246]. The primary disadvantage of charging a battery pack at a higher C-rate is the significant degradation of the cells. This degradation adversely affects the SoH of the batteries, leading to a loss in capacity. Typically, high-rate charging current has more serious effects on the battery degradation rather than the discharging rate. Although some lithium-ion batteries are optimized for 10C discharge due to their high-power density, the maximum charging rate for most commercially available lithium-ion batteries is restricted to 3C [246,247]. High charging rate induces/prompts side reactions, including lithium plating, mechanical effects and heat generation, which will speed up the battery degradation [229,247]. In cold regions at high latitudes, low temperatures significantly limit the charging rate due to the reduced diffusion coefficient in the liquid phase and the slow interfacial kinetics in the solid phase [248]. This knowledge must be expanded to develop advanced, health-aware fast charging control algorithms at the application level. Health-aware fast charging certainly requires some measured or predicted quantities to integrate them into the close-loop fast charging control procedure. To minimize/mitigate the intense aging phenomena, the quantities must be kept/maintained within allowable and tolerated limits/window of malicious cell reactions during operational conditions. This simple task description is complicated and problematic to fulfill in practice because battery aging mechanisms are varied and interconnected and occur at each component in the cell; that is, the anode, cathode, and electrolyte [249,250].

6. Battery balancing System

The main and indispensable tasks of BMS are monitoring, managing, and balancing battery cells, modules, and packs. In order to provide power and energy demands for EVs, a large number of battery cells need to be connected in series or series-parallel; not all the cells in the battery pack are identical in terms of capacity, internal resistance, and self-discharge rate, inconsistencies between battery cells certainly cannot be overlooked. The cell voltage imbalance can be attributed to a wide range of intrinsic and extrinsic factors such as manufacturing process, internal resistance, battery pack design, degradation, imbalanced State of Charge (SoC), and variation of the ambient temperature. The slight difference between battery cells takes its toll on the performance of the battery pack/battery string because of the bucket effect [251,252]. A battery balancing system is a viable solution to tackle the aforementioned problem. The lack of an appropriate Battery Balancing System (BBS) renders BMS unable to overcome these imbalances and causes a suboptimal operation that eventually leads to cell degradation, which might result in a shortening of battery lifetime, and potential safety issues. BBS is comprised of two fundamental components: the balancing control system and the balancing circuit. The main objective of the balancing control system, as the software section of the battery balancing system, is minimizing and removing inconsistency in the battery cells with minimum balancing time and power loss, as well as providing high and optimized performance for the battery system. Furthermore, the conventional battery balancing circuits are the components through which the energy transfer between cells occurs. In fact, Battery Equalizer Circuit is basically a power electronic controller that takes active measures to equalize voltage or the state of charge in each individual cell [251]. As a result, every cell has the same SoC during charging and discharging, even in conditions of high dispersion in capacity and internal resistance. If all the cells have the same SoC utilization, they degrade equally at the average degradation rate of the pack. If this condition/state is accomplished, then all cells have the same capacity during the whole lifetime of the battery pack, avoiding premature end of life due to the end of life of only a single cell. The conventional battery equalization circuits and algorithms can be categorized into two methods: Passive and active balancing. In passive balancing mode, the excessive charge is dissipated as heat, while in active balancing mode, the excessive charge is moved from highly charged cells to the cells with less charge, thus utilizing stronger cells to support the weaker ones. In view of the BMS, the cell equalization system operates in three modes: cell charging balancing mode, which occurs when the balancer charger transfers the pack's energy to the cell with low energy, named pack to cell mode; cell discharging balancing mode, which happens when the balancer charging back the extra energy of cell to the pack, in this case cell to pack mode is in operation, and idle mode, when cell charger balancer is not in operation [26,251–254]. Fig. 11 shows balancing approaches/methods and balancing control variables.

6.1. Passive balancing

Passive balancing is a simple and economical approach that uses shunt resistors to dissipate the excess energy of the cells with higher level of voltage or SoC, in the form of/as heat. Although this method requires a simple control system and has less computational requirements, it suffers from low efficiency and large heat generation, which can cause damage to the BMS board. This method is widely used in low-cost system applications.

Generally, there are two topologies based on the control strategy for the passive balancing method. Fixed shunting resistor and switched shunting resistor, which are low-cost and small-sized equalizers that can be easily implementable. In the fixed shunting resistor scheme, Fig. 12 (a), fixed resistor is in parallel with each cell. Without an external controller, equalization is done. In the second topology, a switch is used in series with each resistor that is in parallel with each cell, Fig. 12 (b) [2]. For this method, two control strategies are applicable. The first and the simple ones, all switches are controlled by an on/off signal. In this regard, all resistors are either connected or disconnected simultaneously. The second mode is based on the cell voltage, which is measured continuously. If cells are imbalanced, the switch decides

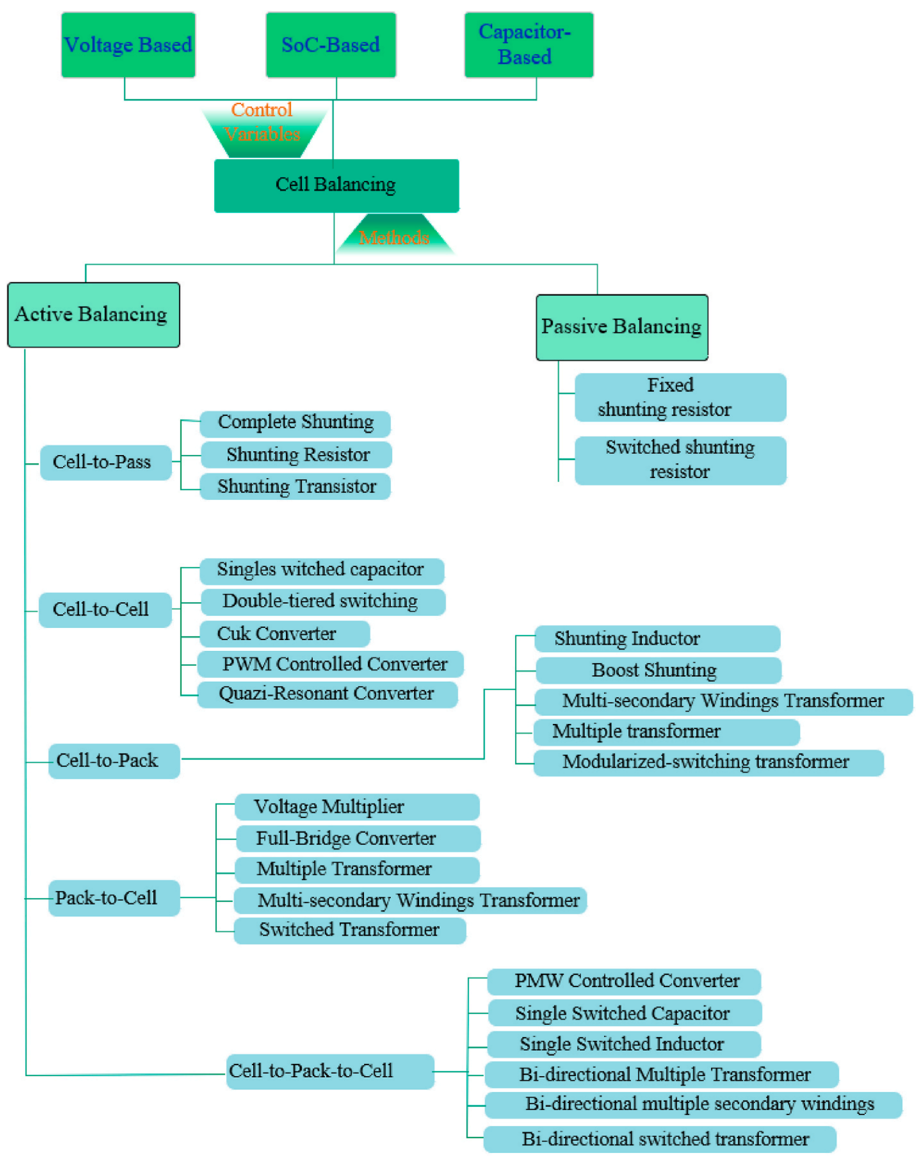


Fig. 11. Balancing methods and balancing control variables.

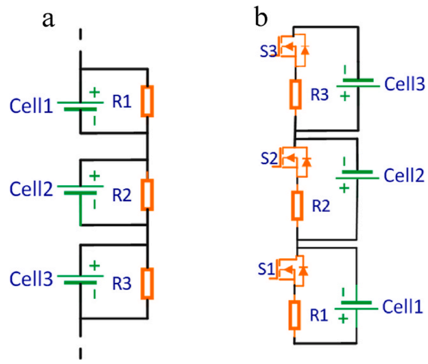


Fig. 12. Schematic view of both passive balancing topologies.

which resistors connect. So, only selected cells are connected for a specific period of time; this method is more efficient than the fixed shunt resistor [30,37,255].

6.2. Active balancing

To reduce energy losses, diverse energy transfer topologies have been proposed as active balancing approaches. In fact, in comparison with burning out the excess energy, shuttling energy between imbalanced cells is a much better option. Active balancing methods, in terms of energy path can be divided into five categories, namely: cell bypass, cell-to-cell, cell-to-pack, pack-to-cell, and cell-to-pack-to-cell. The power electronics topologies that are used in the active balancing methods can be divided into three groups: inductor or transformer, capacitor, and converter-based [251]. The circuitry design and component list for each topology are illustrated in detail in Table 7.

6.2.1. Cell bypass

In cell bypass methods, the current of cells that reach their maximum or minimum voltage is bypassed, allowing the other cells in the pack to equalize. This approach is simple, low-cost, and easy to apply, making it ideal for low-power applications. However, it is typically activated only at the end of charging or discharging cycles. As is shown in Table 7, The methods in this category can be classified into three subtypes/approaches: complete shunting, shunt resistor, and shunt transistor. These approaches are efficient, cost-effective, and easily modularized; however, they are primarily applicable to low-power applications. Complete shunting employs two power switches to disconnect cells once they reach their voltage limits. The shunt resistor method uses resistors to bypass current around the cell, leading to some energy loss. To address this issue, the shunt transistor method only shunted the current at the end of the charging process, resulting in reduced energy loss.

6.2.2. Cell-to-cell approaches

In cell-to-cell approaches, energy is transferred directly between cells, moving excess energy from higher-voltage cells to lower-voltage cells. Although this category is highly efficient, complexity and slow balancing speed are the main shortcomings of this group. This category includes five distinct topologies including: switched capacitor [256], double-tiered switching capacitor [257], Cuk converter [258], Pulse width modulation (PWM) controlled converter [259,260], and Quazi resonant converter [261].

As is shown in Table 7, the switched capacitor topology continuously switches energy between adjacent cells using capacitors. The double-tiered switching capacitor speeds up the process by using two capacitors, although it increases cost and size. The Cuk converter method transfers energy between two adjacent cells in two steps, offering higher efficiency but requiring complex control strategies. Pulse-width modulation (PWM) controlled converters are also used in high-power applications, transferring energy through inductance, though the control complexity makes the use of this approach challenging. Quasi-resonant converters function similarly to PWM converters but use resonant circuits which provides a zero-current switching function. The ZCT allows the reduction in switching loss and improving efficiency.

