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Review article

A review of battery energy storage systems and advanced battery management system for different applications: Challenges and recommendations

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ABSTRACT

Energy storage systems are designed to capture and store energy for later utilization efficiently. The growing energy crisis has increased the emphasis on energy storage research in various sectors. The performance and efficiency of Electric vehicles (EVs) have made them popular in recent decades. The EVs are the most promising answers to global environmental issues and CO_2 emissions. Battery management systems (BMS) are crucial to the functioning of EVs. An efficient BMS is crucial for enhancing battery performance, encompassing control of charging and discharging, meticulous monitoring, heat regulation, battery safety, and protection, as well as precise estimation of the State of charge (SoC). The current understanding of EV technology, its advancements, limitations, and effects on achieving BMS (Sustainable Development Goals) SDGs remains unexplored, despite the existence of several studies on the topic. This article reviews various aspects of battery storage technologies, materials, properties, and performance. This review highlights the significance of battery management systems (BMSs) in EVs and renewable energy storage systems, with detailed insights into voltage and current monitoring, charge-discharge estimation, protection and cell balancing, thermal regulation, and battery data handling. The study extensively investigates traditional and sophisticated SoC estimation methods, highlighting their pros and cons. The review underscores the critical role of advanced BMSs for successful EV adoption and addresses the challenges that must be overcome. This comprehensive resource offers valuable insights for engineers, researchers, and EV manufacturers, presenting detailed analyses, applications, challenges, and recommendations relevant to the field.

1. Introduction

Energy storage systems (ESS) serve an important role in reducing the gap between the generation and utilization of energy, which benefits not only the power grid but also individual consumers. An increasing range of industries are discovering applications for energy storage systems (ESS), encompassing areas like EVs, renewable energy storage, micro/smart-grid implementations, and more. The latest iterations of electric vehicles (EVs) can reliably replace conventional internal combustion engines (ICEs). Different fossil fuels are used by ICE-powered

Abbreviations: EV, Electric vehicle; Li-ion, Lithium-ion; V2G, Vehicle to grid; PV, Photovoltaic; PVB, Photovoltaic battery; MPPT, Maximum power point tracking; FL, Fuzzy Logic; PbA, Lead-acid; SoC, State of charge; SoH, State of Health; SoF, State of function; SoP, State of power; SoE, State of Energy; SoS, State of Safety; BMS, Battery management system; CAN, Controlled area network; CNN, Convolutional Neural Networks; EMI, Electromagnetic interference; ISO, International Organization for Standardization; KF, Kalman filter; ANFIS, Adaptive Neuro-Fuzzy Inference System; SPKF, Sigma-Point Kalman Filter; EIS, Electrochemical Impedance Spectroscopy; EKF, Extended Kalman Filter; ECM, Electrochemical Models; AF, Adaptive Filter; LCO, Lithium cobalt oxide; LFP, Lithium iron phosphate; LMO, Lithium manganese oxide; LNMC, Lithium nickel manganese cobalt oxide; LNCA, Lithium nickel cobalt aluminium oxide; LTO, Lithium titanate oxide; NAMHE, Noise Adaptive Moving Horizon Estimation; LSTM, Long Short-Term Memory; LNO, Lithium Nickel Oxide; NN, Neural Network; AEKF, Adaptive Extended Kalman filter; CC, Coulomb Counting; ADC, Analog-to-digital conversion; ANN, Artificial neural network; SVM, Support Vector Machine; RC, Resonant converter; PTT, Pulse Test Technique; OCV, Open-Circuit Voltage; RES, Renewable energy sources; DNN, Deep Neural Networks; RUL, Remaining useful life; SDG, Sustainable Development Goals; GA, Genetic Algorithm; SMO, Sliding Mode Observer; NLO, Nonlinear Observer; UKF, Unscented Kalman Filter; UPF, Unified particle Filter; RVM, Regression Vector Machine; PSO, Particle Swarm Optimization; AFS, Artificial fish swarm; RMSE, Root Mean Square Error; MMAE, Multiple Model Adaptive Estimation.

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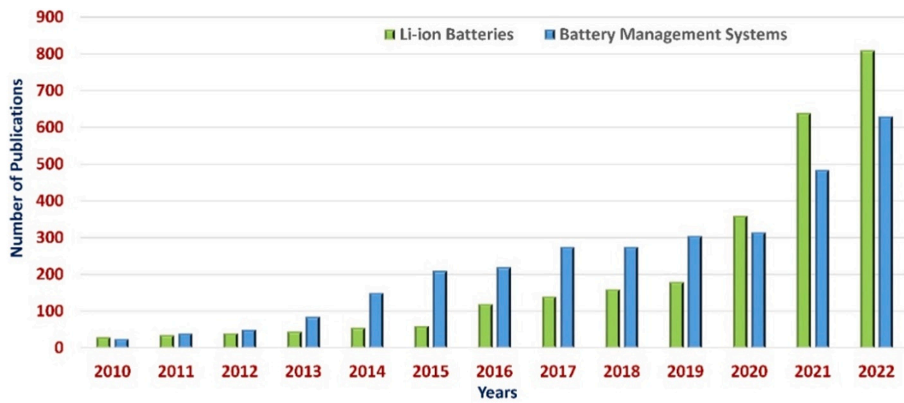

Fig. 1. A detailed analysis of the number of reviewed published articles on BMS.
(Data sources: Scopus; keywords: Li-ion battery for EV and battery management system; access date: 25 November 2022). https://www.sciencedirect.com/search?qs=Li-ion%20batteries%20for%20EV.

transportation (cars, trucks, aircraft, etc.). Carbon dioxide (CO2), sulfur dioxide (SO2), carbon monoxide (CO), and nitrogen oxide (NO) emissions have two primary causes: internal combustion engines (ICE) and industries. These gases cause air pollution, which adds to the greenhouse effect. Increasing carbon emissions are the principal cause of global warming and are now one of the most significant concerns for scientists and academics. However, there exists a requirement for extensive research on a broad spectrum of concerns, which encompass, among other things, the selection of appropriate battery energy storage solutions, the development of rapid charging methodologies, the enhancement of power electronic devices, the optimization of conversion capabilities, and the integration of hybridizing algorithms or methodologies.

This article provides an overview of the many electrochemical energy storage systems now in use, such as lithium-ion batteries, lead acid batteries, nickel-cadmium batteries, sodium-sulfur batteries, and zebra batteries. According to Baker [1], there are several different types of electrochemical energy storage devices. The lithium-ion battery performance data supplied by Hou et al. [2] will also be analysed. Nitta et al. [2] presented a thorough review of the history, current state of the art, and prospects of research into anode and cathode materials for lithium batteries. Nitta et al. presented several methods to improve the efficiency of Li-ion batteries in their study. These include scaling down the size of the active material, combining many materials into one, doping and functionalizing the material, fine-tuning the particle shape, coating or encasing the material, and changing the electrolyte.

Lithium batteries are becoming increasingly important in the electrical energy storage industry as a result of their high specific energy and

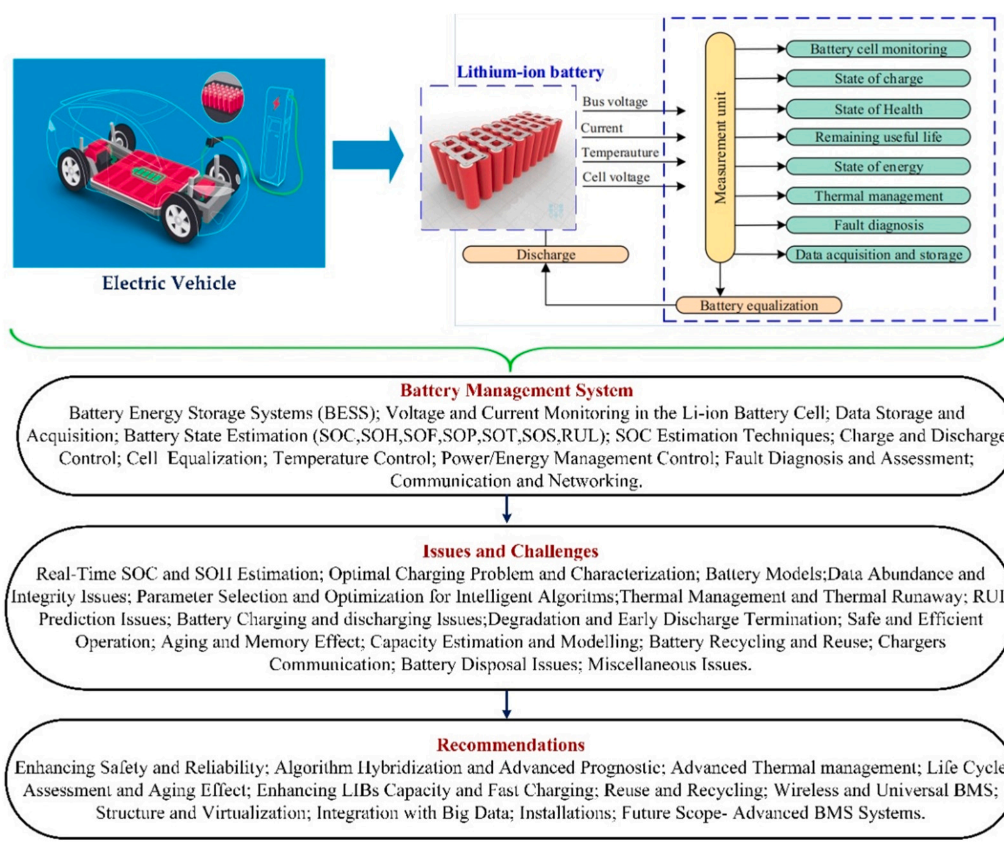

Fig. 2. A comprehensive examination of battery management systems research.

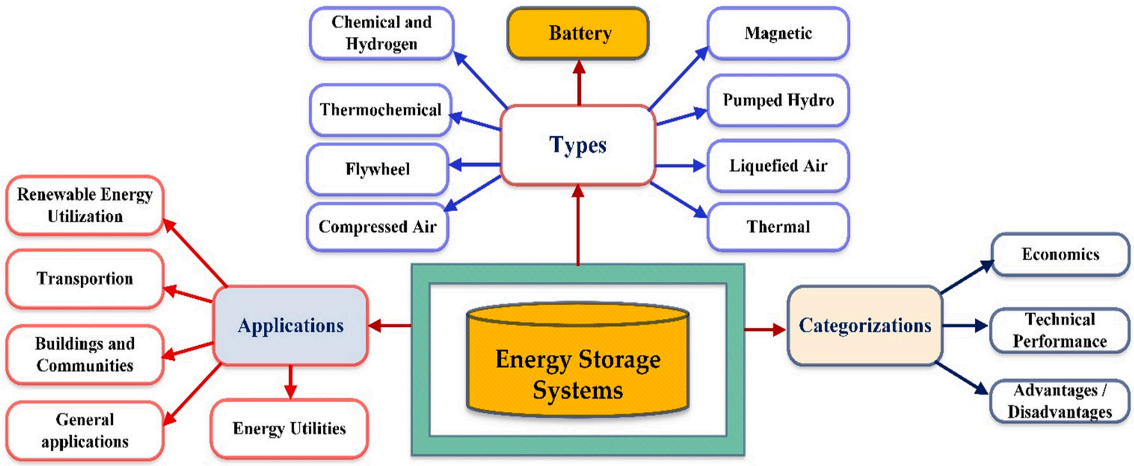

Fig. 3. Categorization of energy storage systems.

energy density. The literature provides a comprehensive summary of the major advancements and key constraints of Li-ion batteries, together with the existing knowledge regarding their chemical composition. The Li-ion battery is classified as a lithium battery variant that employs an electrode material consisting of an intercalated lithium compound. The authors Bruce et al. (2014) investigated the energy storage capabilities of Li-ion batteries using both aqueous and non-aqueous electrolytes, as well as lithium-Sulfur (Li—S) batteries. The authors also compare the energy storage capacities of both battery types with those of Li-ion batteries and provide an analysis of the issues associated with cell operation and development. The authors propose that both batteries exhibit enhanced energy density in comparison to Li-ion batteries and may also possess a greater potential for cost competitiveness relative to Li-ion batteries. Still, it is suggested that more research into the chemical processes involved with Li—O_2 and Li—S cells is needed before they can be sold to the public [3]. Thackeray and colleagues in 2015 presented a comprehensive historical analysis of lithium-ion batteries, including their current state and advancements in lithium-air battery technology [4]. The number of reviewed published articles detailing the comparison across Li-ion batteries and BMS is presented in Fig. 1.

The battery management system (BMS) is an essential component of an energy storage system (ESS) and plays a crucial role in electric vehicles (EVs), as seen in Fig. 2. This figure presents a taxonomy that provides an overview of the research. The Battery Management System (BMS) is a comprehensive framework that incorporates various processes and performance evaluation methods for several types of energy storage devices (ESDs). It encompasses functions such as cell monitoring, power management, temperature management, charging and discharging operations, health status monitoring, data acquisition, cell protection, and lifespan estimation [5]. To ensure the effective monitoring and operation of energy storage devices in a manner that promotes safety and well-being, it is necessary to employ a range of techniques and control operations [6]. These measures should be designed to operate autonomously and without delay [7].

Electric vehicles (EVs) are regarded as an energy storage system (ESS) that is communicated inside a smart/micro-grid system. This system uses synchronized charging energies to offset the uneven power output from solar and wind sources. The integration of renewable energy sources into the electrical grid may be effectively facilitated through the utilization of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) systems. This study aims to address the current limitations by emphasising the potential of integrating electric vehicles (EVs) with photovoltaic (PV) systems. The research started with providing an overview of energy storage systems (ESSs), battery management systems (BMSs), and batteries suitable for EVs.