6.2.3. Cell-to-Pack

The cell-to-pack approach involves transferring/shuttling energy from the most charged cell to the battery pack, which then redistributes it among all the cells. This method is commonly/widely used in high-power applications but can suffer from slow balancing speeds and complex control mechanisms. The subcategory within this group are classified as shunting inductor, boost shunting, multi-secondary winding transformer [262], multiple transformers [263–265], and modularized switching transformer [266,267]. According the circuit design of the shunting inductors presented in Table 7(a) in the case of imbalanced states, the corresponding switches are activated to transfer energy from the highest-voltage cell to the pack through the inductor. Although this method is well-suited for high-power application, the balancing speed is low. Boost shunting, which operates/functions similarly to a boost converter. This methods like the shunting inductor is suitable for high power application, however, suffers from complex control system. Based on the circuit topology of the multi-secondary winding transformer shown in Table 7(c), this method stores excess energy as a magnetic field and feeds it back to the pack through primary winding, similar to aforementioned topologies in this group, this method also is well-suited for high-power application, but cost, bulk size, and low balancing speed are the main challenging. Multiple transformers work by transferring energy to the pack using individual transformers for each cell, making it highly effective for high-power applications but at the cost of control complexity and size. The modularized switched transformer similarly transfers energy via switches and diodes, see Table 7(e), this method is also appropriate for high-power applications, but has several disadvantages likes cost, size, complicated/complex control, and low speed.

6.2.4. Pack-to-Cell

In the pack-to-cell method, energy is transferred from the battery pack to the least charged cell, ensuring that all cells receive the energy they need to balance. As illustrated in Table 7, the topologies in this group include voltage multiplier, multiple transformer [263] configurations, full-bridge converter [268,269], multi-secondary winding transformer, and switched transformer [270]. All the topologies within this structure are efficient for high-power applications. The voltage multiplier uses capacitors and diodes to distribute energy. If the switching frequency will be low, this approach is efficient and relatively low cost.

Multiple transformers are used to induce current into the least charged cell when an imbalance is detected through the secondary winding see Table 7. This approach is costly. The full-bridge converter is a versatile PWM-based converter that can function/operate as an AC/DC or DC/DC converter, making it highly efficient, and easy to modularized, although suffering from complicated control systems. In the multi-secondary windings transformer the same as all the transformers-based topologies the corresponding switches to the primary side activated, the energy will be stored in inductor and then transferred to the cell with low level of voltage. In this method cost, size and complex control system are the main issues. The switched transformer is similar to the multi-secondary windings transformer but uses a single transformer to distribute energy to the lowest voltage cells, with the same issues as multi-secondary windings transformer.

6.2.5. Cell-to-pack-to-cell

The cell-to-pack-to-cell approach utilizes cell-to-pack and pack-to-cell methods for shuttling/transferring energy. The subdivided of this method generally categorized two main groups. The first one that transfers the energy from the most charged cell to the pack and from the pack to the lowest charged cell regardless of whether the cells are adjacent or not, which includes the PWM-controlled converter, single-switched capacitor [271], and single-switched inductor. The second subcategory allows the cell-to-pack balancing in the case that the cell has a higher value of voltage than the threshold and pack-to-cell balancing when the cell has a lower voltage than the threshold. The methods in this subcategory are namely: bidirectional multiple transformer, bidirectional multi-secondary transformer, and bidirectional switched transformer.

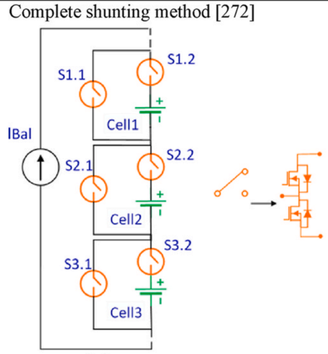
The PWM-controlled converter uses/utilizes a buck-boost converter to transfer energy. Cost, size, and control complexity are the main concerns of this method. The operation of the single-switched capacitor and single switched inductor is similar. Although these methods are cost-effective and highly efficient, their balancing speed is relatively slow.

Bidirectional transformers, such as the bidirectional multiple transformer and bidirectional switched transformer, allow energy transfer between the cells and the battery bus, offering efficient energy shuttling during both charging and discharging cycles. The bidirectional multi-secondary winding transformer uses inductors and switches to transfer energy between the battery pack and the weakest cells or between highly charged cells and others, offering flexible control but at a high cost and complexity.

Table 7
Active balancing methods, including circuit and the quantity of components.

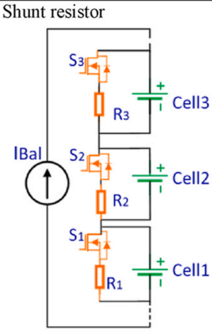
Topologies: Cell bypass

Complete shunting method [272]



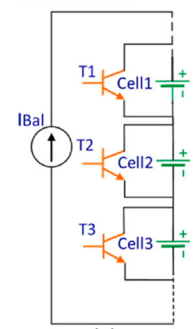
(a)

Shunt resistor



(b)

Shunt transistor

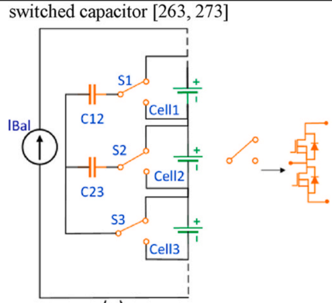


(c)

	R	L	C	D	T	Sw
Complete shunting method [272]	-	-	-	-	-	4n
Shunt resistor	n	-	-	-	-	n
Shunt transistor	-	-	-	-	n	-

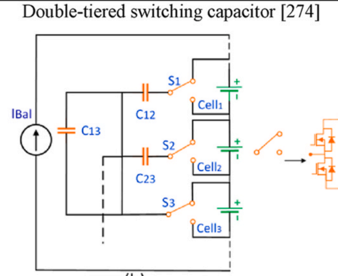
Topologies: Cell to Cell

switched capacitor [263, 273]



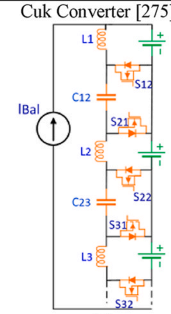
(a)

Double-tiered switching capacitor [274]



(b)

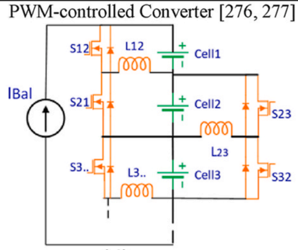
Cuk Converter [275]



(c)

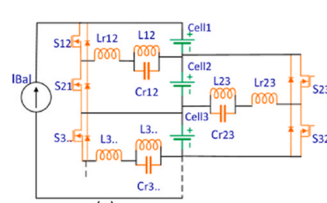
	R	L	C	D	T	Sw
switched capacitor [263, 273]	-	-	n-1	-	-	2n
Double-tiered switching capacitor [274]	-	-	2n-3	-	-	2n
Cuk Converter [275]	-	n	n-1	-	-	2n-2

PWM-controlled Converter [276, 277]



(d)

Quazi Resonant Converter [278]

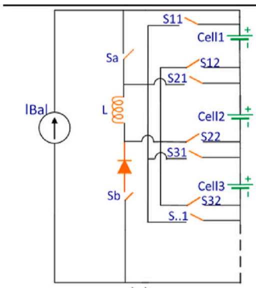


(e)

	R	L	C	D	T	Sw
PWM-controlled Converter [276, 277]	-	n-1	-	-	-	2n-2
Quazi Resonant Converter [278]	-	2n-2	n-1	-	-	2n-2

Cell to pack

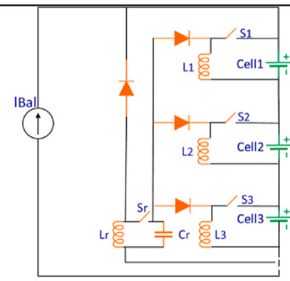
Shunt Inductor



(a)

R	L	C	D	T	Sw
-	1	-	1	-	2n+2

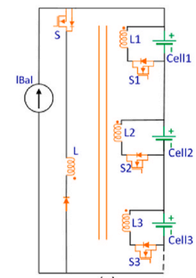
Boost Shunting [278]



(b)

R	L	C	D	T	Sw
-	n+1	1	n+1	-	n+1

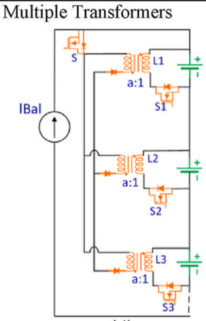
Multisecondary- winding Transformers



(c)

R	L	C	D	T	Sw
-	n+1	-	1	-	n

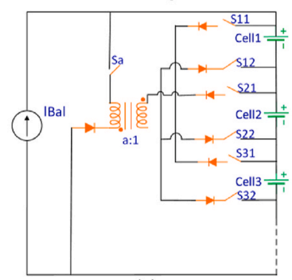
Multiple Transformers



(d)

R	L	C	D	T	Sw
-	-	-	n	n	n

Modularized Switching Transformer

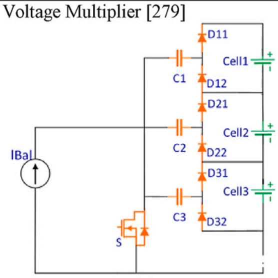


(e)

R	L	C	D	T	Sw
-	-	-	2n+1	1	2n

Pack to cell

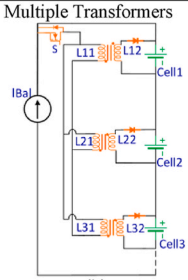
Voltage Multiplier [279]



(a)

R	L	C	D	T	Sw
-	-	n	2n	-	1

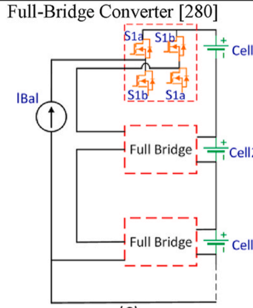
Multiple Transformers



(b)

R	L	C	D	T	Sw
-	-	-	n	n	1

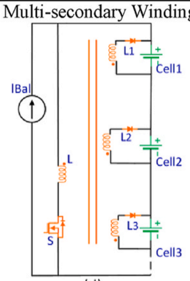
Full-Bridge Converter [280]



(C)

R	L	C	D	T	Sw
-	-	-	-	-	4n

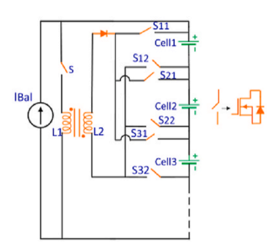
Multi-secondary Windings Transformer



(d)

R	L	C	D	T	Sw
-	n+1	-	n	-	1

Switched Transformer

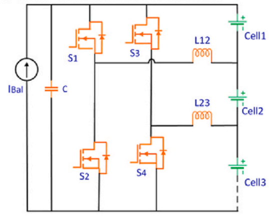


(e)

R	L	C	D	T	Sw
-	-	-	1	1	2n+1

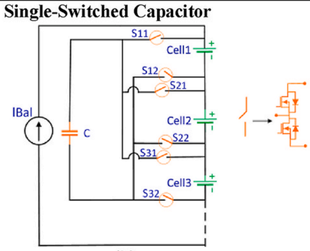
Cell to pack-pack to cell

PWM-Controlled Converter



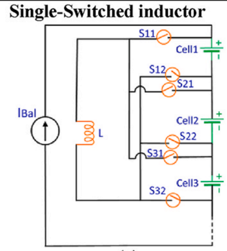
(a)

Single-Switched Capacitor



(b)

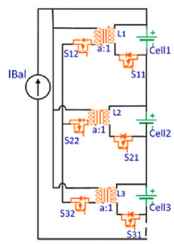
Single-Switched inductor



(c)

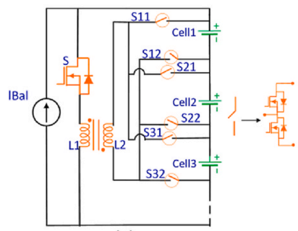
R	L	C	D	T	Sw	R	L	C	D	T	Sw	R	L	C	D	T	Sw
-	n-1	1	-	-	2n-2	-	-	1	-	-	4n+1	-	1	-	-	-	4n

Bidirectional Multiple Transformer



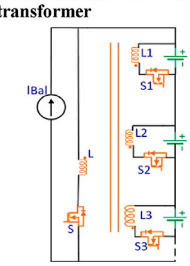
(d)

Bidirectional switched transformer



(e)

Bidirectional Multi-secondary winding transformer



(f)

R	L	C	D	T	Sw	R	L	C	D	T	Sw	R	L	C	D	T	Sw
-	-	-	-	N	2n	-	-	-	-	1	4n+1	-	n+1	-	-	-	n+1

R: Resistor, L: Inductance, C: Capacitor, D: Diode, T: Transformer, Sw: Switch, and n: the number of the battery cell

In addition to the design of the balancing circuit, the design of the control strategy is of great significance in speed of balancing and the overall conversion efficiency. In fact, the efficiency and speed of the balancing system are two of the determining factors in the selection of a balancing circuit system and balancing control strategy. Among the aforementioned balancing circuits, converter-based topologies have been shown to have a higher level of balancing efficiency and speed balancing in comparison with capacitor-based or inductor-based. Table 8 makes a comparison between different types of energy flow in an active balancing circuit.

The frequently useable balancing control strategies in terms of control variables can be classified into three categories: capacity-based, voltage-based, and SoC-based. Voltage is the frequently utilized variable because it is a simple parameter which is easily understandable and measurable. However, this variable cannot reflect the internal state of cells and is affected by internal parameters. In comparison with operating voltage, SOC and capacity reflect the internal states of cells, are not affected by the aging process, and provide the full use of the power of the battery pack. However, the aforementioned variables are not measurable straightforwardly [37], and consequently need to be estimated, which makes the process complex and time-consuming [38].

The conventional topology used in the aforementioned approaches is mainly based on DC-DC converters, which is complicated, costly, and low-efficient. This topology is effective in overcharging and over-discharging individual cells, which can positively affect the safety and longevity of the battery pack. The widely used structures in this topology are fly-back transformers or multi-winding transformers. Note that these structures are applicable for balancing a limited number of cells connected in series.

Table 8
Comparison between active cell equalization in terms of energy flow.

TYPE	Advantages	Disadvantages
ACTC	Easy implementation, Simple control scheme	Time-consuming, low-efficiency
DCTC	Relatively high speed	Very low efficiency
CTP	High-speed balancing	Low efficiency due to transformer losses
PTC	High-speed balancing	Low efficiency due to transformer losses
CTPTC	High-speed balancing	Bulky size and high cost

Generally, there are a large number of criteria for battery balancing circuitry systems, namely impact on SoH, balancing time, efficiency, cost, and volume. Although applied active balancing approaches deal with the problems associated with low efficacy, they suffer from significant disadvantages such as the complexity of hardware and additional cost, which are a major concern for their commercializing, and challenges regarding accurate assessment of control variables. In order to meet most of the mentioned criteria, a large number of studies have been conducted.

In [144], a hierarchical active balancing method has been proposed in which the battery cells are grouped into different packs, and the bottom layer is applied with the Adjacent Cell-to-Cell structure. The top layer is introduced to decouple the battery cells in different packs so that the balancing time and energy loss can be reduced. Despite remarkable improvement in terms of cost and efficiency, the proposed structure is highly complicated. Reference [145], a cell balancing approach based on switch-matrix and forward converter has been applied in which extra energy from most charged cells is transferred to the auxiliary battery pack and then to less charged cells [146]. Hybrid balancing approaches combine the advantages of passive and active balancing approaches with the purpose of mitigating the above drawbacks [272]. Hybrid balancing is applied as a module-level active balancing circuit with a cost-effective cell-level passive balancing to reduce the complexity of the control system and communication system. Consequently, adjacent cells can be grouped into modules with module-level active balancing. Besides, cell-level passive balancing can be performed within each module, providing the benefit of cell-level active balancing in terms of lifetime extension. This approach, moreover, reduces the number of DC-DC converters used in conventional active balancing circuits, which results in lower hardware complexity. This approach is depicted in Fig. 13.

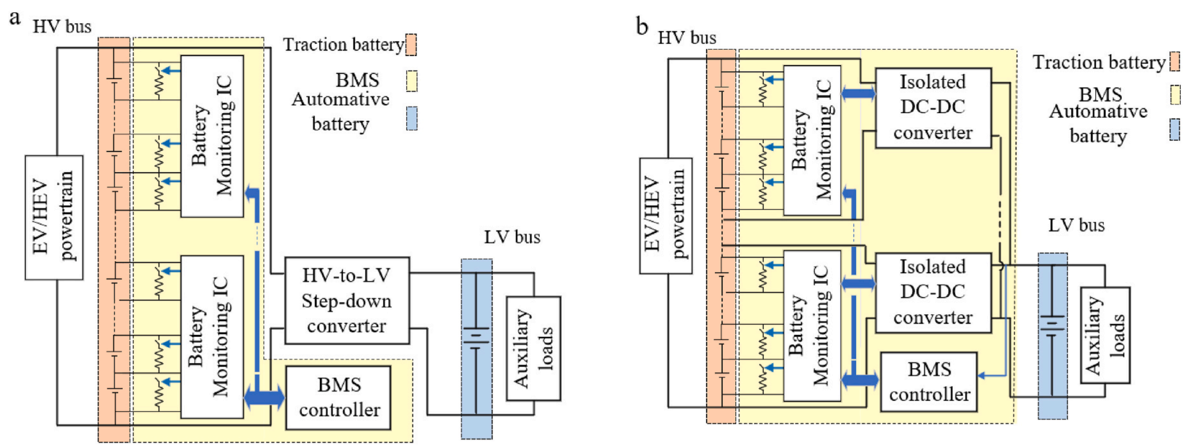


Fig. 13. (a) Conventional passive balancing system; (b) Modular system using a hybrid balancing system.

In [147], a modular topology, which is categorized in the "cell to string to cell" category, uses fewer components compared to the aforementioned topology and requires less time for equalization. However, despite proposed modifications in terms of cost and performance, such as modular-level balancing strategies and hybrid modular-level strategies, finding and designing a reduced-order and distinctive approach with the purpose of lowering hardware complexity, cost, computational time, conversion efficiency and reasonable performance, is still the need of the hour. Table 9 provides the quantitative analysis of the various active balancing approaches in different aspects.

7. Streamlined fault diagnosis in BMS

One of the most crucial and advanced functionalities of the next-generation BMSs is reliable fault diagnostics. Because of meeting the requirement of power traction, hundreds or thousands of single cells, which have different internal characteristics, need to be connected in series, parallel, or series-parallel. Over time, factors such as aging, frequent bumps, vibrations, and temperature fluctuations can exacerbate inconsistencies between these cells, potentially leading to overheating and other issues. During battery operation, these inconsistencies can appear as performance issues or, in extreme cases, hazardous events like fires, explosions, or thermal runaway. Hence, timely and accurate fault detection and response by the BMS are essential to prevent such dangerous situations or battery failures. An onboard battery system typically comprises lithium-ion batteries, BMS, sensors, connectors, data acquisition sensors, thermal management systems, cloud connectivity, and so on. Considering the mentioned structure, failure can happen in batteries, sensors, or actuators [283,284]. Fig. 14 depicts different possible faults that might occur in any battery system [40]. Building on the terminology outlined in the fault diagnosis system [285], Table 10 provides a streamlined review of fault diagnosis in the battery system.

7.1. Fault causes and failure mechanisms in battery system

Safety issues are one of the most crucial factors impacting the worldwide adoption and competitiveness of battery-powered vehicles. Considering the battery characteristics, the main failure causes of battery system can be classified as mechanical, electrical, and thermal abuses, as depicted in Fig. 15. Each one of the abuses can create anomaly conditions in the safe operation of the battery system, which, in extreme cases, lead to hazardous events like fire, explosion, and thermal runaway. Thus, the early detection and timely response of the BMS are imperative to prevent battery failures.

7.1.1. Mechanical abuses

Despite precautions measures in large-scale EV applications regarding the placement and reinforcement, the occurrence of some real-life situations like accidents and high-impact forces can lead to mechanical abuses, mainly including bending, indentation, collision, penetration, vibration, and compression which results in adverse consequences such as external short circuit, internal short circuit, capacity fading, and electrolyte leakage. To comprehensively assess the mechanical robustness and discern the failure mechanisms, standardized tests expose the battery system to various high-impact forces and nail penetration; simulating accidents and handling errors in real-world situations/scenarios is pivotal. Through this process, the safe operation thresholds, in which the battery system can perform without any safety problems or the period of time it can operate under existing mechanical stress, are specified [286–288]. Ref. [289,290] provide in-depth insight into the impact of mechanical abuses on battery behavior and potential aspects for the innovation of mechanical protection and safe operation of battery systems.

7.1.2. Electrical abuses

Electrical abuses, including external short circuits, overcharges, and over-discharges, encompass scenarios where the electrical operation of the battery exceeds the recommended and allowable limits/thresholds [287].

7.1.2.1. External short circuit (ESC). When two electrodes with different voltage values (cathode and anode of the same cell) are connected by the external conductor leads to the external short circuit. The external short circuit can be caused by water immersion, deformation during the car collision, contamination with conductors, or electrical shock during maintenance [283,284]. Following the external short circuit behavior analysis in the battery system in Ref. [291], the peak-plateau-drop was a typical characteristic of the external short circuit [292]. Although some heat generated in the external shot circuit, the high peak current can still lead to fast temperature rise and cell swell, which are dangerous. The observed cell swell indicate that gas was generated during external short circuit. In summary, this phenomenon is more like to fast discharging process at a current where ESC is limited by the mass transport speed of $Li+$ [293].

7.1.2.2. Overcharge. Charging a battery cell beyond its allowable limits, which can be caused by the malfunction of the charger or failure in BMS as a result of sensor failure. Heat and gas generation are the two common characteristics of overcharging. The heat generation comes from ohmic heat and side reactions. Side reactions occur between the lithium dendrites and electrolyte, generating gas and thickening solid electrolyte interface (SEI) [292]. After lithium-ion was completely removed from the positive electrode, the battery voltage would rise sharply. The exothermic reaction and gas production reaction had been accelerated.

Table 9
Comparison between active balancing approaches.