The following are some of the contributions made by this review:

- This review provides a comprehensive analysis of several battery storage technologies, materials, properties, and performance.
- This article provides a comprehensive explanation of the advanced techniques, algorithms, and optimization methodologies utilized in electric vehicles (EVs).
- This research work comprehensively investigated the categorization of traditional and sophisticated SoC estimation methodologies as well as the associated advantages and drawbacks.
- Battery management systems (BMSs) are discussed in depth, as are their applications in EVs, and renewable energy storage systems are presented in this article.
- This review covers topics ranging from voltage and current monitoring to the estimation of charge and discharge, protection and equalization to thermal management, and actuation of stored battery data.
- This review demonstrates the difficulty of EV adoption without addressing existing problems and developing superior BMSs.
- The Engineers and researchers working on electric vehicles and manufacturers of EVs will benefit from the detailed discussion, analysis, applications, challenges, and recommendations presented in this article.

The following sections of this article are divided into six categories: Section 2 offers an overview of different battery energy storage technologies that have been demonstrated to differ in important performance areas, such as specific power and specific energy. Section 3 presents in depth the major components of battery management systems: algorithms, methodologies, approaches, controllers, and optimization technologies. Section 4 reports on BMS applications. Section 5 highlights the outstanding difficulties and recommendations. Section 6 concludes with the conclusions and future tendencies.

2. Energy storage systems (ESS)

An energy storage system (ESS) is a technology that captures and stores energy for later use. The classification of energy storage encompasses several categories. In the present scenario, Fig. 3 illustrates the diverse energy storage categories, providing information on their technical and economic specifications alongside their respective applications [8].

2.1. Battery energy storage systems (BESS)

Electrochemical methods, primarily using batteries and capacitors, can store electrical energy. Batteries are considered to be well-established energy storage technologies that include notable

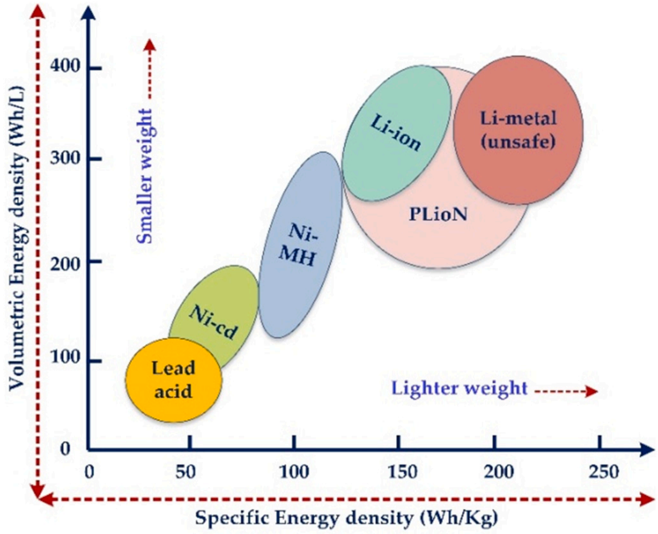

Fig. 4. The specific and volumetric energy density of various battery types.

characteristics such as high energy densities and elevated voltages [9]. A comprehensive examination has been conducted on several electrode materials and electrolytes to enhance the economic viability, energy density, power density, cycle life, and safety attributes of batteries. Fig. 4 shows the specific and volumetric energy densities of various battery types of the battery energy storage systems [10].

Fig. 5 shows the classification of various Li-ion battery materials. This section provides a comprehensive examination and evaluation of the diverse attributes, qualities, and essential constituents of battery storage in the context of electric vehicle (EV) applications [10].

2.1.1. Lead–acid (Pb–acid)

Lead-acid batteries are still widely utilized despite being an ancient battery technology. The specific energy of a fully charged lead-acid battery ranges from 20 to 40 Wh/kg. The inclusion of lead and acid in a battery means that it is not a sustainable technology. While it has a few downsides, it's inexpensive to produce (about 100 USD/kWh), so it's a good fit for low-powered, small-scale vehicles [11].

2.1.2. Nickel–cadmium (NiCd) battery

The high energy density of nickel-cadmium (NC) batteries was widely used in the 1990s. NC battery technology is used in fields like telecommunications and portable services to improve things like power quality and energy reserves. When compared to NiMH batteries, NC batteries have a far longer lifespan at 1500 cycles. Toxic metals like cadmium are used in the production of NC, which is one of the material's significant downsides. Cadmium harms both the environment and human health [12].

2.1.3. Lithium-ion battery

One of the most popular EV batteries is lithium-ion. Li-ion batteries are noted for their excellent energy density, efficiency, lifespan, and high-temperature performance. It's still good for battery-powered EVs [13]. The battery's biggest benefit is component recycling. Major drawbacks are the high cost per kWh (135 USD/kWh) and the material's unavailability. In terms of voltage, power, and energy, the LMO, LNMC, and LNCA batteries are excellent [14]. For excellent lifetime and safety, utilize LFP and LTO batteries. Additionally, LTO is cost-effective and high-performance [15]. Table 1 presents a comparative analysis of several categories of lithium-ion batteries [16].

The different positive electrode materials are explored in more detail below [17].

- Lithium cobalt oxide—$LiCoO_2$

In 1991, Sony introduced lithium cobalt oxide (LCO) to the market, employing cobalt oxide as the cathode material, which was widely utilized in lithium-ion battery technology at the time. It also exhibits a moderate lifespan, lasting for a reasonable duration before requiring replacement. Furthermore, it demonstrates significant safety features, making it suitable for use in various electronic devices such as cameras, laptops, and tablets [11].

- Lithium manganese oxide—$LiMn2O_4$

The LMO battery technology was created in the Bellcore lab in 1994. The internal resistance of LMO is decreased, and the charge/discharge current flow is increased thanks to its 3D spinel design. When compared to cobalt-based batteries, LMO has a capacity that is around 33 % lower. LMO is being used in production right now in the Nissan Leaf EV [12].

Table 1
Properties of different Li-ion batteries [14–18].

Battery type	Voltage (V)	Specific energy (Wh/kg)	Charge (c)	Discharge (c)	Lifespan (hrs)
LTO	2.3–2.6	75–85	1	10	3000–7000
LNO	3.6–3.8	160–200	0.7–1	1	>300
LFP	3.2–3.4	90–120	1	1	1000–2100
LMO	3.7–3.9	100–145	0.7–1	1	300–750
LNMC	3.8–4.1	150–210	0.7–1	1	1000–2100
LNCA	3.6–3.7	200–250	0.7	1	~500
LCO	3.7–3.8	160–200	0.7–1	1	600–1000

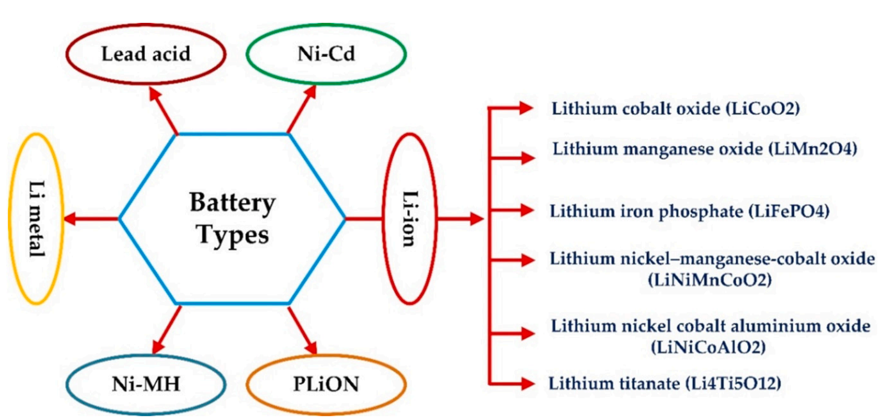

Fig. 5. Classification of various Li-ion battery materials.

Table 2
Comparison of different batteries for EV applications.

Parameter	$LiMn2O_4$ battery	Pb–acid battery	$LiFePO_4$ battery	Ni-MH battery	$LiCoO_2$ battery	Ni-Cd battery
Nominal cell voltage	3.8 V	2 V	3.5 V	1.5 V	3.6 V	1.25 V
Power density	1850	180	1850	150	1850	250–1000
Self –discharge	<10 %	<5 %	<10 %	>30 %	<10 %	>30 %
Peak load current	>30C	5C	>30C	5C	>3C	20C
Weight	Light	Heavy	Light	Moderate	Light	Heavy
Discharge cut-off voltage	2.5–3.0 V	1.75 V	2.4–3.0 V	1.0 V	2.8 V	1.0 V
Specific Energy density	100–145 Wh/Kg	35–55 Wh/Kg	95–125 Wh/Kg	65–125 Wh/Kg	145–185 Wh/Kg	50–85 Wh/Kg
Life cycle (80 % discharge)	500–1000	250–350	1000–2000	200–300	500–1000	1000
Charging time	<1 h	8–16 h	<1 h	2–4 h	2–4 h	1 h
Cut off charge voltage	3.6 V	2.40 V	4.20 V	3.60 V	4.20 V	3.6 V
Memory	No	No	No	Little	No	Yes
Overcharge tolerance	Very low	High	Very low	Moderate	Very low	Low
Eco-friendly	Yes	No	Yes	Yes	Yes	No

- Lithium iron phosphate—$LiFePO_4$

The findings of the investigation indicated that phosphate exhibits superior performance compared to LCO or LMO batteries in conditions of elevated temperatures and when subjected to overcharging. Phosphates have favourable thermal stability, functioning effectively throughout a temperature range spanning from −30 °C to 60 °C.

- Lithium nickel manganese cobalt oxide—$Li(Ni,Mn,Co)O_2$

The commercialization of lithium nickel manganese cobalt oxide (LNMC) battery technology occurred in 2004. Additionally, LNMC exhibits elevated power and energy density, along with enhanced longevity and performance. An increase in the proportion of manganese results in an augmentation of specific power, whereas an increase in the percentage of nickel leads to an augmentation of specific energy.

- Lithium nickel cobalt aluminium oxide—$Li(Ni, Co, Al)O_2$

Nickel-cobalt aluminium oxide (NCA) batteries were introduced in 1999. The use of nickel as a cathode material reduces lithium cobalt oxide's cobalt dependence. Tesla, a prominent player in the automotive industry, is presently employing LNCA battery technology in the advancement of electric vehicles [13].

- Lithium titanate—$Li4Ti5O_{12}$

The use of LMO and LNCA as cathode materials and titanate as the anode material establishes the spinel architecture of lithium titanate (LTO). The LTO technology has exceptional performance capabilities and boasts an extended operational lifespan. In addition, it is worth noting that LTO demonstrates safe operational performance even under freezing temperature conditions [14]. Table 2 displays a comparison of different types of batteries that could be suitable for electric vehicles [15].

The careful choice of materials is of utmost importance, particularly concerning the positive electrode. This component plays a critical role in determining the battery's key properties, including power output, safety, cost, and longevity [16]. Energy storage systems play a crucial role in the pursuit of a sustainable, dependable, and low-carbon energy future. By improving the productivity and effectiveness of diverse energy-generating and consumption processes, these systems are of utmost importance [17]. The proliferation of ESS is anticipated to experience significant growth in the foreseeable future due to technological advancements and decreasing prices [18].

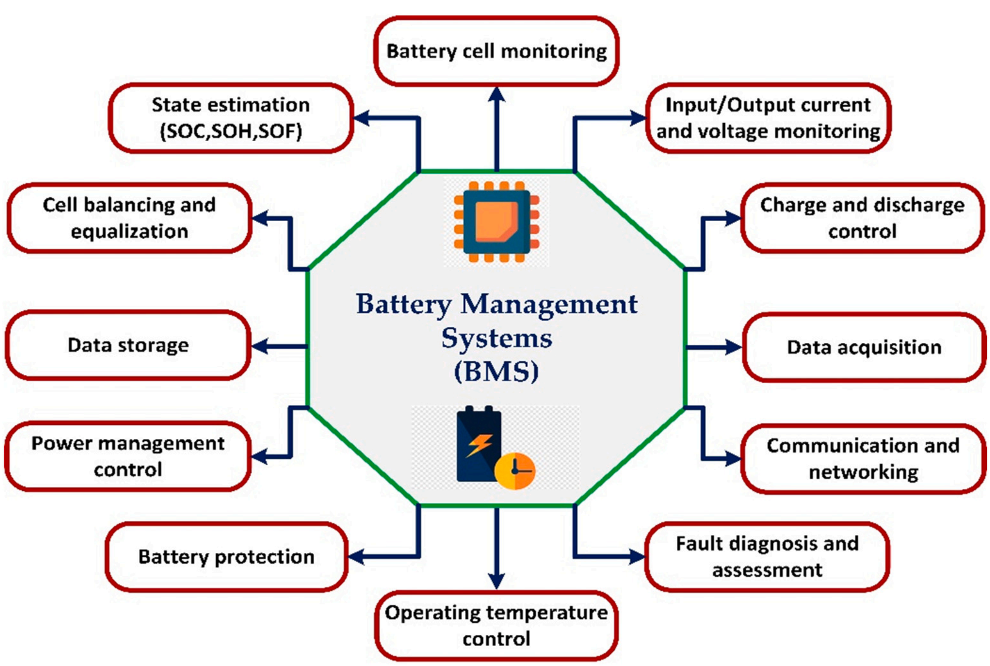

Fig. 6. An overview of BMS.