Methods	Component					Balancing speed	Balancing time	Efficiency	Experimental situation
	SW	T	L	C	D				
bidirectional modified Ćuk converter [273]	2n-2	–	2n-2	n-1	–	–	–	87.8 %	Use three bidirectional Cok converters, which allow the maximum acceptable equalizing current to vary with the change of the battery pack's external current.
Half bridge converter with an inductor and a capacitor [274]	2n	–	n	n	–	–	Lead acid: cell-level 90 min Module level 192 min Li-ion: 5min	90.8 %	Phase shifted half-bridge based multi-cell to multi-cell (4 cells, 2 modules)
Transformer based equalization circuit [275]	2n+6	1	–	–	–	–	78 min For balancing of two cells with 80 % SoC and 73.1 % SoC	Static 80.4 % Equalization power 0.78W	12-series connected cell, the proposed approach has been validated for cycling dynamic conditions (charging and discharging as well)
Modified switched capacitor approach [276]	4n-3	–	–	n	–	–	6 cell Conventional: 5.83 min Proposed: 3.33 min	–	Utilizing a pair of complementary pulse signals with constant switching frequency and fixed duty ratio controls all of the switches in this approach and makes a comparison of the conventional switched cell with the proposed one, which directly transfers the energy from a higher voltage to a lower one (4 series connected cells)/ fsw: 22 kHz
Cell to cell equalized based on the three resonant state switched capacitor [277]	5n-5	–	n-1	n-1	–	High	34.26 min with zero voltage gap	Max efficiency at power transferring: 0.59 is equal to 89.1 % (2 cell)	A cell-to-cell equalizer with zero current switching and zero voltage gap was proposed to compensate for low efficiency and low speed for high voltage gap cells.
Cuk converter with coupled inductor [278]	n	–	–	n/2	–	–		max efficiency: 94 %	For ultra-light application
Buk-boost converter [279]	2n-2 Low frequency, n high frequency	–	n-1	–	–	–	Static condition: Two mode Max time: 23 min Discharging with 1 A: Max time: 18 min Charging with 1 A: 32 min	–	For six series of connected cells, different operation condition, namely static, charging, and discharging, has been analyzed. The equalization process includes two modes: unit-to-unit and middle-to-unit.
[280]	N+1 Bi-directional+4 (Bridge network) mn+6m + 5 Bi-directional	–	1 (bridge network) m+1	–	–	–	323.7 min 114.29 min	79.42 % 88.4 %	16 cells connected in a series 4 module/each module is composed of 4 cells
[281] Non-isolated DC/DC converter	4 FET n+1	–	1	–	–	–	Discharge with active balancing Idis 1C = 10 A tB = 58.93	>90 %	8 cells connected in series
[282] combination of wireless power transmission and switch array	2n+1	1	–	2	–	–	66.6<t balancing <133.13 min	>87.2 %	WPT provides physical isolation, which is hardly achieved by the traditional equalization methods. Four series cells connected

SEI decomposition, separator melting, positive electrode decomposition, electrolyte decomposition, binder decomposition, and electrolyte combustion occurred successively, leading to the thermal runaway of LIBs. Considering the outcome of the overvoltage test, the charging current considerably affects the result. The cell can explode under high current while the cell only swells under slight charge [285,293,294].

7.1.2.3. Overdischarge. Forced discharge or over-discharge is another crucial scenario in the electrical abuse condition. Similar to overcharge, failure in the BMS, specifically, the sensor failure leads the cell with the lowest voltage to be over-discharged. The mechanism of forced discharge is different from the other, and the potential hazard might be ignored [292]. Overdischarge can lead to capacity fading/degradation. During the process of overdischarge, the over delithiation of the anode causes the decomposition of SEI, which will produce gases like CO or CO2, resulting in the cell swell [295].Once the cell is recharged after overdischarge, new SEI will be created on the anode surface. Meanwhile, the regenerated SEI layer changes the electrochemical synthesis of anode [296] which is accompanied by resistance increase and thereby capacity degradation [292].

Dissolution of the copper collector is an important mechanism of over-discharge failure, which may cause ISC, in addition to capacity degradation [288,292]. In summary, Slight undervoltage might only cause aging of negative electrodes, such as structural collapse, SEI decomposition, and rebirth. Once the negative electrode potential escalated to the copper collector dissolution potential,the safety of the battery cell will be reduced [286].

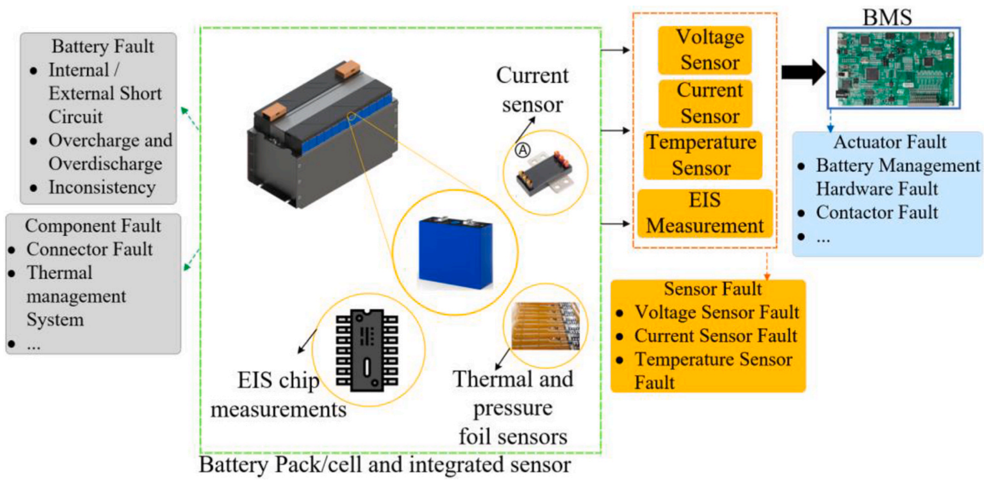


Fig. 14. Different possible faults in battery systems.

Table 10
Terminology for fault diagnosis definition.

Definition of the terminology used for fault diagnosis	
Fault	An anomaly due to which a system is unable to perform a specified function
Fault cause	The key factors causing a fault
Fault mechanisms	The nature of changes in physical processes that eventually develop into a fault
Fault features	The feature or parameter that reflects the abnormality caused by a fault
Fault mode (type)	The macroscopic behavior of a fault, also known as the type of fault
Fault detection	The process of determining whether a fault has occurred
Fault isolation	The process of determining the type and/or location of a fault
Fault diagnosis	The process of detecting, isolating, and estimating a fault

7.1.3. Thermal abuse

Thermal abuses refer to overheating of the battery pack by an external heat source, which results in thermal runaway (TR). To determine/assess the thermal stability of LIBs, LIBs are exposed to/subjected to low to high temperatures, which is beyond their normal operation range, self-cascaded exothermic reactions occur inside the cells SEI decomposition, side reaction between negative electrode and electrolyte, separator melting, positive electrode decomposition, electrolyte decomposition, binder decomposition, electrolyte combustion and other processes, that may lead to TR [286]. Refs [297–300] provide detail insight into the effect of heating power and the position of the heating on the TR.

7.1.3.1. Internal short circuit (ISC). Almost all causes of thermal runaway lead to ISC. ISC is the more dangerous fault type, accounting for 40 % of EVs fires [283]. Generally speaking, ISC occurs when the cathode and anode connect to each other due to failure of the separator (melting of separator). Once the ISC is triggered the massive amount of the electrochemical energy stored in the material is released with heat generation. An ISC can be triggered by electrical (overcharge and deep discharge), mechanical (nail penetration or crush), and thermal abuse [288,293]. Mechanical and thermal abuses can lead to enormous ISC, directly triggering TR. However, less intensive (Soft)ISC only leads to the heat generation [292]. The energy release rate changes with the degree of separator crack and the time from ISC to TR. As all the cell products pass the corresponding standard cell, the possibility of the induced ISC is quite low [292]; however, there is a type of ISC, called spontaneous or which is referred to self-induced ISC which is originated/comes from contamination or defect during manufacture [288, 293]. As self-induced ISC is relatively unpredictable, which can lead to TR without early warning/detection, the battery manufacturer must form/establish a strict foreign/contamination material detection materials mechanism to alleviate battery safety accidents. The hazard level of the ISC can be assessed by the self-discharge rate, and exotic heat generation [292] and it is categorized into three levels. Level 1: the cell displays self-extinguish features without manifest heat generation, level 2: fast voltage drop and temperature rise, the characteristics of ISC become apparent, and level 3: the collapse of the separator, intensive heat generation, and unstoppable TR.

7.2. Fault types

From the control perspective, fault types in the battery system can be divided into battery fault, sensor fault, and actuator fault. Fig. 16 depicts the different fault types in the battery system along with the causes and potential consequences.

7.2.1. Battery faults

According to Refs. [283,301,302], battery fault includes overcharge, overdischarge, external short circuit, swelling, internal short circuit, and thermal runaway, mainly covered by aforementioned sections.

7.2.2. Sensors associated to BMS and their faults

The design and integration of sensors are critical for the advancement/smartness of battery cells and state-of-the-art battery management systems. To date, voltage, current, and temperature sensors are extensively utilized in battery systems. As the automotive industry is moving towards smart cells, to cope with this improvement, the suitability of existing sensors needs to be further investigated, due to spatial limitations and measurement range specifications. In fact, there is a growing demand for emerging sensing technologies for measuring multi-physics processes that cannot be measured in traditional BMSs [303].

7.2.2.1. Current and voltage sensor. Generally, two common current sensors have been applied/employed/utilized for battery current measurement systems: Hall-effect and shunt resistor.Recently some innovative methods have been utilized for cell current measurement [304]. proposes an equivalent resistor for current measurement and [305] presents three-in-one flexible microsensors with three functions,

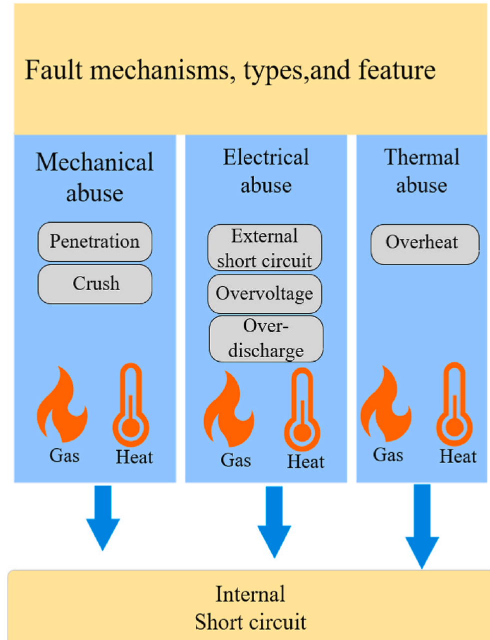


Fig. 15. Fault mechanisms, types, and features.

compactness, withstanding in harsh environments, and optional locations. The aforementioned approach can be utilized for the smart battery cell. Most voltage measurement techniques have been introduced in recent years namely resistance voltage dividers, optical coupling isolation amplifier, discrete transistor, distributed measurement, optical coupling relay, etc, which mostly are in the patent instead of being applicable in industrious battery system. Recently, integrated circuits as a promising voltage measurement method, have been applied to voltage measurements [303,306], for example, NXP semiconductors launched an intelligent battery chipset which not only accurately measures the voltage, but also at the same time capable of measuring the current and temperature of the battery. The merits, demerits, and features of current sensors applied in battery system are summarized in Table 11.