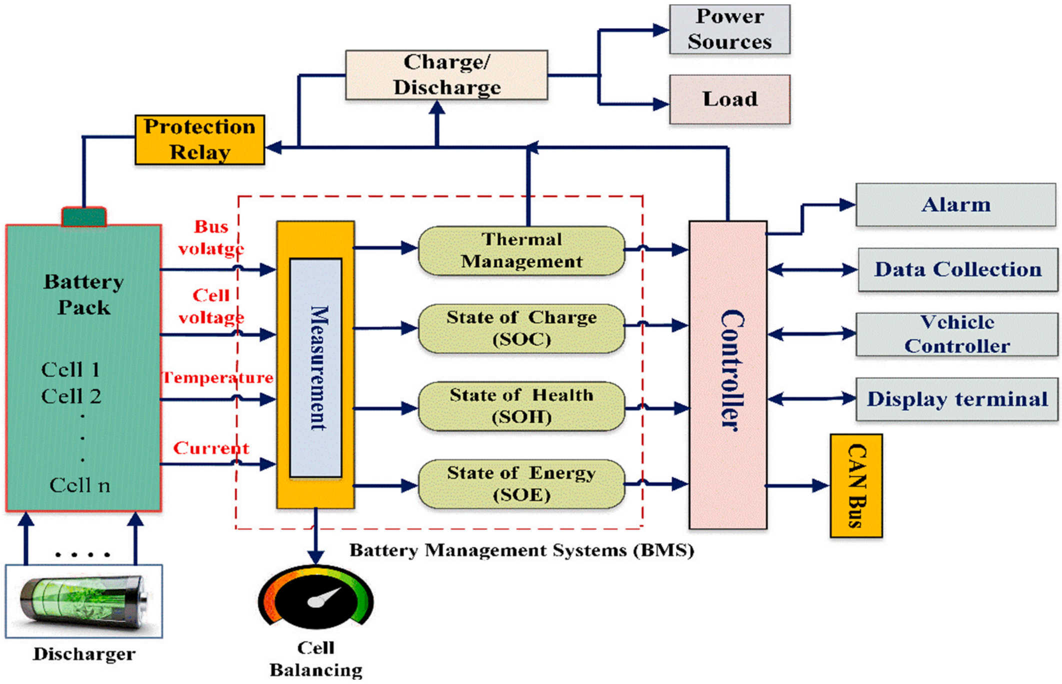

Fig. 7. Cell monitoring block diagram of BMS.

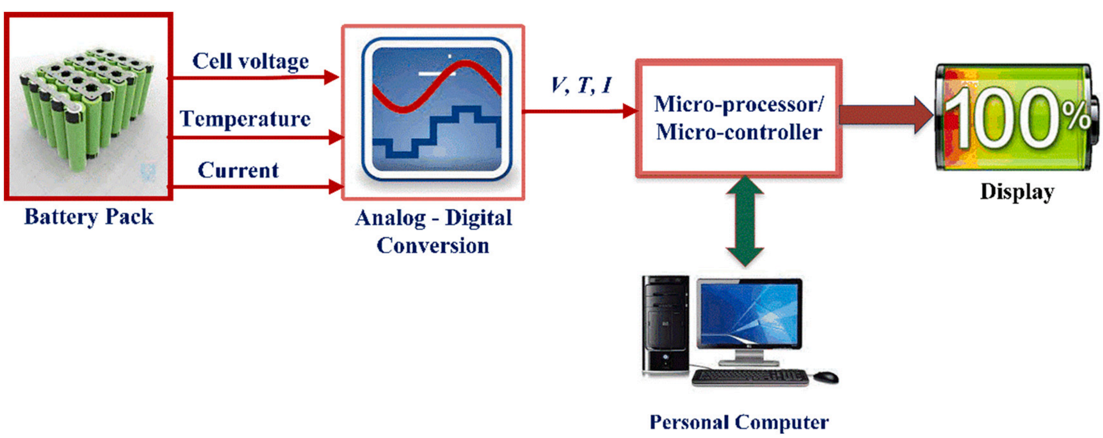

Fig. 8. Voltage and current measurement block diagram of BMS.

3. Battery management systems (BMS)

Battery management systems (BMSs) are systems that help regulate battery function by electrical, mechanical, and cutting-edge technical means [19]. By controlling and continuously monitoring the battery storage systems, the BMS increases the reliability and lifespan of the EMS [20]. This is accomplished through a variety of control techniques, including charge-discharge control, temperature control, cell potential, current, and voltage monitoring [21]. The key components of the BMS for its efficient operation are represented in Fig. 6.

3.1. Battery cell monitoring

In order to carry out the responsibilities of the BMS, it is necessary to have access to data on the charging and discharging, health, temperature, and problem diagnostics of the batteries, as represented in Fig. 7. While the battery is being charged or discharged, the cell might have a variety of responses. So, it's important to constantly keep an eye on your batteries to learn more about their states and performance metrics [22]. Managing, guarding, balancing, and regulating operations can all benefit from the data gleaned by monitoring battery cells.

3.2. Voltage and current measurement

Series and parallel battery cell connections to the battery bank produce sufficient voltage and current. There are many voltage-measuring channels in EV battery packs due to the enormous number of cells in series. It is impossible to estimate SoC or other battery states without a precise measurement of a battery cell [23]. Using high-voltage current sensors, the battery module's current is measured and then converted to a digital signal using an analog-to-digital converter (ADC), as represented in Fig. 8. The voltage and current measurements are then used to calculate accurate estimates of SoC, SoH, and RUL [24].

3.3. Data acquisition

The current, voltage, temperature, and state of charge (SoC) are only a few of the characteristics of the battery pack that may be measured and

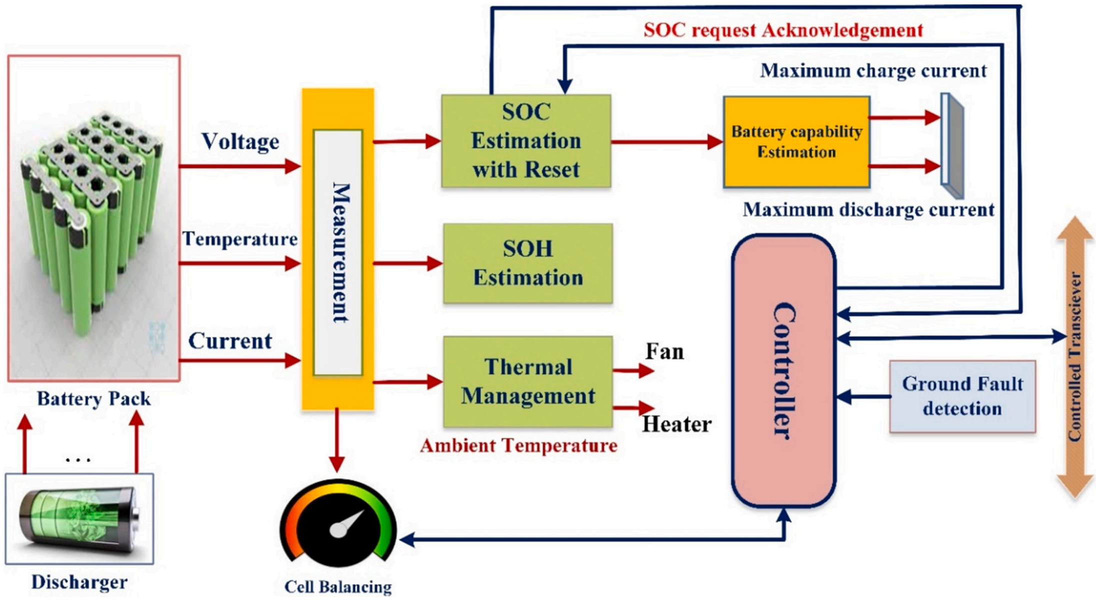

Fig. 9. Data acquisition block diagram of BMS.

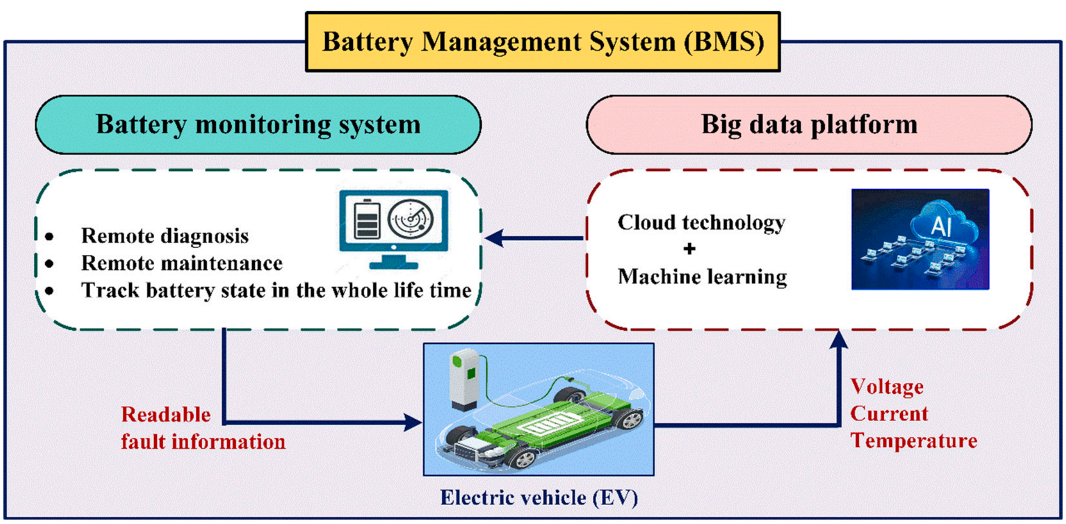

Fig. 10. BMS-based cloud-integrated EV data acquisition framework.

estimated with the use of a data acquisition system (DAS). The DAS is an integral part of the BMS, which has a microprocessor and programmed instructions as shown in Fig. 9. The ADC component is responsible for handling data conversion in the DAS. Exchange data and have conversations with the BMS using a controller area network (CAN) bus and serial communication interface (SCI) modules. Fig. 10 shows a BMS that uses a cloud-based DAS platform to measure battery current, voltage, and temperature [24].

3.4. Battery state estimation

Accurate battery status estimation is of utmost importance to effectively estimate both battery charge and health. One way to figure out the battery management system's monitoring parameters like state of charge (SoC), state of health (SoH), remaining useful life (RUL), state of function (SoF), state of performance (SoP), state of energy (SoE), state of safety (SoS), and state of temperature (SoT) as shown in Fig. 11 [25].

3.5. State of charge (SoC)

The state of charge (SoC) can be defined as the ratio of the present accessible capacity to the maximum battery capacity. Where 'Qo', 'Q' and 'Qm' represents the initial charge, quantity of electricity delivered or supplied to the battery and maximum charge that can be stored in the battery respectively. The state of charge may also be considered the other way around and it is called the Depth of discharge (*DoD*). It can be calculated as following equations.

$$SoC\ (\%) = \frac{(Qo + Q)}{Qm} \times 100 \tag{1}$$

$$DoD\ (\%) = 100 - SoC\ (\%) \tag{2}$$

The SoC value ranges from 0 to 100 %. If the SoC is 100 %, the battery is fully charged, whereas a SoC of 0 % indicates that the cell is totally discharged. Various techniques can be employed to estimate the SoC, as seen in Fig. 12. The operational intricacies of these approaches are elaborated upon in the subsequent discussion. In recent times, there

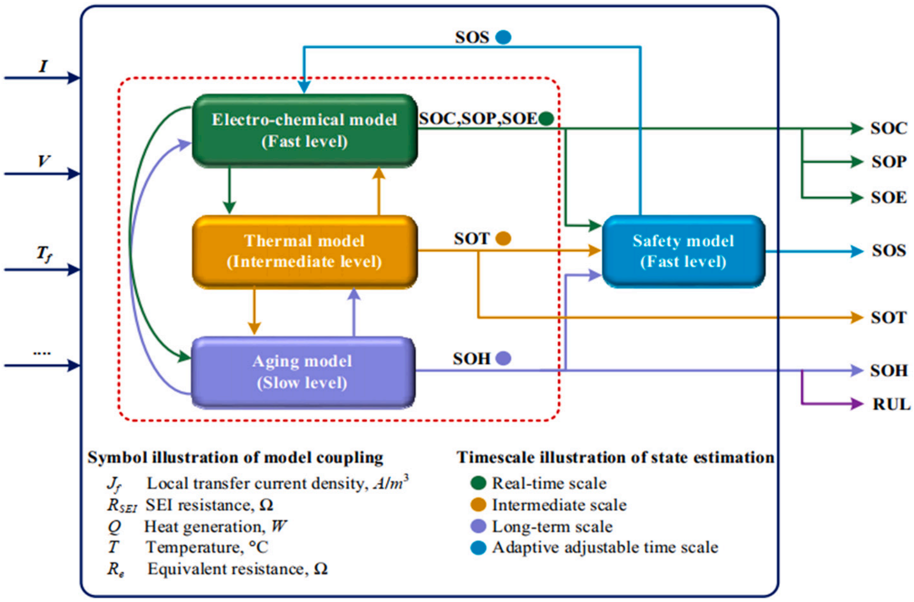

Fig. 11. BMS-supported battery state estimation framework.

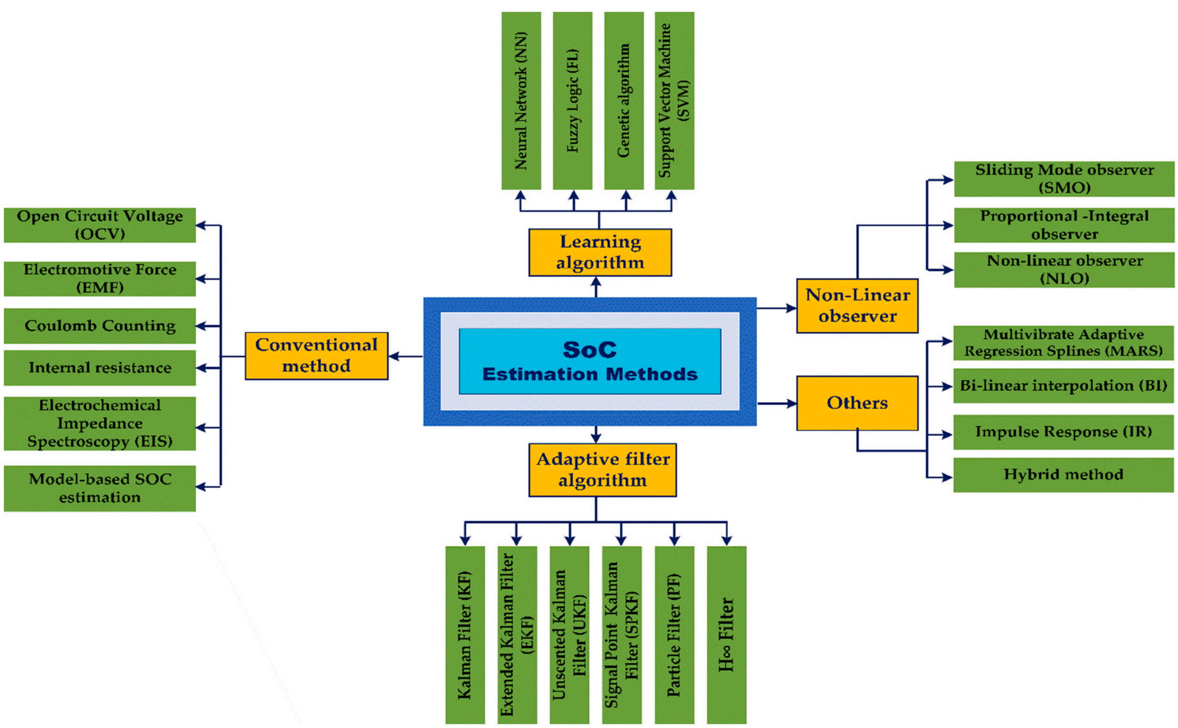

Fig. 12. A classification of SoC estimation techniques.

has been significant interest in the application of machine learning and deep learning techniques for SoC estimation. This is primarily due to its notable advantages, such as enhanced accuracy, greater learning capacity, superior generalization performance, and faster convergence speed [26].

3.5.1. Conventional methods

- Open-circuit voltage method

The open-circuit voltage technique exhibits a notable degree of precision, is readily implementable, and follows a direct approach. However, its primary drawback lies in the extended duration required to reach equilibrium. Hence, the use of an online estimate for SoC is deemed unsuitable. Hence, this approach is suitable only for applications with minimal power consumption. In addition, it is necessary to conduct certain observations to quantify the discharge and charge voltages. As seen in Fig. 13 from the article [18], batteries exhibit hysteresis characteristics, resulting in the charging process occurring at high open circuit voltage (OCV) levels while the discharge process takes place at lower OCV levels. This phenomenon has been extensively studied and documented [27].

- Coulomb Counting (CC) method

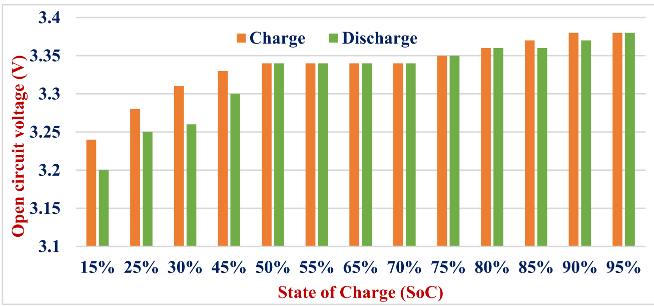

Fig. 13. OCV vs SoC were tested at 25 °C.

Table 3
Comparison of common SoC estimate techniques.

SOC method	Merits	Demerits
OCV [27]	• Simple to implement. • Highly precise. • Cost-effective.	• Offline • Low speed
CC [28]	• Low power required. • Simple to implement.	• Low accuracy. • Difficulty in defining the SOC initial values.
EIS [30]	• Low cost • Highly accurate for stabilized impedance value. • Operates in online mode.	• Temperature effect • Aging effect.
Model-Based [33]	• Operates in online mode. • Highly accurate.	• It depends on the accuracy of the model.

The constant-current (CC) methodology is considered the most straightforward method for estimating the SoC of a battery. This technique offers the advantage of being easily implemented and requiring minimal power calculations. The process of charging and draining the battery is contingent upon the integration of the electric current with respect to time [28]. The expression can be found in Eq. (3).

$$SoC = 1 - \frac{\int i.\eta dt}{Cm} \tag{3}$$

where "η" indicates the Coulombic efficiency, "i" indicates the current of the battery, and "C_m" indicates the total capacity.

- Electrochemical Impedance Spectroscopy (EIS)

To ensure the successful implementation of the Electrochemical Impedance Spectroscopy (EIS) technique, it is crucial to utilize an appropriate electrochemical model. Battery impedance is evaluated by employing capacitances and inductances across a broad range of frequencies [29]. Two capacitive arcs and one inductive arc operating at both low and high frequencies are analogous to the described circuit architecture. The model impedances are calculated using a method called nonlinear least squares fitting (LSF). This method is used across different states of charge (SoC). The aforementioned technique offers several advantages, including cost efficiency, online operability, and a notable degree of precision [30].

- Model-based SOC estimation

Due to its inability to operate in real-time, the open-circuit voltage method necessitates sufficient idle time for monitoring SoC [31]. Consequently, its application is precluded during vehicle motion. Hence, the creation of a battery model is crucial for the implementation of online SoC estimation in the context of online systems [32]. The battery models that are often utilized consist of electrochemical models and equivalent circuit models. The concept can be articulated as follows:

$$Vt = Voc - Vdr - Vep \tag{4}$$

where terminal voltage (*Vt*), open-circuit voltage (*Voc*), potential difference (*Vdr*), and electric potential (*Vep*). Methods for measuring the SoC are analysed in Table 3.

3.5.2. Adaptive filter (AF) algorithm

- Kalman filter (KF) algorithm

The Kalman filter is a widely used and sophisticated technique that finds frequent application in the fields of automotive engineering, navigation tracking, and aerospace technology [34]. One notable characteristic of the Kalman filter is its inherent ability to self-correct [35]. The Kalman filter linear model consists of a state equation that forecasts the present state and a measurement equation that modifies the present state [36]. These equations may be stated as follows:

$$\text{State equation}: x_{n+1} = A_n x_n + B_n u_n + f_n \tag{5}$$

$$\text{Measurement equation}: y_n = C_n x_n + D_n u_n + z_n \tag{6}$$

The covariance matrices in consideration are denoted as A, B, C, and D. The variable x stands for the system state, while the symbol for process noise is f. The variable u stands for the control input, and the variable y is a representation of the measurement input. Lastly, the measurement noise is denoted as z. The RC battery model proposed in the article [37] is known as the Kalman filter. In order to describe the dynamic characteristics of batteries, the mathematical equations of the RC model are transformed into a state-space model. The application of the Kalman filter results in a lower estimated root mean square (RMS) error for the SOC compared to the observed error [38].

- Extended Kalman Filter (EKF)

The Extended Kalman Filter (EKF) has been utilized to operate in the context of nonlinear applications [39]. The use of partial derivatives and first-order Taylor series expansion linearizes the battery model. The state-space model is linearized, and at each moment in time, it establishes an equation that correlates the projected battery value with the observed voltage [40]. This process is conducted to accurately estimate the restrictions for the state of charge (SoC). If the scheme exhibits a high degree of nonlinearity, there is a possibility of encountering an error in the process of linearization [41]. Ultimately, the enhanced dual AEKF technique was implemented, resulting in SoH and SoC estimate errors that fell within the range of 1 % [42].

- H ∞ filter

The proposed model utilizes a straightforward approach that does not require knowledge of specific noise details or measurement features. The system robustly operates under particular conditions by considering just the time-varying properties of the battery. The accuracy of the model is affected by hysteresis, aging, and temperature influences [43]. The adaptive H ∞ filter was first described in [44] to estimate the SoC. This method evaluates system functions using a polynomial function and compares them to the adaptive extended Kalman filter. The AHF demonstrated superior performance in terms of accuracy and computing efficiency compared to alternative approaches [45].

- Sigma Point Kalman Filter

This technique is an alternative approach to state computation, characterized by its nonlinearity. In comparison to the extended Kalman filter, it is capable of producing more accurate results. Sigma-Point Kalman filter (SPKF) numerical approximation is sensitive [46]. The

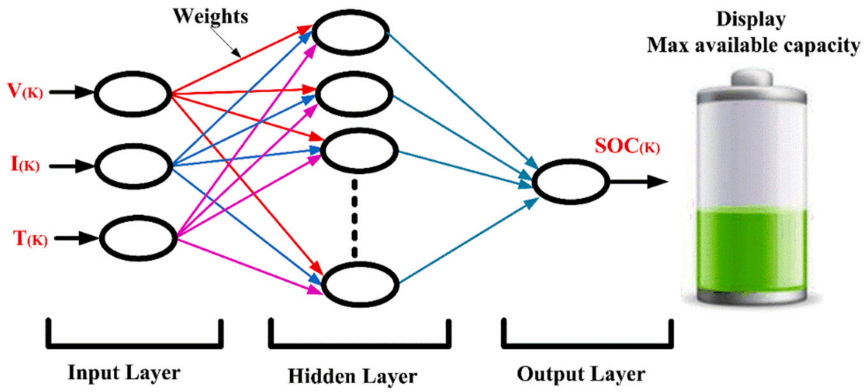

Fig. 14. A neural network-based framework for SoC prediction

Table 4
Comparison of adaptive filter SoC estimation techniques.

Method	Merits	Demerits
KF [34]	• Self correction nature • Accurate • Intelligent control tool	• Can't directly estimate for SOC • Complex calculations
EKF [42]	• Estimates the probability of nonlinear dynamic errors • Improves accuracy	• Limited durability • Error in linearization
H ∞ filter [44]	• Cost of computation • Precise performance	• Aging and temperature might cause accuracy values to deviate
SPKF [46]	• Robustness • Improvement in precision	• Heavy calculations • Complicated

Table 5
Comparison of learning SoC estimation methods.

Method	Merits	Demerits
NN [50]	• Accomplished work of batteries in nonlinear circumstances	• Huge memory is required.
FL [51]	• High accuracy • Effective in operation	• Complex • Costly • Storage is required
GA [54]	• Accuracy is good • Robust	• Computation is high • To obtain effective output tuning of parameters is required.
SVM [56]	• Performs outstandingly for nonlinear models • Performs well	• Computation is high • Process error

programme selects sigma points with the same mean and covariance as the model. The SPKF has the advantage of possessing a comparable calculating method. In addition, the omission of Jacobian matrices in the consideration of the Extended Kalman Filter (EKF) leads to a reduction in complexity [47]. The SPKF exhibits enhanced precision, reduced memory consumption, and a decreased computing workload [48].

3.5.3. Learning algorithms

• Neural network (NN) algorithm

An artificial neural network (ANN) is an algorithm that possesses the ability to learn autonomously and exhibits intelligent behaviour. The estimation of the state of charge (SoC) is achieved by utilizing trained data, even in the absence of prior knowledge of the original SoC data [49]. The neural network topology, as shown in Fig. 14, comprises input, hidden, and output layers. One advantage of a neural network (NN) is its ability to effectively operate under non-linear battery conditions. One of the limitations associated with this approach is the substantial data requirement for training as well as the need for significant memory capacity to retain the acquired information [50]. In Table 4, an examination of several approaches for estimating the SoC using adaptive filters is presented.

• Fuzzy logic algorithm

The most prominent algorithm for expanding nonlinear, complicated prototypes using training data is FL. Defuzzification, rule-based inputs and outputs, and reasoning membership functions are used in fuzzy logic [51]. The nonlinear model estimation function is strong. A complex computation, dispensing unit, and memory storage are needed. FL was used to estimate SoC using CC technique data [52]. SoC and impedances are inputs at three frequencies in this approach. It forecasts SoC with a maximum inaccuracy of ±5 %. Li-ion battery SoC is best estimated by the sophisticated ANFIS [53].

• Genetic algorithm (GA)

The primary use of a genetic algorithm is the identification of the optimal parameter to enhance the efficiency of the system. The use of this method has been seen in the fields of mathematics, physics, and engineering, where it has been employed to ascertain nonlinear optimum parameters. The use of numerous driving cycles served to validate the strategy. The results obtained from this method exhibited enhanced accuracy, with an error rate of <1 % [54].

• Support Vector Machine Algorithm (SVM)

The Support Vector Machine (SVM) algorithm is a regression approach that operates using a kernel function. The purpose of the kernel function is to transform non-linear data into a linear form, allowing for more effective analysis in extreme measurements. In article [55], the support vector machine (SVM) approach was employed to estimate the state of charge (SoC) of batteries. One of the advantages of support vector machines (SVMs) is their ability to effectively handle high-dimensional models and nonlinear data representations. The estimation of the SoC is efficiently and precisely achieved through the use of training data. One limitation of this approach is the necessity for trial and error, which may be time-consuming [56]. In Table 5, an examination of several methods used for estimating the state of charge algorithms is presented.

3.5.4. Nonlinear observer (NLO)

• Sliding Mode Observer (SMO)

The Sliding Mode Observer (SMO) algorithm is a training controller

Table 6
Comparison of nonlinear observer SoC estimating techniques.

Method	Merits	Demerits
SMO [57]	• Robustness • Stability improves	• Difficult to alter switching gain
NLO [59]	• Accuracy improves • Convergence speed improves	• Finding of gain matrix to minimize the error is challenging.

Table 7
Comparison of deep learning SoC estimate techniques.