7.2.2.2. Temperature sensor. Temperature is an essential agent that specifies the safe and reliable operation of batteries because the temperature gradients can lead to local aging differences, thereby global aging of batteries. Surface and internal temperature sensors can be categorized into three electrical temperature sensors, Fiber Bragg grating sensors, and non-contact sensors/infrared imaging [294], Fig. 17. Electrical temperature sensor encompasses thermistors, resistance temperature detector (RTD), and thermocouples. As illustrated in Table 12 compared to other non-embedded temperature sensors, FBGs have the highest accuracy and sensitivity with fast response, moreover, the distributed measurement method in comparison with single-part measurement is more effective.

7.2.2.3. EIS measurement. Battery impedance manifests the resistance faced by charged particles as they move through the varied battery components. The resistance which can serve as a robust indicator of battery states and a valuable tool for battery fault diagnosis, influenced by the convoluted physical and chemical processes inside the battery [310]. Moreover, the non-destructive internal temperature of the battery can be measured through this parameter [311]. On the other side, battery impedance can also serve as a tool for monitoring the irreversible lithium plating [312,313]. However, acquiring battery EIS requires specialized laboratory equipment including a perturbation excitation generation device along with a current and voltage synchronous device, and impedance calculation function. At present, most of the onboard applications are focusing on the precision/accuracy of the excitation producer device and insufficient sampling frequency making it challenging for energy storage systems [294]. Although recently some promising steps have been taken towards tackling this problem/issue [314–316], still low sampling frequency is not sufficient for EIS testing requirements. Further investigation shall be taken into account concentrating on adequate sampling frequency for EIS testing.

7.2.2.4. Sensors faults. In addition to battery faults, sensor faults can cause critical issues for the operation of the LIBs, since the BMS sends the command based on the feedback from sensor measurements. In practical application, because of inherent defects, aging, and harsh working environments, sensors undergo measurement value bias, drift, and measurement freezing. Besides, operating at high temperature for a long period of time takes its toll on sensor component, thereby affecting on the BMS performance and LIBs performance [285,317]. Sensors in LIBs include voltage, current, and temperature sensors. Faults in the current sensor affect the state estimation accuracy. Estimated SoC, along with temperature sensors, update the battery model parameters in real-time for high-accurate estimation. Due to safe operation, the voltage and temperature level of LIBs must not exceed the allowable limits, so in this case, faults in temperature and voltage sensors can cause accidents. Moreover, voltage and temperature sensor faults lead to balancing errors and thermal management issues in the BMS [285].

7.2.3. Actuator fault

Actuator malfunctions exert a more direct influence on the operational efficacy of control systems in comparison to battery and sensor malfunctions. Various potential actuator issues within a LIBs system, encompassing terminal connector complications, malfunctions in the cooling system, controller area network bus anomalies, high-voltage contactor issues, and fuse malfunctions, are delineated in Ref. [285]. For example, If the cooling system fails, the battery cannot maintain in safe operating limit, which can trigger the TR. Contactor and fuse faults can lead to the overcharge and the over-discharge process continuing, which results in the occurrence of the arc or spark, thereby melting battery terminals.

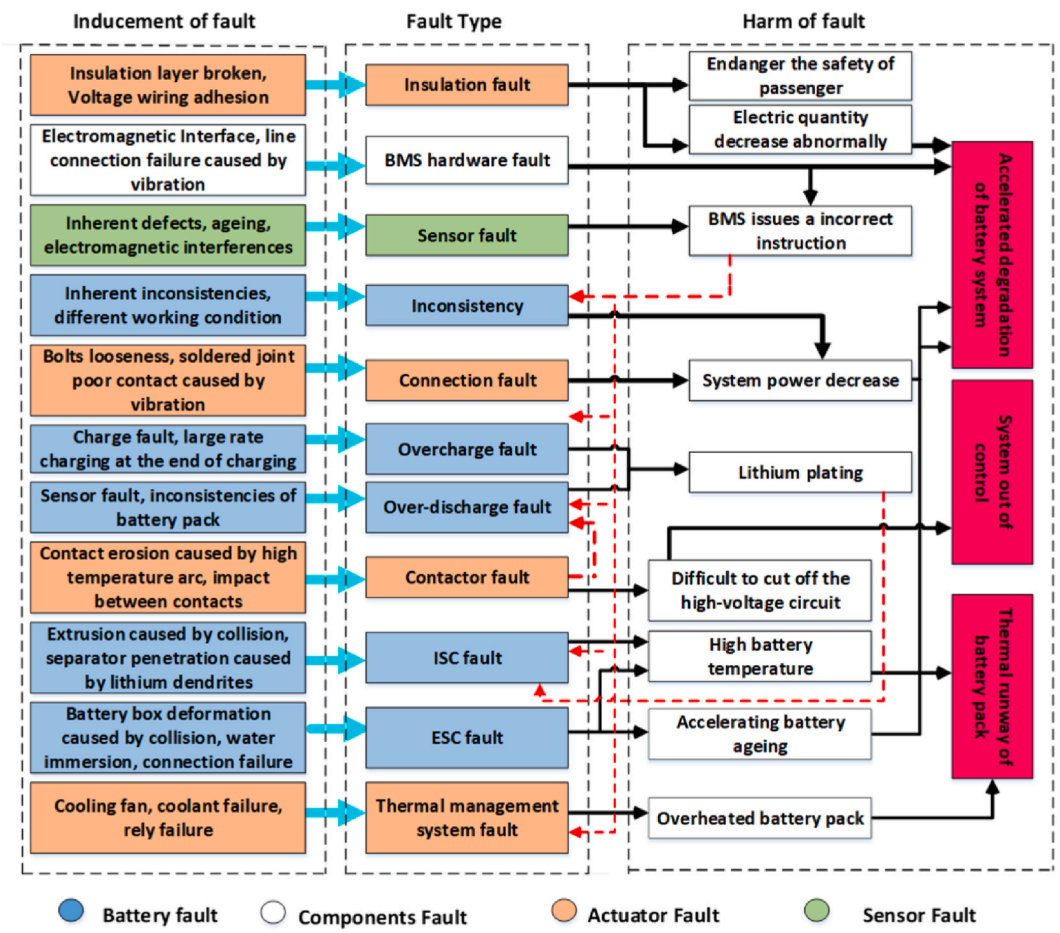


Fig. 16. Fault causes, fault types, and fault effects in the battery system.

Table 11
Comparison of different types of the current measurement sensors using in the battery system.

Features	Shunt resistor [307]	Magnetic fluxgate sensors [294,308]	Hall effect current sensor [309]
Accuracy	✓ High accuracy, easily affected by high temperature ✓ Lack of offset at 0 current ➢ Not suitable for high current as serves as the heating	✓ High	✓ Average accuracy ✓ Independent of temperature ✓ No offset at 0 current ➢ Large deviation at low current
Range	Usually less than 20A	Medium to high current ranges	Up to 1000A
Volume	Small	Large	Average
cost	Cheap	Expensive	Average
Energy dissipation	Low	High	High
Galvanic Isolation	Not required	Required	Required

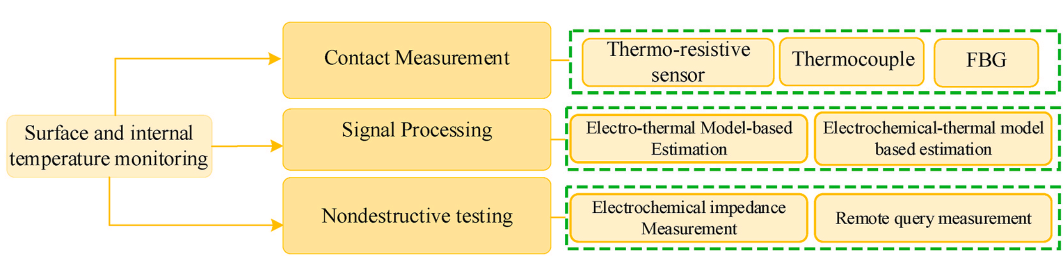


Fig. 17. Surface and internal temperature measurement methods applicable for the battery system.

Table 12
Comparison of different temperature measurement methods in battery system.

Features	Thermal resistor	Thermocouple	Fiber Bragg Grating	Thermal Imaging technology
Accuracy	Average	Relatively high accuracy	High accuracy with fast response time	High spatial resolution but influenced by measurement equipment and environmental factors
Robustness	Average	High robustness	Immune to the electromagnetic interface but affected by mechanical interfaces	Sensitive to environmental interferences
Operating range	Relatively narrow	wide range	wide	Providing distribution map
Cost	Relatively low	low	High	Relatively high
Feasibility	Easy implementable for multi-sensor integration	Easy to integrate	Appropriate for specific applications like TR	Applicable requiring global temperature distribution

7.3. Safety standards and analysing hazard and risks

Ensuring the safety of electric vehicles (EVs) equipped with high-capacity energy storage devices presents significant challenges that must be addressed for their widespread commercial adoption. High-performance traction battery systems need to be inherently tolerant to the aforementioned abuse conditions, namely overcharge, external short circuit, over-discharge, mechanical shock, etc.

To guarantee the safety and mitigate potential thermal runaway risks associated with lithium-ion batteries (LiBs), a comprehensive framework of battery safety standards has been established. These standards regulate and facilitate the responsible use of commercially available LiBs by defining standardized testing protocols and performance benchmarks. Prior to mass production or market release, LiBs must undergo and successfully pass these rigorous safety evaluations to achieve certification for specific applications, such as automotive or consumer electronics. Without such certification, adherence to essential safety measures and adequate product quality cannot be assured [293,318].

The growing prevalence of hybrid electric vehicles (HEVs) and EVs has unfortunately led to a rise in LiB-related incidents. Consequently, these safety standards are subject to continuous review and improvement to maintain optimal LiB safety for current applications. Notably, various internal safety organizations and government entities have collaborated to develop these crucial battery safety standards. Table 13 list the main safety standards in Li-ion batteries [319]. ISO 26262 is an internationally recognized standard for functional safety in automotive systems, providing a comprehensive framework for identifying and mitigating risks associated with electric vehicle (EV) components, including high-voltage battery systems. The standard outlines a systematic approach to ensure the safety of electrical and electronic (E/E) systems throughout their lifecycle, from design and development to production and operation. In the context of battery systems, ISO 26262 emphasizes the importance of rigorous risk assessment processes to identify potential hazards and implement appropriate safety measures. The risk assessment begins with a thorough hazard analysis and risk assessment (HARA) to classify the severity (S), exposure (E), and controllability (C) of potential faults. This classification informs the determination of Automotive Safety Integrity Levels (ASIL), which dictate the stringency of safety requirements and design strategies [320,321]. These criteria are systematically integrated into a matrix, producing an Automotive Safety Integrity Level (ASIL) in accordance with the risk graph matrix specified by ISO 2626 in Table 14 In this table, Quality Management (QM) indicates that no special safety requirements are necessary. The other classes, A, B, C, and D, correspond to progressively stringent Automotive Safety Integrity Levels (ASIL), with Class D representing the highest level of safety requirements.

Table 13
List of the main safety standards in Li-ion batteries.