Algorithm	Merits	Demerits
LSTM [63]	• Proven effectiveness in managing long-term dependency. • The calculation is less demanding during the online stage.	• A costly equipment is needed to improve complex training execution.
GRU [64]	• Long-term sequential dependencies are recorded. • LSTM gating mechanism concerns resolved.	• Involves a significant quantity of training data and storage space.
CNN–LSMT [66]	• Enhanced tracking accuracy • Strength in nonlinear fitting.	• Complicated structure

that enhances the resilience and stability of a system in the presence of model uncertainty and environmental disruptions. In article [57], a sophisticated SMO was proposed as a means to address the nonlinearity of battery dynamic characteristics. By incorporating an RC circuit into the system, this was possible. This approach offers a means of regulating the discharge or charge rate during the conjunction time at a high level of sophistication. The constraints were extracted by employing a battery pulse and formulating the state equations based on the circuit model and terminal voltage [58].

- Nonlinear observer (NLO)

The SoC has been estimated using several observers, such as a linear observer and a nonlinear observer [59]. NLO-dependent SoC estimates were initially introduced in article [60] using a similar first-order RC circuit. Results from this model employing a driving cycle and a discharge test were faster, more accurate, and less expensive than those using extended KF and SMO [61]. The nonlinear observer SoC estimation technique comparison is shown in Table 6.

3.5.5. *Advanced SOC estimation techniques*

- Deep Learning Algorithm (DLA)

The use of deep learning (DL) techniques has improved our capability to estimate SoC. Notable examples include recurrent neural networks, convolutional neural networks, gated recurrent units, and long short-term memories. In terms of SoC estimates, the LSTM network excels because of its potent capacity for self-learning [62]. LSTM networks evaluate battery SoC using voltage, current, and temperature. In addition, DNN encodes the battery's temperature-dependent behaviours into DNN weights, enabling competitive estimation performance throughout a wide temperature range [63]. Battery SoC at various temperatures is estimated using GRU, and the efficiency of two commonly used lithium-ion batteries is compared [64]. CNN is another promising deep-learning architecture. A convolutional neural network (CNN) and long short-term memory network (LSTM) hybrid were presented in the article [65] to mimic the intricate battery dynamics. The CNN was utilized to collect sophisticated spatial characteristics from the raw data. Both CNN and LSTM networks can capture the spatial and temporal characteristics of the battery data [66]. Several deep-learning SoC estimation techniques are compared and contrasted in Table 7.

Table 8
SoC estimation hybrid methods analysis.

Method	Merits	Demerits
CC and KF [67]	• Low power usage for CC. • KF self-corrects and is smart.	• CC and KF errors need sophisticated computations.
EKF [68]	• Nonlinear dynamic error prediction. • Increases accuracy.	• Weak resilience • Linearization mistake.
H ∞ filter [68]	• Accuracy high • Strongness • Stability improves.	• Age and temperature affect accuracy.
NAMHE [69]	• Working under uncertain noise levels. • Improved stability and accuracy	• Running the programme increases computational complexity and memory utilization.

Table 9
Overview of Li-ion battery SoC estimate techniques.

Method	Merits	Demerits
Conventional method [28]	• Easy to set up • Low power use • Simple to understand	• Not online-friendly • Vulnerable to age and temperature changes • Model accuracy is crucial • Models are susceptible to aging and temperature
AF [35]	• Effective filtering • High precision • insensitivity to initial SoC • High durability	• High processing complexity. • Expensive • Big noise measurements are not possible
LA [50]	• Decentralized models • High accuracy • Inference based on rules • Capability for nonlinear mapping	• Large training data • Large memory units • Expensive processing • Time-consuming method
NLO [61]	• Stable • Strong tracking ability • Excellent nonlinear processing potential	• Low accuracy • Difficult to establish a suitable gain matrix • Not stable
Hybrid [67]	• More efficient • Durable • Accurate to a high degree	• Longer computing time • Complex calculations

- Hybrid methodologies

A hybrid algorithm combines features from many different algorithms to achieve better performance and accuracy. Since it performs extensive mathematical calculations, it needs a sizable memory unit. Contrarily, a hybrid approach achieves consistent and operational outcomes while also reducing the BMS cost [67].

The analysis of hybrid SoC estimation algorithms is mentioned in Table 8, and the summary of the different SoC estimation methods for Li-ion batteries is mentioned in Table 9.

- The nonlinear model of the Li-ion battery was applied to the H ∞ filter and discrete-time KF. Compared to SMO-based estimating models, this strategy increased accuracy by <1 %. EKF and EKF-assisted ANFIS RMSEs were compared. The hybrid technique enhanced precision and accuracy while saving money [68].
- NAMHE was recommended for Li-ion batteries with unknown noise [69]. The suggested strategy had a lower SoC estimation error than

Table 10
SoC monitoring issues, causes, and solutions.

Ref.	Issues	Causes	Solutions
[70]	Temperature	• Increased electrolyte development and inconsistencies assist particle diffusion and mobility.	• The best temperature range and battery cycle charging rate are recognized.
[71]	Aging effect	• Internal resistance and capacitance deterioration cause it.	• Enhancing one restriction, battery age, will provide an OCV curve model to evaluate battery SoH.
[72]	Cell unbalancing	• Battery manufacturing and chemical properties may fluctuate when discharging and charging.	• Passive and active cell balancing mechanisms were proposed.
[73]	Hysteresis effect	• Impedance, electrochemical problems, concentration polarization, and energy scattering in development are the main causes.	• Li-ion cell hysteresis measurement improves precision despite its influence.
[74]	Battery modelling	• Modelling a battery is difficult due to its complicated dynamics and electrochemical environment.	• ESC and higher-order RC models were proposed
[75]	Self-discharge	• Lost lithium species and SEI development cause self-discharge.	• An ECN model for SoC estimation utilizing prediction error minimization was developed.
[76]	Charge and discharge rate	• The main indicator of excessive discharge current in plastic Li-ion batteries is phase dispersion.	• The current range of the Li-ion battery discharged and charged.
[77]	Communication	• An improved, even charger is difficult to create due to the non-uniform charging process.	• Wireless technology transfers data between charger and battery.

MHE, as shown by the simulation results [69]. Table 10 lists the different SoC monitoring issues, causes, and solutions.

3.6. State of health (SoH)

The state of health (SoH) of a battery is the amount of usable maximum capacity that is left over after cycling, which involves charging and discharging the battery many times [78]. Fig. 15 shows different ways to figure out SoH. The estimation of SoH may be done with the help of the following equations:

$$SoH(\%) = \frac{Qc}{Qn} \times 100 \tag{7}$$

$$SoH\ (\%) = \frac{Rtermi - Rcu}{Rtermi - Rn} \times 100 \tag{8}$$

The symbol '*Qc*' represents the current capacity of the battery, whereas '*Qn*' denotes the new battery capacity. After the battery life, '*Rtermi*' represents the ohmic internal resistance, '*Rcu*' represents the current state and 'Rn' represents the starting state. The SoH of a battery may be readily approximated by considering the battery's capacity deterioration and internal resistance. There exist a range of techniques that have been devised to estimate the SoH of batteries. These methodologies are model-free, model-based, and data-driven. Electrochemical Impedance Spectroscopy (EIS) analysis is better than conventional approaches for model-free capacity and internal resistance estimation. In contrast, model-based techniques use the equivalent circuit model and electrochemical model to estimate battery capacity and internal resistance [79].

3.6.1. SoH estimation experimental methods

Experiments are usually done in labs since they require special equipment and take time. They employ data and measures to assess battery aging. This section describes the primary experimental approaches for battery SoH estimation.

- Internal resistance measurement

The battery's internal resistance is an essential SoH indication that determines its voltage drop when current is supplied. Many authors studied internal resistance measurement methods. The current pulse is

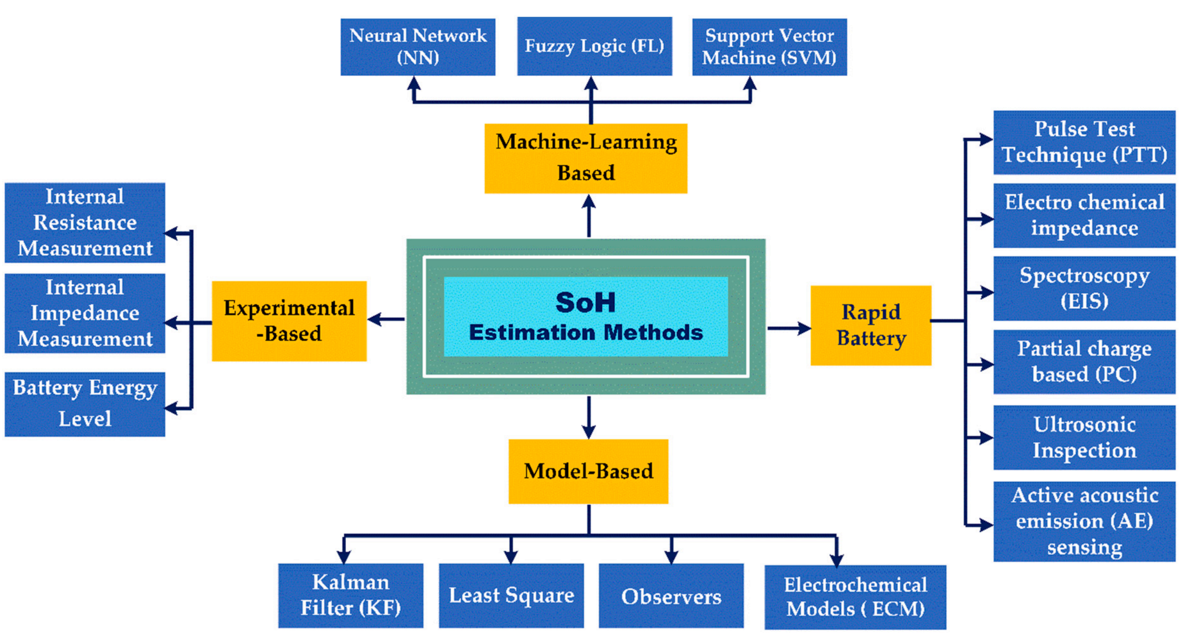

Fig. 15. Classification of approaches for SoH estimation.

Table 11
SoH estimation experimental-based methods.

Methods	Mode of operation	Data calculation	Merits	Demerits	Estimated error
Internal resistance [80]	• Offline	• Polynomial exponential	• Simple and direct method • Accurate	• It works in Offline mode only • Slow	• <1 %
Internal impedance [81]	• Offline	• Exponential function	• Improves the understanding of battery deterioration causes. • Accurate	• Relies on battery chemistry data.	• 2.1 %
Energy level [82]	• Offline	• Linear function and operations	• Accurate • Fast in response	• Not possible when the battery is running (needs full charge).	• 9 % (21st cycle) • 1 % (after 8th cycle)

Table 12
SoH estimation model-based methods.

Methods	Mode of operation	Data calculation	Merits	Demerits	Estimated errors
KF-base [78]	• Online	• Matrix operation	• Accurate and Error bounds	• Valid for nonlinear system • Complex • Computational effort is high. • A high-performance controller is required.	• ±5 %
Least square-based [80]	• Online	• Linear equation	• Precise • Robust • Simple structure	• Relies in terms of accuracy on the selected model • A high-performance controller is required.	• ±5 %
Observer [81]	• Offline	• Polynomial exponential	• Accurate • Robust	• A high-performance controller is required. • High cost	• <1 %
Electrochemical models [82]	• Offline	• Exponential function	• Accurate • Provides the degradation phenomena knowledge of the battery.	• A high-performance controller is required. • Complex • High computational effort	• 2.1 %

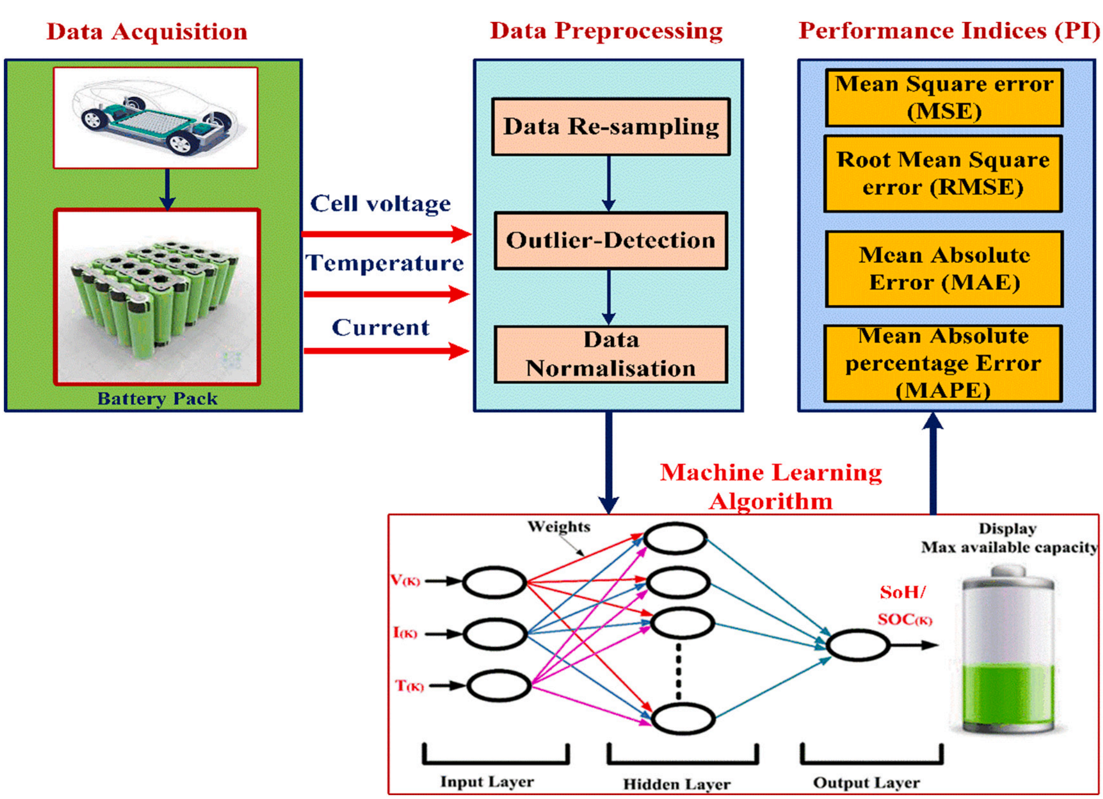

Fig. 16. Machine Learning algorithm functional block diagram.

Table 13
SoH estimation machine-learning methods.

Method	Mode of operation	Data calculation	Merits	Demerits	Estimated error
SVM [78]	• Offline (can be adapted online)	• Exponential function, multiplication and accumulate.	• Accurate • Nonparametric • Robust	• Heavily dependent on the quality and quantity of the training data used. • A high-performance controller is required.	• 2 %
FL [79]	• Online	• Exponential function, multiplication and accumulate.	• Accuracy is high • Robust • Applicable for nonlinear systems	• Heavily dependent on the quality and quantity of the training data used. • A high-performance controller is required.	• 1.4 %–9.2 %
NN [80]	• Online	• Exponential function, vector and matrix operations	• Accurate • Requires less amount of data than Fuzzy Logic.	• Heavily dependent on the quality and quantity of the training data used. • A high-performance controller is required.	• <0.5 %

the most typical approach based on Ohm's Law. After measuring the battery's voltage drop for a particular current, it determines its internal resistance [80].

$$Rbattery = \frac{Vocv - Vbattery}{Ipulse} \tag{9}$$

where $R_{battery}$ is battery internal resistance, V_{OCV} is open circuit voltage, $V_{battery}$ is its voltage, and I_{pulse} is applied current. This approach is extensively used in labs to accurately estimate battery internal resistance in varied operating situations. Due to its time commitment, this procedure is better for stationery and laboratory work.

- Internal impedance measurement

Internal impedance is a battery's resistance and reactance. Age increases a battery's intrinsic impedance, as proved. Hence, a battery SoH indicator. EIS impedance measurement is the most commonly used method to estimate the health condition of the battery [81]. Non-destructive approach evaluates electric system impedance by applying sinusoidal AC current and measuring response output voltage. Frequency determines impedance. Its key benefit is identifying battery aging correctly.

- Battery energy level

Energy storage capacity is a battery's capacity. As batteries age, this trait declines. The battery SoH can be best estimated by empirically evaluating capacity declining over time. A lithium-ion battery was charged and discharged till its end of life. The goal of this study is to determine battery charging capacity based on voltage for different deterioration degrees [82]. The merits and demerits of the studied experimental procedures are in Table 11.

3.6.2. SoH estimation model-based methods

These models employ SoH indicators to characterize battery behaviour. Indicators are used to estimate battery statuses and performance. The literature provides several strategies for identifying these signs. This section outlines the primary model-based SoH estimation approaches. The reviewed model-based methods are listed in Table 12 with their merits and demerits.

3.6.3. Battery machine learning SoH estimation methods

These approaches combine experimental and model-based methodologies. Training data, measurements, and models are used to estimate battery SoH during learning. The literature has several machine-learning techniques for battery SoH prognostics. Fig. 16 shows a functional block diagram of data driven techniques. Advancements in data driven methods, such machine learning algorithms, have greatly increased the accuracy and performance of SoC/SoH estimation. The reviewed machine learning-based methods are listed in Table 13 with their merits and demerits.

3.6.4. Rapid EV battery SoH estimation methods

The quick SoH estimate techniques in this study are electrical parameters-based and material properties-based. There are two categories: pulse test technique (PTT) and electrochemical impedance spectrum (EIS) measurement, and ultrasonic inspection and a suggested active acoustic emission (AE) detection technology [82]. Fig. 17 compares four basic SOH estimate approaches from various angles for practical application. These approaches can quickly estimate EV battery

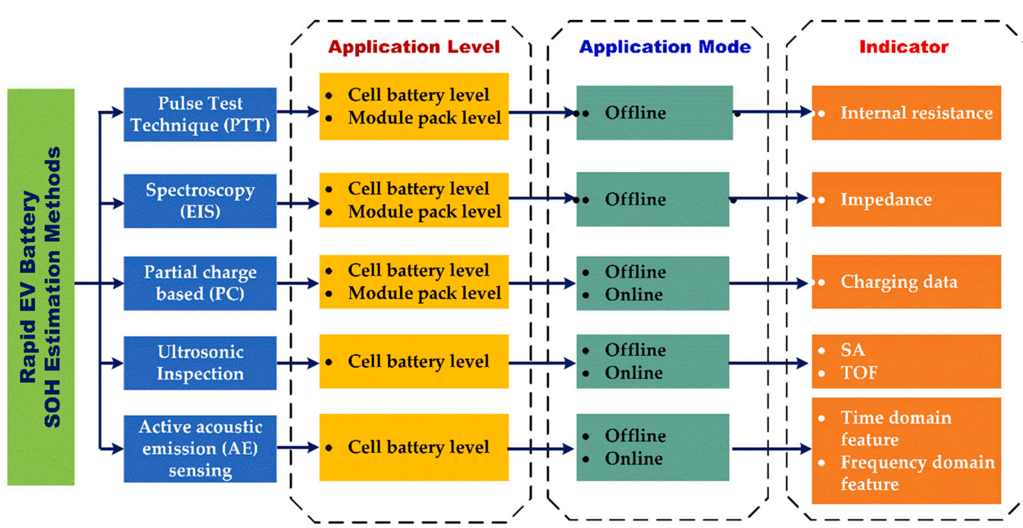

Fig. 17. Comparison of SoH estimation methods in practical applications.

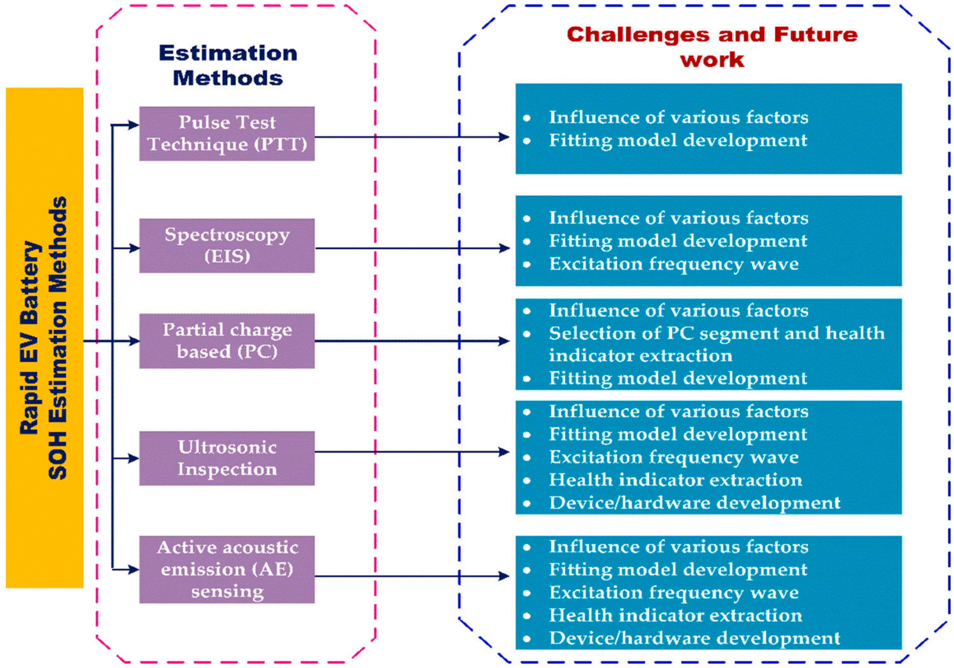

Fig. 18. Challenges and future scope of SoH estimation methods.

SOH online or offline. The problems and future work for improving SOH estimates for lithium-ion batteries in practical applications are presented in Fig. 18. Their uses and future scope are detailed below.

3.7. State of function (SoF)

The state of function (SoF), defined as the working state of a lithium-ion battery pack under specific constraint conditions, is particularly important. One of the most important responsibilities of the BMS is to evaluate the SoF. The SoF concept suited to a certain application's requirements was presented. In some cases, none of the battery-pack status variables, such SoH, SoC, or voltage, can inform the system whether or not the battery meets the requirements of the given application under real operating conditions [83].

It represented "no" and "yes" with rational numbers "0" and "1". The SoF is "1" if the current-voltage exceeds the preset voltage, indicating that the power demand is satisfied. Otherwise, it is "0". Another overhead logical-variable equation characterized the SoF as follows:

$$SoF = \frac{Pb - Pd}{Pm - Pd} \tag{10}$$

'Pb' represents battery power, 'Pd' represents power demand, and 'Pm' represents maximum power (when SoC and SoH are "0" and the operating temperature is constant). State of charge SoC is always used to represent the current status of a battery's charge, whereas SoH is used to show how the battery ages in comparison to a new one. Nonetheless, when we need to characterize the battery pack function state under exact constraint circumstances, the state of function is the best option.

The Fuzzy Logic Control Algorithm (FLCA) is the most recent approach for estimating SoF. The FLCA, an intellectual control method used to estimate the SOF, has an essence. Some particular instances from observed and simulated data are required to investigate the usefulness

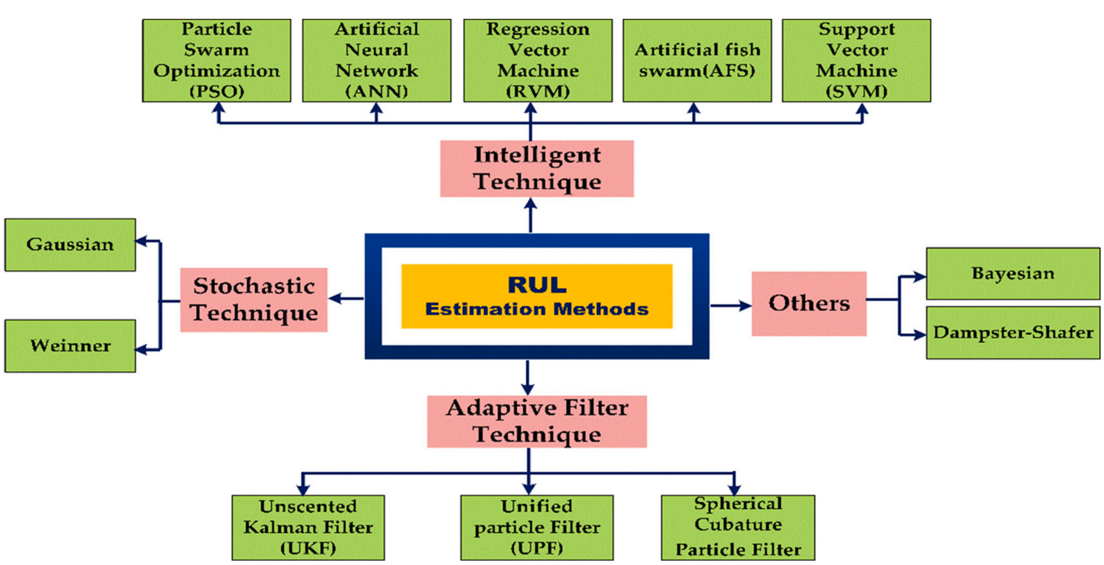

Fig. 19. RUL prediction methods.

Table 14
Comparison of RUL prediction methods.

Method	Lithium-ion battery capacity (Ah)	Temperature	Battery degradation details	Accuracy
UKF [78]	0.9	25 °C	100 cycles and 160 cycles	MAPE 0.1611 and RMSE 0.01156 at 100 cycles. MAPE 0.1857 and RMSE 0.02069 at 160 cycles.
GPM [79]	2	25 °C	60 and 80 cycles	RMSE 0.0158 at 60 cycles RMSE 0.0130 at 80 cycles
UPF [80]	0.9	25 °C	15 cycles and 32 cycles	ER 4.08 %, RMSE 0.00423 at 15 cycles. ER < 2.04 %, RMSE 0.00250 at 32 cycles
Bayesian [81]	2	4 °C and 24 °C	25 %, 50 %, 75 % and 90 % of actual life	RUL 74.7 %, 50 %, 25 % and 10.1 % at 25 %, 50 %, 75 % and 90 %.
RVM [82]	0.9	25 °C	104, 128, 146, 157, 170 and 183 cycles.	Absolute prediction errors are 9, 7, 4, 0, 8, 1 with respect to cycles.
WPME [83]	2	25 °C	68 cycles	Mean square error under 0.001
SVM [84]	2	4 °C and 24 °C	40, 60 and 80 cycles	RMSE 0.1150, 0.0210 at 40th and 60th cycles respectively. RMSE 0.0300 at 80th cycle.
Naïve Bayes [85]	0.9 (type A) 1.1 (type B)	25 °C	15,32 cycles (Type A) 250 cycles (Type B)	SD 6,2 at 18,32 cycles for type A SD 35 at 250 cycles for type B
PSO [83]	0.9	25 °C	80, 95, 100, 126 cycles	Mean prediction errors are 8, 9, 2, 3 cycles with respect to inspection cycles.
LSTM [84]	2.7	25 °C and 40 °C	253 cycles and 354 cycles	SD 28 and 11 at 253 and 354 cycles respectively.
AFS [85]	0.9	20 °C–25 °C	300 cycles	Training RMSE 0.0836 Validation RMSE 0.1757

and significance. SoF is a battery's ability to complete a task. It describes how well the battery meets power demand. SoF is estimated using SoC, SoH, and temperature [84]. The fuzzy logic control technique, adaptive characteristic maps, and similar circuit models may compute the SoF [85]. KF and ANN algorithms are used in model-based SoF estimation for accuracy. The fuzzy logic technique estimates the battery SoF using SoC, SoH, and C-rate parameters [86].