Scope	Fault	Standards/battery chemistry(Li-ion)
Mechanical Test	Impact	IEC 62619:2022 Impact test, UL 1642:2020 Impact Test UL 1642:2020 Round Bar Crush Test UL 1973:2022 Impact Test GB 40165-2021 Heavy impact GB 40165-2021 Squeeze
	Drop	IEC 62619:2022 Whole Drop test IEC 62619:2022 Edge and Corner Drop test IEC 63056:2020 Drop test UL 1973:2022 Drop Impact test VDE-AR-E 2510–50:2017–05 Drop Test GB 40165-2021 Fall down
Electrical test	External short circuit	IEC 62619:2022 External short-circuit test IEC 63056:2020 Protection against short circuit during transport and installation UL 1973:2022 Short circuit test UL 1642:2020 Short-Circuit Test VDE-AR-E 2510–50:2017–05 External short circuit GB 40165- 2021 High temperature external short circuit GB 40165- 2021 Short circuit control
	Overcharge	IEC 62619:2022 Overcharge test IEC 62619:2022 Overcharge control of voltage IEC 62619:2022 Overcharge control of current UL 1973:2022 Overcharge test UL 1973:2022 High Rate Charge GB 40165-2021 Overcharge GB 40165-2021 Overcharge control GB 40165-2021 Overflow charging control
	Over discharge/ deep discharge	IEC 62619:2022 Forced discharge test IEC 63056:2020 Over-discharge control of voltage UL 1973:2022 Overdischarge protection test UL 1642:2020 Forced Discharge Test GB 40165-2021 Forced discharge
Thermal test	Over Temperature	UL 1973:2022 Failure of Cooling/Thermal Stability System IEC 62619:2022 Overheating control GB 40165-2021 Overheating control
	Thermal propagation	ISO 6469-1/AMD1:2022 Thermal propagation test GB38031:2020 Thermal propagation test
	Thermal abuse	IEC 62619:2022 Thermal abuse test UL 1642:2020 Heating Test UL 1973:2022 Heating Test GB 40165-2021 Thermal abuse
Internal short circuit		IEC 62619:2022 Internal short circuit test

UL: Underwrites Laboratories, GB: Chinese standard.

7.4. Faut diagnosis system

Fault diagnosis process in LIBs can be divided into three steps, namely fault detection, fault isolation and fault prognostic. Fig. 18 shows the procedure of the fault diagnosis in LIBs. Data acquisition is the first step in this procedure; the required data, mainly including voltage, current, and temperature in a battery system, are collected and stored in this step. Feature extraction is to analyze the stored measured data in the

Table 14
Risk graph matrix of ISO26262.

	Exposure class	Controllability class		
		C1	C2	C3
S1	E1	QM	QM	QM
	E2	QM	QM	QM
	E3	QM	QM	A
	E4	QM	A	B
S2	E1	QM	QM	QM
	E2	QM	QM	QM
	E3	QM	A	B
	E4	A	B	C
S3	E1	QM	QM	A
	E2	QM	A	B
	E3	A	B	C
	E4	B	C	D

data acquisition step and extract key electrical and thermal feature from the data [302]. Feature extracting includes the following four steps: data prepossessing which filters the noise from the data for further sequent, feature representation which refers to transferring the raw data into a format that capture the condition of the equipment, feature extracting which refers to the characteristic or parameters that the anomalies reflect in that character, and feature selection.

The accuracy of this step is highly depends on the applied methods. The three approaches using in this step are signal-based processing, model-based, and data-driven methods [285,302]. The task of signal processing is to extract useful/practical information that reveals the health condition of the system. The techniques and algorithms in this approach are classified into three categories: time domain, frequency domain, and time-frequency domain analysis [285,322]. Refs. [323–330] are including spectral analysis, wavelet transformation, and entropy-based, Empirical Mode Decomposition (EMD), and Principal Component Analysis (PCA) methods which utilize the signal-based feature extracting in the fault diagnosis process. Although this method without accurate model of the battery system extract feature, fault identification might be challenging since some failures in battery system have similar electrical and thermal consequences [302].Moreover, signal processing cannot detect the small problems because this approach only detect the failures which their consequences in battery system reach a certain level [285,302].

According to the measurements, the model-based state estimation and parameter identification methods can be utilized to extract fault features [285] Battery faults can be manifested through deviations in corresponding battery model parameters. For instance, internal short circuit faults and thermal faults often are accompanied by a decrease in SoC, and an increase in ohmic internal resistance [302,331]. The models utilized in this method including ECM, Thermal Model (TM), EM, and physics-based model. To analyze the battery states and parameters filters, observers [332] and recursive least square (RLS) [333], genetic algorithms, and particle swarm optimization algorithm [334] needs to be applied in the battery models to extract key battery states or parameters. In this approach, the accuracy of feature extraction highly depends on the model accuracy. In contrast to model-based methods, data-driven approaches to fault feature extraction achieve enhanced representational fidelity through online learning, enabling more accurate fault detection. However, this enhanced accuracy comes at the cost of increased computational demands. The commonly/widely used approach in this category is including Artificial Neural Network (ANN), SVM, LSTM, and K-means.

As is shown in Fig. 18, fault diagnosis in LIBs includes fault detection, fault isolation and fault estimation. Fault diagnosis methods in the LIBs system are categorized into two groups including model-based, and non-model-based approaches [301].

7.4.1. Model-based diagnosis methods

The model-based approaches use the mathematical model of the battery system so as to detect a failure in the battery system. In fact, it is based on residual signals, which are compared with a fault threshold to determine whether the system is faulty or not Fig. 19. In Ref. [334], the authors applied a dynamic-neighborhood particle swarm optimization algorithm so as to detect the ESC fault in the battery system. In Ref. [332], considering the thermal model of the battery system and implementation of the nonlinear observer, a thermal fault has been detected. In Ref. [335], at first, recursive least square has been applied for the estimation of equivalent circuit model, then Kalman filter is designed for joint estimation of SoC and voltage, and finally, based on the state observer, insulation fault has been detected.

7.4.2. Non-model-based diagnosis methods

Non-model-based methods include data-driven, signal processing, and knowledge-based approaches, which primarily rely on the battery data.

Data-driven methods take advantage of a large volume of data that are acquired from the system under various operation modes and, by means of artificially intelligent algorithms, detect the fault in the battery system [336,337]. Data-driven fault diagnosis will still be regarded as one of the most promising methods. Digital twin [338] technology is another alternative for online fault diagnosis to prevent catastrophic accidents. Besides, big data analysis [339], data mining, and AI will try to establish a comprehensive fault diagnosis system for large-scale battery systems. Based on the cyber–physical platform, the CC technology [340] may help solve the computational requirements of real-time fault diagnosis and provide an intelligent and cost-effective maintenance platform for regional batter networks. Table 15 provides a list of

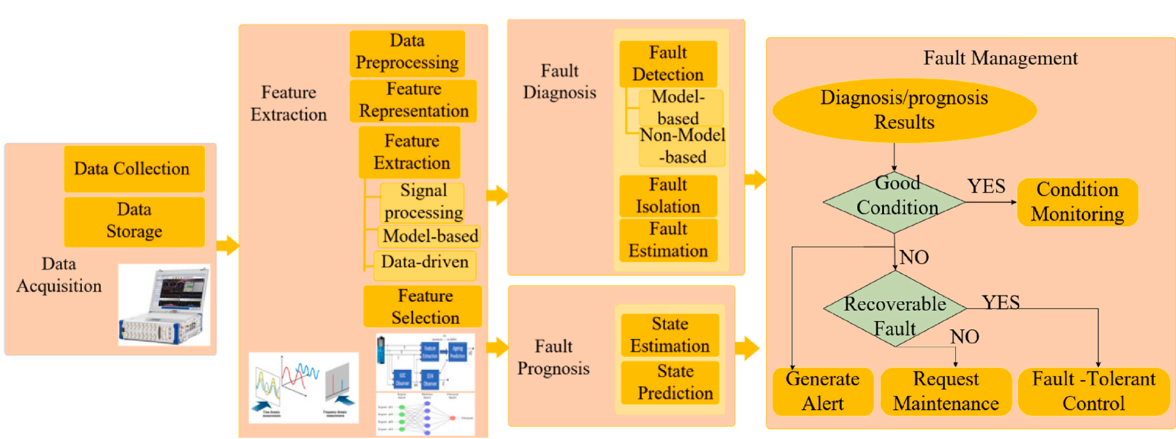


Fig. 18. Fault diagnosis process in battery system.

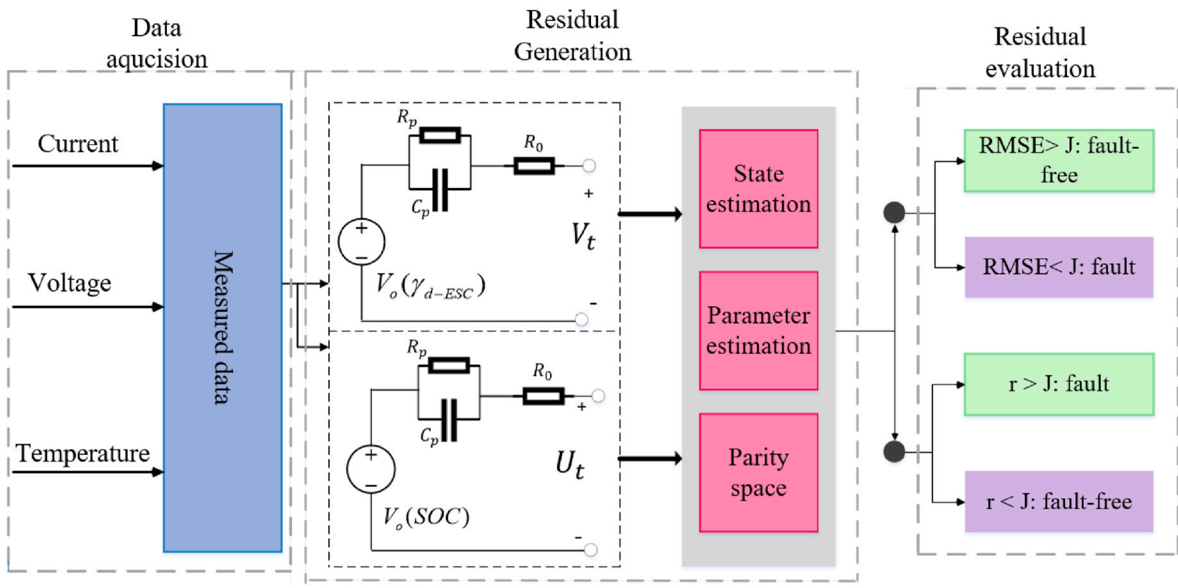


Fig. 19. Model-based fault detection procedure in LIBs [1].

model-based and non-model based approaches using for fault diagnosis in battery system.

7.4.3. Self-adaptive diagnosis methods

In terms of enhancement in fault tolerance, recent research progress has witnessed an innovative and smart approach in which a cell has the freedom to be joined and bypassed without any physical movement. This approach can be a promising step towards the smartness of BMS and provide multifold benefits. For example, quick isolation of faulty cells and continent and timely cell balancing are some of the advantages that this configuration can be supplied. The modularized architectures for BMS are the widely used design in practical applications. However, there are still many challenges and deficiencies regarding these architectures. In fact, as the performance of the whole battery system is affected by the weakest cell, the efficiency of the battery will not be used well. Besides, any failure at the cell level can propagate into neighbor cells, which results in malfunction in the entire system. In the new classification for smart BMS based on the decentralization of parameter monitoring and control function, smart batteries can be categorized into two groups.