3.8. Remaining useful life (RUL)

RUL estimates the number of cycles until the battery's SoH hits 0 %. The optimal model for estimating RUL is not ubiquitous owing to data unavailability, model complexity, and system limitations. This study divides RUL approaches into four categories: adaptive filter, intelligent, stochastic, and others as shown in Fig. 19 [84].

3.8.1. Adaptive filter technique

A non-linear time series prediction model is used with the UKF algorithm to provide a new technique for predicting RUL. Health prognosis can be improved by adaptive filtering. However, fluctuating currents and temperatures might influence model accuracy.

3.8.2. Intelligent techniques

Zhang et al. (2018) explored LSTM-based recurrent neural networks for RUL prediction. Various lithium-ion cells were used to collect experimental data at varying current rates and temperatures. Despite offline training data, the model predicts RUL well. Wang et al. (2014) suggested an SVM-based multi-step prediction model for reliable RUL prediction. Characterizing the training dataset using working temperature and energy efficiency. Results from trials indicate that the model accurately detects health features with few parameters.

3.8.3. Stochastic technique

To evaluate the deterioration of lithium-ion battery health, the stochastic process is better characterized. The algorithm still has a problem in generating correct findings when taking into account the effect of random current, time-varying temperatures, and self-discharge characteristics.

3.8.4. Others technique

According to Ng et al. (2014), a model for predicting RUL under varying current rates and ambient temperatures using Naive Bayes may be used to lithium-ion batteries. When compared to SVM, the prediction results are more accurate and resilient. He et al. (2011) used Bayesian Monte Carlo (BMC) and Dempster-Shafer Theory (DST) to create a double-index deterioration model that could forecast RUL. The battery's usable life determines optimal EV performance. Charged and discharged batteries degrade capacity, which can cause serious breakage, economic loss, and safety hazards. Therefore, EV technology must estimate battery RUL to be safe, accurate, durable, and dependable. Continuous charging and discharging leaves the battery at 70 % or 80 % of its initial capacity, requiring replacement. Table 14 summarizes the comparison of various RUL prediction methods.

3.9. Charge and discharge control

The battery's measuring block digitizes analog measurements at each node for analysis of current, temperature, and voltage. To limit the maximum charging and discharging currents, a capacity estimation block is used. The cell balance block uses the results of the capacity estimation to regulate excessive discharging or charging [87]. Fig. 20 demonstrates their method for controlling the charging and discharging of EVs using a systematic approach based on charging reliability indicators [88].

There are four types of charging strategies that may be characterized as follows:

i. Constant Current (CC) Charging
Constant-current charging entails sending a constant current to the battery during the charging process. The charging rate remains constant as the battery voltage increases. When the battery voltage is low, this method is frequently utilized in the early stages of charging.

ii. Constant Voltage (CV) Charging
When charging at a constant voltage, the battery's voltage is maintained as the charging current gradually decreases towards zero as the battery nears full charge. By controlling the voltage between the battery terminals, this method protects the battery from being overcharged.

iii. Constant Current/Constant Voltage (CC-CV) Charging
The CC-CV charging approach uses constant current and constant voltage. It quickly charges the battery with constant current until a specified voltage is attained. After that, the charging changes to a constant voltage to prevent overcharging and enable the battery to fully charge.

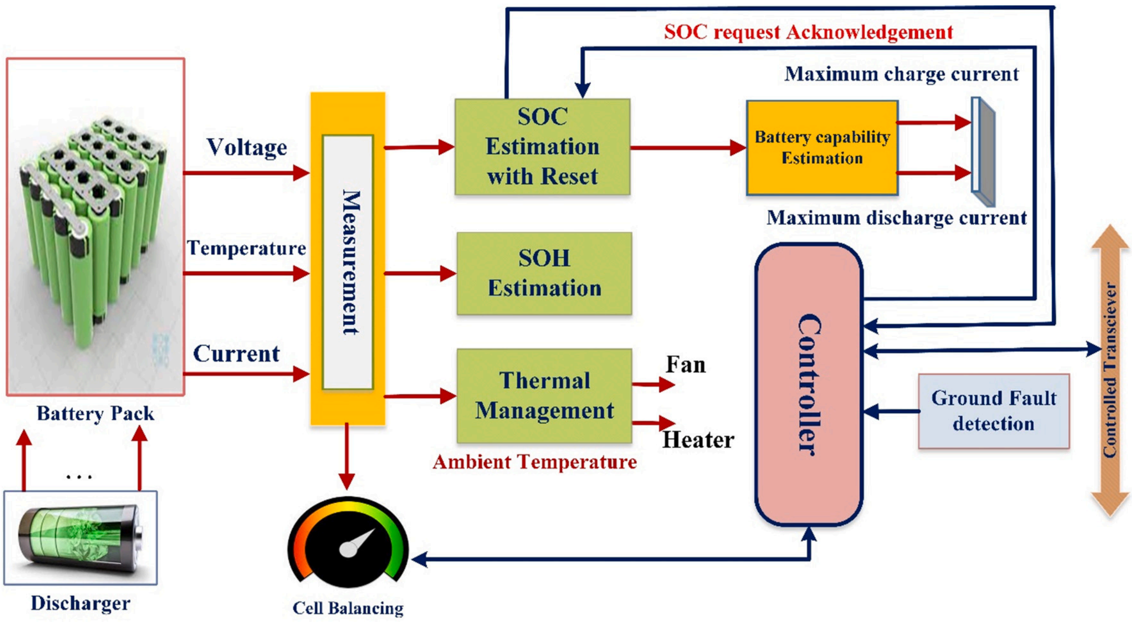

Fig. 20. Charge and discharge control block diagram of the BMS.

Table 15
Comparison of various charging strategies.

Criteria	CC charging	CV charging	CC-CV charging	MCC charging
Efficiency [87]	Moderate	Low	High	Moderate
Lifespan [87]	Low	Medium	High	Medium
Charging Speed [88]	High	Medium	Medium	Low
Complexity [88]	Small	Small	Medium	More

iv. Multistage Constant Current (MCC) Charging
Multistage constant-current charging charges the battery in stages with each current constant. Larger batteries, or battery banks, employ this method. Managing heat can increase charging efficiency. MCC charging continuously injects multistage series current into the battery. MCC charges slower than CC-CV. MCC currently improves performance with fuzzy logic.

Charging strategies depend on battery type, chemistry, and performance goals. Charging efficiently, safely, and without overcharging improves battery life. Table 15 lists the comparisons of the charging strategies.

3.10. Battery equalizer control

The Battery Management System (BMS) is capable of safeguarding the battery from irregularities resulting from both undercharging and overcharging. This is achieved through the implementation of individual cell monitoring and charge equalization management. To optimize

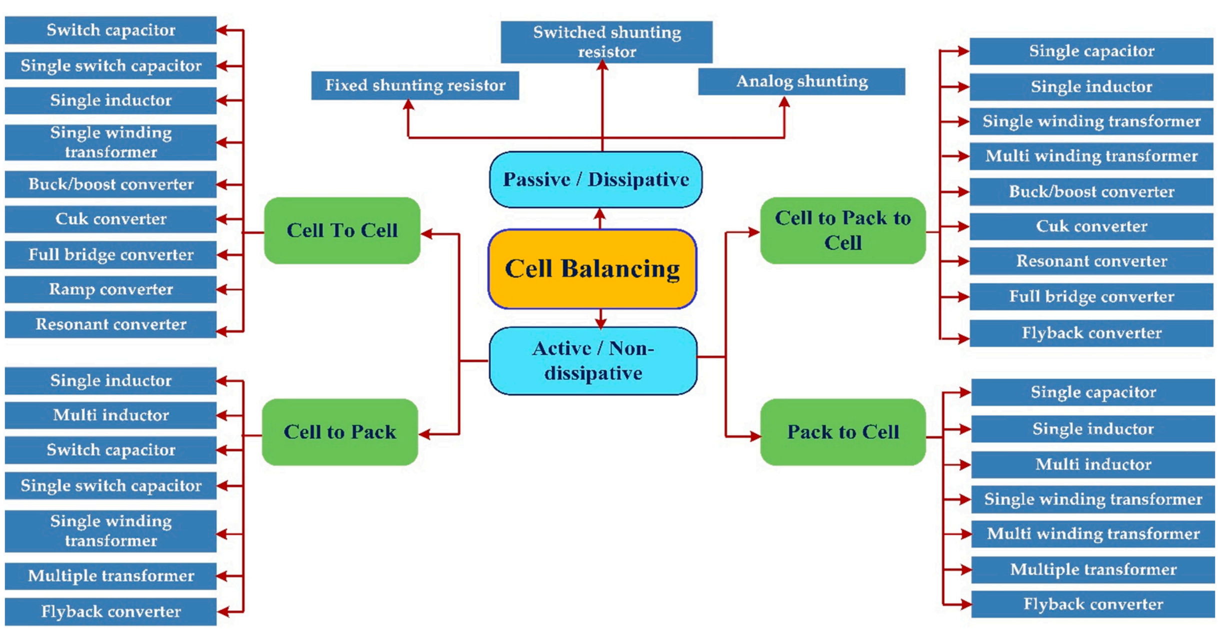

Fig. 21. Charge equalization controllers for lithium-ion batteries.

Table 16
Comparison of operations various cell balancing methods.

Cell balancing method	Mechanism and operation	Ref.
Passive balancing:		
1. Resistor-Based	• High-value resistors are connected in parallel with each cell. • When a cell's voltage exceeds a certain threshold, the resistor conducts and dissipates excess energy as heat.	[90]
2. Zener Diode-Based	• Zener diodes are connected in parallel with cells. • When a cell's voltage crosses a threshold, the Zener diode conducts and allows current flow to balance the voltage.	[91]
Active balancing:		
1. Voltage-Based	• Active electronics (DC-DC converters) monitor cell voltages. • When an imbalance is detected, energy is transferred from higher-voltage cells to lower-voltage cells.	[92]
2. Charge Transfer	• Active switches transfer charge directly between cells. • Energy from higher-voltage cells is moved to lower-voltage cells.	[90]
3. Capacitive	• Capacitors are connected in parallel with cells. • When an imbalance occurs, energy is transferred between cells through the capacitors.	[93]
4. Flyback Converter	• Specialized DC-DC converters store energy from higher-voltage cells and release it to lower-voltage cells.	[93]
5. Hybrid Balancing	• Hybrid methods combine passive and active balancing techniques to optimize efficiency and cost-effectiveness. • For instance, a BMS might use passive balancing most of the time and switch to active methods when imbalances become significant.	[94]
6. SOC Balancing	• Similar to voltage-based or charge transfer balancing, but focused on equalizing the energy content (SOC) of cells.	[95]

Table 17
Performance comparison of various cell balancing methods.

References	Performance indicator	Passive balancing	Active balancing
[90]	Efficiency	Lower	Higher
[91]	Speed of Balancing	Slower	Faster
[92]	Complexity and Cost	Lower complexity and cost	Higher complexity and cost
[93]	Voltage Difference Handling	Limited to minor imbalances	Suitable for large imbalances
[90]	Applicability	Smaller systems, minor imbalances	Larger systems, high-voltage cells
[94]	Heat Generation	Generates heat	Minimizes heat generation
[95]	Control Precision	Limited	Higher precision

and sustain the consistent performance of the battery, it is imperative to prioritise the equalization of voltage and charge across battery cells [89]. The control of battery equalizer may be classified into two main categories: active charge equalization controllers and passive charge equalization controllers, as seen in Fig. 21. Table 16 lists the comparison of operations of various cell balancing methods, and Table 17 lists the performance comparison of various cell balancing methods.

3.11. Operating temperature control

Longevity, energy conversion efficiency, and battery safety are just a few of the areas where temperature plays a major role [96]. Increasing the battery's operating temperature, which degrades battery performance, has been traced back to the quick charge-discharge cycle [97]. The operating temperature has an impact on the electrolyte's

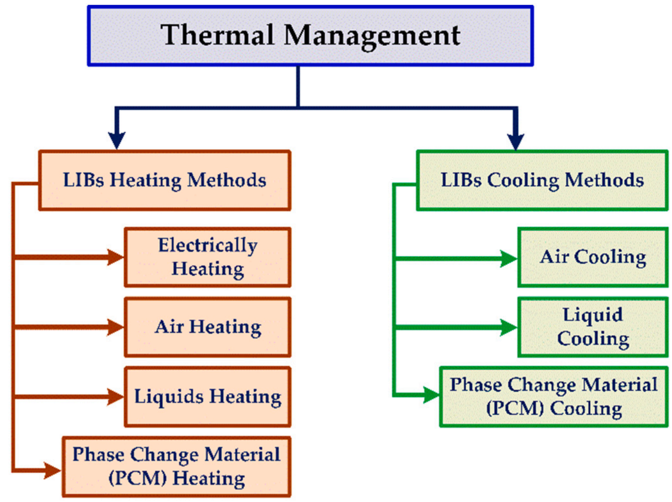

Fig. 22. Classification of temperature control methods.

performance, and when the temperature is too high, problems with thermal runaway and safety arise. Batteries lose capacity and function poorly when exposed to temperatures between 40 °C and −10 °C. Therefore, the heat control of an EV's battery pack plays a vital role in real-time scenario [98].