7.4.3.1. Self-reconfigurable cell battery. In this topology, cell-level sensors and actuator switches are implemented to control the cells, but a central control system is still required. Actually, the cell's status is transmitted to the central control system, then based on the receiving feedback, the switches action. Considering the cell connection, the number of switches can be different from one to six. The more number of switches, the more flexible and reconfigurable the battery system, but on the other hand, the more complexity and overall cost.

7.4.3.2. Self-regulated smart cells. Self-regulated smart cells are completely independent entities with extensive functions and capabilities. Each cell has its own actuator, controller, sensors, and communication device, which removes the necessity for a central control system. The typical actuators in this topology include switches, power converters, and passive balancing components.

Both of the aforementioned topology have their own advantages and disadvantages. The self-reconfigurable multi-cell battery mainly focuses on pack-level optimization, which requires a central controller.

However, self-regulated smart cell exclusively focuses on cell-level optimization. The Conventional centralized or modularized BMS uses pack or module level sensors such as voltage current and temperature, while the smart cell batteries use the mentioned sensors at the cell level, which results in increasing overall cost. Regardless of cost impact, self-regulated smart cells provide manifold benefits in terms of design and operation flexibility, high fault-tolerant, and enhanced safety [303].

8. Emerging research trends on BMS technologies

Significant advancements in Battery Management Systems (BMS) are being driven by cutting-edge technologies such as multi-model co-estimation, digital twins, Software Defined Vehicles [349], the integration of IoT and cloud computing, and smart power electronics [350]. These technologies aim to enhance the performance, lifetime, reliability, and safety of battery systems for both transport and stationary applications, facilitating predictive maintenance, end-of-life management and potential second-life applications. Several EU-funded projects, such as NEXTBMS, BATMAX, NEMO, ENERGETIC, BATSS and InnoBMS, under Horizon Europe calls HORIZON-CL5-2022-D2-01-09, HORIZON-CL5-2022-D2-01-05 and HORIZON-CL5-2023-D5-01-02, focus on utilizing cutting-edge innovations and technologies to develop next-generation Battery Management Systems (BMS). These initiatives aim to advance BMS capabilities setting the stage for highly efficient, scalable, and sustainable BMS solutions crucial to the future of electric vehicles and renewable energy systems.

Fig. 20 illustrates the roadmap for BMS technology development, spanning from 2025 to 2050, and shows various phases of transition - short-term (2025), mid-term (2035), and long-term (2050). Short-Term Transition (2025): early innovations will focus on improving co-estimation methods, smart power electronics, and proof-of-concept of Electrochemical Impedance Spectroscopy (EIS) measurements. EU projects in this phase prioritize enhancing battery diagnostics and the readiness for future battery materials, aligning with the short-term goals outlined in EU battery initiatives. Mid-Term Transition (2035): research efforts will focus on real-time EIS measurements at a battery module level, physicochemical models as virtual sensors integrated with cloud connectivity to perform detailed diagnostics and IoT. Vehicle-to-Grid (V2G) technology, digital twin models, and the Battery Passport initiative are critical in this phase. These developments aim to provide scalability for new battery chemistries and contribute to data-driven decision-making algorithms in the BMS, supporting EU goals for sustainable energy and mobility solutions. Long-Term Transition (2050): Future BMS trends will prioritize advanced SoX diagnostics using physicochemically consistent models, enhanced cyber-secured BMS

Table 15
A brief review of the model-based and non-model-based fault diagnosis methods.

Methods	Robustness/ implementation/ accuracy	Fault type	Achievement
Model-based			
[341]		Current sensor fault	Multimodal fusion for SoC estimation and fault diagnosis of current sensor
[342]		Internal short circuit	Using the integration of EKF with ECM-thermal, applicable to add in commercial BMS.
[343]	Poor/difficult/low	Current and voltage sensor fault	Residual is defined as differences between the true SoC calculated by CC, and the estimated SoC by the joint estimation methods (RLS and UKF), The sensor noise in this study is Gaussian white noise
[344]		Soft short circuit	Residual is defined as the difference between estimated SoC through H∞ observer and calculated by CC.
Non-model- based			
[345]		Internal short circuit	The local-gravitation outlier detection method is utilized for the early detection of ISC in various severe condition
[346]	Strong/difficult/ high	Internal short circuit	The machine learning algorithm, gradient boosting decision tree is used to accurately detect the ISC fault and location of fault by using only partial voltage curves under arbitrary operating condition.
[347]	Strong/difficult/ high	Over discharge/ deep discharge	Two-layer ML-based The first layer compares the battery voltage with the cut-off voltage and in the case of the battery voltage larger than the off, eXtreme Gradient Boost detects the over-discharging.
[348]		Battery fault	Based on the Symplectic geometry mode decomposition and 2-dimensional feature clustering, more focus on the evolution of voltage anomaly and the distinction between inconsistency and faulty cell without the consideration of fault cause
[326]	Strong/Easy/high	Battery faults including short circuit and open circuit	The modified sample entropy is applied to detect battery faults through voltage fluctuation.

systems, battery swapping technologies, and V2V (Vehicle-to-Vehicle) communication. These advancements will be further supported by EU-funded projects focusing on battery safety, circular economy, and cyber-physical integration within energy grids.

Subsections to explore include multi-model co-estimation, IoT and digital twins, battery swapping systems, smart power electronics, cyber-secured BMS, and the evolving concept of the battery passport—aligned with the upcoming EU Battery Regulation (2027). Additionally, large-scale initiatives like Battery 2030+ will play a major role in achieving the European Green Deal through sustainable battery innovations. EU-funded research will continue to play a pivotal role in driving safer, more efficient, and reliable battery management systems for the future of electric mobility and energy storage.

8.1. Multi model co-estimation

Despite enormous advancements in the new design of smart BMS and progressive research, there are still challenges about the smartness of BMS and its commercialization.

The widely useable model for battery systems in conventional BMS is the electrical model. However, the impact of electrochemical, mechanical, and optical characteristics on battery status is inevitable. Although developing a high-fidelity battery model improves the accuracy of state estimation, complexity will be increased. The next generation of BMS will not only focus on electrical measurement but also on electrochemical, mechanical, and optical characteristics taken into consideration [351]. Lin M. et al. [352] proposed a multi-feature-based multi-model so as to estimate SoH. First seven factors of the SoH are extracted by multiple sources, then by applying multiple linear regression, support vector regression, and Gaussian process regression model, the preliminary predictions of SoH are produced. Lastly, at last, a random forest is utilized to fuse the predictions of the SoH.

8.2. IoT, cloud computing, and digital twin

The main priority for the BMS is safety, which shall diagnose critical failures and command alternative control signals or shut down the system in the worst situation and optimize performance. However, the conventional BMS only monitors and controls the battery system with a fixed structure/configuration, which does not provide optimal performance for the battery [353,354].To achieve this target, some research has been done. Han et al. proposed a dynamic reconfiguration of the battery system [355]. Dai et al. suggested a multi-layer structure for battery systems, which improved the battery life cycle and safety [356].

Nevertheless, there are enormous improvements, but there are still problems associated with hard data sharing, computing capacity, and storage space limitation [357].In fact, for enhancement in the management system of batteries, a large amount of data for a variety of operational conditions is required. However, the current/onboard BMS uses a limited amount of data only during the vehicle stages, which can lead to sub-optimal performance of the battery system. A large amount of data not only requires large memory, but also the computational process is complex [358].

These days, with the improvement/advancement/development of communication and internet technologies, the structure and function of the BMS have undergone massive changes. The growing development of the Internet of Things (IoT) and the increasing capabilities of sensing equipment can be of great assistance for acquiring a massive amount of data. In fact, IoT is a network of networks of uniquely distinguishable nodes and things that can gather, transmit, and process data [353].

With the advancement in semiconductor industries and network technology, the fifth/sixth generation and next generation of network technologies appear. By emerging vehicular cloud computing [359], a large amount of data acquired by the local server is transmitted to a cloud platform for complex computational algorithms, including AI data-driven, big data, data mining, and so on, which are time-consuming and cannot be handled by local or onboard BMS. Considering the development of the mentioned technologies, the concept and implementation of digital twins have become a hot topic./has developed in leaps and bounds. A digital twin is a virtual model of a physical object that is able to acquire data from the physical model so as to represent, process, and estimate the physical model's present and future state [360–362]. However, this technology is in an emerging state; it has demonstrated great performance in the prediction and optimization of

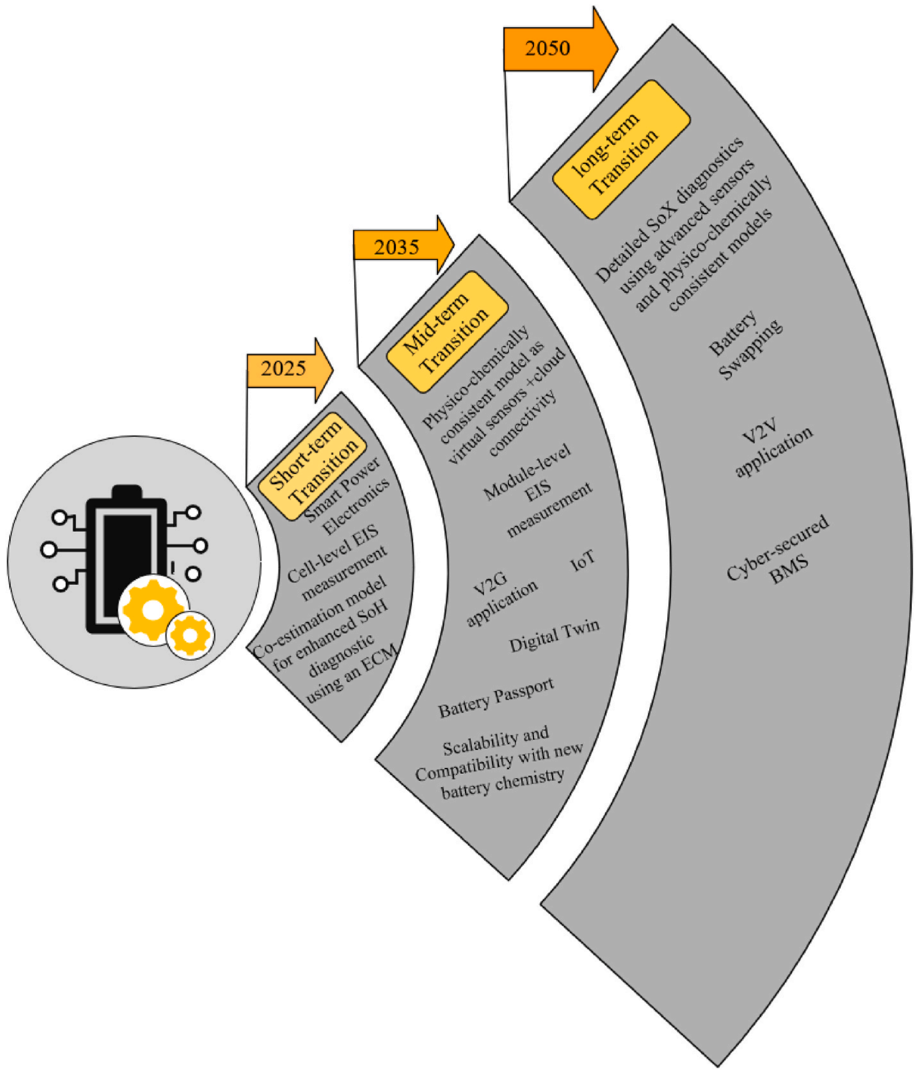


Fig. 20. Technical roadmap of the BMS.

complicated systems [361]. As lithium-ion batteries have complex entities, the application of the digital twin merging with AI approaches and communication technologies, including CC, alleviates the issues of the current/conventional battery management system.

8.3. Battery swapping approach

Although, in recent decades, the EV industry has attracted considerable public attention, there are still some fundamental issues/barriers limiting the adoption of EVs on a large scale, including charge duration, low driving range of a single charge (range anxiety), and high cost of battery [363–368].To tackle the charging problems/issues and further deployment of EVs, the construction of an electric vehicle supply is a prerequisite [369]. Battery swapping as an alternative time-efficient and cost–effective approach can tackle the aforementioned problems to a great extent. In this method, a depleted battery substitutes with the fully-charged battery at the battery-swapping system. Then, the BSS transferred the drained battery to the battery charging station to recharge it. After that, the recharged battery back to BSS for swapping in EVs [368,370]. This BSS concept was developed by Better Place company. According to their idea, car ownership was separate from battery ownership. Despite the strong start, the company went bankrupt in 2013 because of financial issues and the imitation of infrastructure. Tesla's Motor Company introduced another business model in which the core of the business model, instead of battery swapping, is car production. In fact, in this model, Tesla offers supercharging instead of leasing the battery, which does not provide Tesla owners with financial benefit, which results in showing no real willingness for battery swapping technology [366]. There are some companies, namely NIO and BAIC, which explore/examine the feasibility and possibility of large-scale deployment of BSS. Renault offered a new concept of BSS in which a 40 kWh battery suitable for daily urban travel fixed to the rare of the vehicle and a swappable 50 kWh battery in front of the vehicle support long-distance trips. The swappable battery can be uninstalled in support of smart/intelligent charging and B2G. In a BSS, EV users, BSS operators, and grid operators are the main contributors/participants. BSS can play a pivotal role in the development of smart cities and smart grids in terms of energy storage and energy regulation. Actually, in addition to some advantages such as lower initial purchase cost, short time for swapping compared to recharging time, and lengthened lifecycle in centralized battery management, BSSs cannot only be used/utilized as a virtual power plant for grid load shifting but also can reduce the burden of the uncontrolled EV charging on power grid [363,368].To be more specific, if a large number/a great deal of EVs are charged in the course of peak electricity consumption, it can lead to increased network loss, peak-on-peak phenomenon, reduced power quality, and transformer overload; however, the use of BSS can be of great assistance in solving/tackling power quality problems/issues including harmonics caused by EV charging [368].

8.4. Smart power electronic

The equalization management system, one of the key portions of BMSs is critical to tackling problems such as inter-cell inconsistencies, which result in inconsistencies in SoC and capacity. Based on the conducted research, different balancing circuits can be implemented. Among them, converter-based circuits have provided good efficiency and speed compared to other circuits. However, there are still problems regarding the complexity, computational complexity, and cost. Wide band gap semiconductor devices using SiC (silicon) and Gan (Gallium Nitride) technology allow operation at high switching speed, high voltage, and high temperature [371].

8.5. Cyber-secured BMS

Besides fault topics, the advanced BMS in the future generation of EVs may face a variety of cybersecurity risks, including maintenance vulnerabilities, weak security credentials, internet connectivity for analytics, and consumer-managed physical security. These risks can lead to battery depletion, accelerated degradation, or catastrophic failures like overcharging, posing threats to safety and human life. Despite the severity of these risks, not much research has been conducted in the area of cyber-secured BMS and secure data logging [372]. To mitigate these gaps, a robust cybersecurity architecture is essential, incorporating strong authentication, encryption, regular updates, network security, physical protection, and secure data acquisition for both on-premise and cloud environments. Emerging trends such as AI-driven threat detection, blockchain for data integrity, and zero trust models further enhance BMS security, ensuring safe and reliable operation in increasingly connected environments [373].

8.6. Battery passport

From 2027, as part of the Battery Regulation [374], battery packs over 2kWh, industrial batteries and those from LMT (Light Means of Transport) will need to be compliant with the Battery Passport. Alongside physical identification and information relating to the materials and manufacture, the BMS will need to report ten additional parameters. These are grouped into parameters for determining the Performance and Durability Requirements, and those expected to determine the State of Health and Expected Lifetime. These are shown in Table 16, Table 17 and relating to Regulation (EU) 2023/1542 at time of writing.

As yet, there no agreed standard algorithms for how to generate these parameters, which present new challenges for both the legislative and research communities. Some methods specific to the Battery Passport requirements are already being published, such as round-trip efficiency methods [375], Fig. 21, shows the scope of information to be made available via the battery passport is extensive with up to 90 data attributes covering seven content clusters. However, further understanding of these methods are required. Since the regulation affects all products being sold into the European market, this also affects non-European manufacturers. The availability of these parameters is seen as an enabler towards the circularity of battery systems, supporting lifetime management, re-use, and ultimately re-cycling.

9. Conclusion

As the widespread adoption of EVs is bound with the safe, efficient, and reliable operation of the BMS, this paper offers a thorough and comprehensive review of all of the challenging and underdevelopment aspects of the advanced BMS with a primary focus on the battery modeling, which is the building block of precise internal state estimation providing the valuable insight into the operational condition, enabling the optimization of the charging and balancing topologies, and early stage prediction/detection of possible faults in BEES within EVs. Despite the enormous and remarkable recent improvement in all aspects of the BMS functionalities, there are still challenges regarding the potential of BMS functionalities, especially in terms of operation under real-world conditions. This paper distinguishes them and underscores the significance of tackling these challenges, along with pointing out some ongoing EU projects with the aim of addressing challenges in the

Table 16
Parameters related to electrochemical performance and durability.

Main Parameters
1. Rated capacity (in Ah) and capacity fade (in %)
2. Power (in W) and power fade (in %)
3. Internal resistance (in Ω) and internal resistance increase (in %)
4. Where applicable, energy round trip efficiency and its fade (in %)
5. The expected life-time of the battery under the reference conditions for which it has been designed, in terms of cycles, except for non-cycle applications, and calendar years
Additional Information
1. Applied discharge rate and charge rate.
2. Ratio between nominal battery power (W) and battery energy (Wh).
3. Depth of discharge in the cycle-life test.
4. Power capability at 80 % and 20 % state of charge.
5. Any calculations performed with the measured parameters, if applicable.
Electric vehicle batteries
1. State of Certified Energy (SOCE)
Stationary battery energy storage systems and LMT batteries
1. The remaining capacity
2. Where possible, the remaining power capability
3. Where possible, the remaining round trip efficiency
4. The evolution of self-discharging rates
5. Where possible, the ohmic resistance

Table 17
Parameters for determining the expected lifetime of stationary battery energy storage system and LMT batteries.

1. The date of manufacture of the battery and, where appropriate, the date of putting into service
2. The energy throughput
3. The capacity throughput
4. The tracking of harmful events, such as the number of deep discharge events, time spent in extreme temperatures, time spent charging in extreme temperatures
5. The number of full equivalent charge-discharge cycles

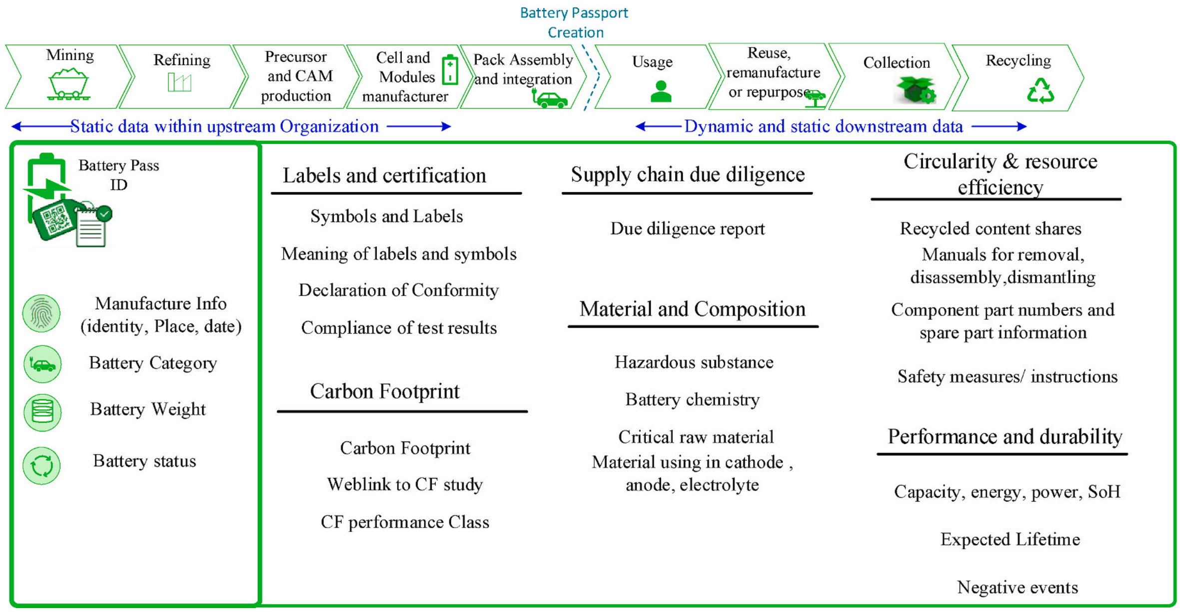


Fig. 21. Data category for battery passport.

practical operation of the BMS and taking steps towards advanced industrial-ready BMS within EVs. An additional facet of advanced BMS that ensures the safe and reliable operation of electric vehicles (EVs), thereby accelerating their adoption, is the implementation of a virtual environment or Digital Twin (DT) framework. This paper underscores/ highlights that the DT of the BMS can markedly expedite the evolution of BMS toward state-of-the-art (SOA) BMS endowed with advanced functionalities. Concurrently, this paper underscores the scalable physics-based model for edge and cloud-based BMS and its capabilities in delivering highly accurate state estimators, which serve as the foundation for early fault detection and prognosis in battery systems. Furthermore, this work presents a comparative analysis of various applicable methods across different functionalities, including battery modeling, State of Charge (SoC) and State of Health (SoH) estimation, charging strategies, balancing techniques, and fault detection, along with safety standards tests. To conclude, this review not only encapsulates the recent developments and enhancements in the BMS evaluation but also highlights/identifies the challenges and gaps that require further research and serves as a guiding light for ongoing advanced and smart BMS in the EV application.

CRediT authorship contribution statement

Pegah Rahmani: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sajib Chakraborty:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Investigation, Funding acquisition, Conceptualization. **Igor Mele:** Writing – review & editing, Writing – original draft, Resources, Methodology, Formal analysis. **Tomaž Katrašnik:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Stanje Bernhard:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Stephan Pruefling:** Writing – review & editing, Writing – original draft. **Steven Wilkins:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Omar Hegazy:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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