To maintain the battery at its ideal working temperature, a battery thermal management system (BTMS) must carry out essential functions like heat dissipation through cooling, heat augmentation in the case of low temperatures, and facilitating appropriate ventilation for exhaust gases. The classification of BTMS may be based on the heat transfer medium, which includes air, liquid, and phase-change material (PCM) [96]. An explosion ensues as a result of an imbalance in the electrochemical characteristics of a lithium-ion battery (LIB) caused by elevated temperature. An explosion is triggered when the lithium-ion battery (LIB) experiences a temperature rise, leading to the release of carbon monoxide (CO), acetylene (C_2H_2), and hydrogen sulfide (H_2S) from its internal chemical components [99]. Additionally, an internal short circuit manifests inside the power circuit topology of the lithium-ion battery (LIB). Fig. 22 illustrates several heat management techniques, and further elaboration may be found in reference [100]. Table 18 describes the temperature control techniques for BMS applications.

3.12. Power/energy management control

Electric vehicle (EV) performance is dependent on several factors, including energy storage, power management, and energy efficiency. The energy storage control system of an electric vehicle has to be able to handle high peak power during acceleration and deceleration if it is to effectively manage power and energy flow. There are typically two main approaches used for regulating power and energy management (PEM) [104]. By linking ESS, auxiliary ES, ICE, and generators together in a power transfer train, a low-level component control technique improves the performance and adaptability of the PEM [105].

3.13. Fault diagnosis and assessment

Battery management systems for electric vehicles are required under a standard established by the International Electro-Technical Commission (IEC) in 1995 to include battery fault detection functionalities that can issue early alerts of battery aging and danger. It is common practice to utilize analytical model-based, signal-processing, knowledge-based, and data-driven approaches in EV applications for problem diagnostics [106].

The model-based technique identifies the offending parameters by

Table 18
Temperature control techniques for BMS applications.

Temperature control method	Description	Applications	References
Active Cooling:			
Liquid Cooling	Circulates cooling fluid through channels in a battery pack.	EVs, PHEVs, grid storage	[96]
Air Cooling	Uses fans or blowers to direct airflow over the battery pack.	EVs, consumer electronics, UPS	[96]
Refrigeration	Utilizes refrigeration systems to actively remove heat.	High-performance EVs, data centres	[97]
Passive cooling:			
Heat Sinks	Uses materials with high thermal conductivity to dissipate heat.	EVs, laptops, electronic components	[97]
Phase Change Materials (PCMs)	Absorb/release heat by changing phase (solid to liquid).	EVs, solar batteries, medical devices	[98]
Thermal Insulation	Provides thermal barriers to prevent external temperature changes.	EVs, spacecraft, cold storage	[98]
Heating:			
Heating Elements	Electric elements warm up the battery pack in cold conditions.	EVs in cold climates, cold storage	[98]
Exothermic Reactions	Some chemistries release heat during operation for warming.	EVs in cold climates, medical devices	[98]
Cell Balancing for Temperature:			
Passive Balancing	Transfers energy between cells to equalize temperatures.	EVs, consumer electronics	[98]
Active Balancing	Uses circuitry to redistribute energy for uniform temperatures.	EVs, large-scale energy storage	[98]
Temperature-Dependent Charging/Discharging:			
Charging Rate Adjustment	Adjusts charging rate based on battery temperature.	EVs, grid storage, renewable energy	[99]
Discharging Rate Adjustment	Manages discharging rate based on temperature.	EVs, grid stabilization, backup power	[99]
Thermal Modelling and Prediction:			
Thermal Models	Predicts temperature changes under various conditions.	EVs, energy management systems	[99]
Predictive Algorithms	Uses data to predict temperature changes and adapt control.	EVs, smart grid, renewable integration	[99]
Safety Measures:			
Temperature Thresholds	Sets limits; triggers actions like reducing power or cooling.	EVs, stationary storage, aerospace	[100]
Emergency Shutdown	Shuts down battery if temperatures exceed critical levels.	EVs, aerospace, critical systems	[100]
User Interaction and Notifications:			
Driver Alerts	Notifies the driver if the battery temperature is unsafe.	EVs, consumer electronics	[101]
Adaptive Control:			
Learning Algorithms	Adapt strategies over time based on past scenarios.	EVs, smart energy management	[102]
Integrated Design:			
System Integration	Aligns thermal strategies with an overall vehicle and battery design.	EVs, stationary storage, renewable energy	[103]

comparing the residual signal to a predefined threshold. The problem is that measurement and process noise might muddy the diagnostic results. The signal processing-based technique relies heavily on time-domain analysis to acquire the test data necessary for fault analysis [107]. Further, a knowledge-based approach to defect diagnostics employs machine learning and expert systems, both of which may be used to estimate a battery's remaining useful life. In Fig. 23, a flowchart detailing their suggested method for problem identification in a lithium-ion battery system [108]. The BMS runs a battery parameter estimation suite of tests in accordance with the recommendations made in Table 19 [15].

3.14. Communication and networking

The communication system employs physical transmission mediums such as cables or data lines [109]. A fundamental BMS typically comprises essential components such as a microcontroller, debugger, Controller Area Network (CAN) bus, and host computer. The AS8505, which is an integrated circuit designed for monitoring battery condition, establishes communication with the microcontroller by utilizing I/O lines and a Controller Area Network (CAN) bus. This communication enables the regulation of cell data and facilitates the balancing process [110]. ZigBee, Wi-Fi, GSM, Bluetooth, GPRS, and GPS have been identified as potential technologies for battery monitoring [111]. The proposed approach for battery management is a data-driven and customized strategy that leverages big data and cloud computing, as seen in Fig. 24.

Unpredictably, the several currently promoted BMS each independently perform the elemental abilities. Table 20 compares and contrasts various BMS products, and Table 21 compares the performance studies among BMS components.

4. Applications of battery management system (BMS)

Battery management systems (BMS) play a crucial role in the management of battery performance, safety, and longevity. Rechargeable batteries find widespread use in several applications. Battery management systems (BMS) have emerged as crucial components in several domains due to their ability to efficiently monitor and control the performance of batteries. The following are notable applications where BMS plays a critical role. Fig. 25 presents how BMS is grid-integrated with different possible sources for power electronics converter applications and similarly, the PV-Battery integration block diagram for the grid is presented in Fig. 26.

The operational life of the battery in a photovoltaic (PV)-battery-integrated system is significantly reduced, and its performance is significantly affected due to repeated charging and discharging cycles. This study presents a suggested intelligent power control technique for a

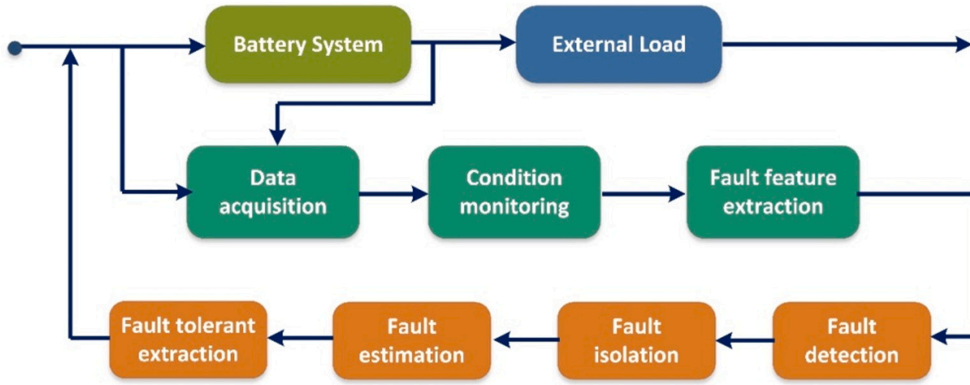

Fig. 23. Fault diagnosis process of a battery system.

Table 19
BMS parameter testing guidelines.

S.No.	Parameter of testing	Standards and guidelines
1.	Cell balancing	IEE 1679.1
2.	Thermal management	IEE 1679.1
3.	Over-discharge	UL1973, NAVSEA S9310
4.	Temperature range	IEE 1679.1
5.	Control of current	IEC62619, NAVSEA S9310
6.	Cell operating range	IEC62619, IEE 1679.1
7.	Thermal runaway fault	IEE 1679.1
8.	Overheating control	IEC62619
9.	Heating and cooling control	IEE 1679.1
10.	Control of voltage	IEC62619, UL1973, UL9540

standalone PV battery system, aiming to enhance the battery's dependability throughout its operating lifespan. The control technique being presented operates in two distinct regulatory modes, namely maximum power point tracking (MPPT) mode and battery management system (BMS) mode. The unique controller employs an MPPT system to effectively monitor and optimize the power output of the solar cells, maximizing their energy harvesting potential across various air conditions. Instead, a backpropagation neural network (BPNN) algorithm has been used in the battery management system (BMS) mode to create a way to estimate SoC [112]. This technique facilitates the effective management of battery storage operations, including charging, discharging, and islanding techniques, to extend the battery's lifespan. An advanced BMS can handle multiple operations; hence, it was determined that the most effective advancement of EV technology is shown in Fig. 27 for BMS-EV integration [113].

In general, the applications of battery management systems span across several industries and technologies, as shown in Fig. 28, with the primary objective of improving battery performance, ensuring safety, and prolonging battery lifespan in different environments [114].

5. BMS challenges and recommendations

Battery management systems (BMS) monitor and control battery performance in electric vehicles, renewable energy systems, and portable electronics. The recommendations for various open challenges are mentioned in Fig. 29, and finally, a few add-on constraints are mentioned in Fig. 30.

5.1. BMS challenges

- Battery Storage Technology: Fast charging can lead to high current flow, which can cause health degradation and ultimately shorten battery life, impacting overall performance. Small batteries can be combined in series and parallel configurations to solve this issue.
- Battery Balancing and Temperature Issues: Passive balancing and thermal management are important tasks in battery management

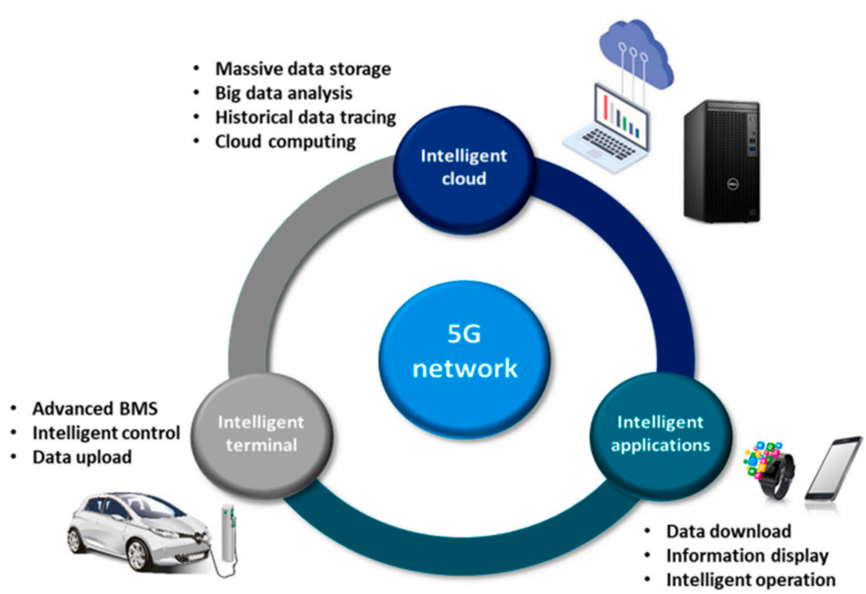

Fig. 24. Superior BMS design utilizing 5G for EVs.

Table 20
Comparative studies among BMS products.

Parameters	Maxim DS2726 [18,85]	TI BQ78PL114 [18,85]	OZ890 [18,85]
Cell constraints measured	Voltage and current	Voltage, temperature, impedance, and current	Current and voltage
Status estimation	Not available	SOC	SOC
Protection	Short circuit current, over-current, and over-voltage	• Three power field-effect transistors • One secondary safety output fuse	Short circuit current and over-current
Pack parameters measured	Not available	Not available	Temperature
Communication	Not available	Power LAN and SM Bus	CAN
Non-dissipative equalization	Not available	Inductive charge	Not available
Data collection	Not available	PC-based GUI only	EEPROM
Dissipative equalization	Charge shifting	Not available	External resistance stable

systems. They help to address weakened cells and ensure efficient energy dissipation by using external resistors.

- Battery Environmental Issues: EVs help reduce emissions, but the negative impact of non-renewable resources arises when batteries are not properly recycled or reach the end of their lifespan.
- Real-Time SOC and SOH Estimation: Present methods for estimating battery SoC and SOH in practical situations are challenging due to low-cost BMS limitations. Owners must choose between replacing batteries, increasing their financial burden, or waiting for storms.
- Battery Models: BMS batteries require precise testing in various environments due to physical and data-driven techniques.
- RUL Prediction Issues: Due to modelling constraints, system noise, and sensor quality, RUL cannot be accurately predicted using BMS. Only suitable for specific battery types and unreliable health indicators.
- Safe and Efficient Operation: Batteries face safety concerns due to changing factors impacting reliability and stability and maintaining proper operational conditions, particularly for BMS peripheral control units.
- Aging and Memory Effect: There are three main causes of battery deterioration: internal resistance, capacitance loss, and overheating. In order to deal with memory's effects and possible imbalances, a model that takes cell aging variables into account is required.
- Battery Recycling and Reuse: Recycling batteries helps the environment and expands recycling options. A BMS is essential for safe battery functioning throughout its lifespan.
- Battery Disposal Issues: Used batteries are considered hazardous trash and must be disposed of in a certain way to avoid potential fires, chemical spills, and other catastrophes. Disposal is costly due to transportation, treatment, and final disposal fees, as well as potential regulatory issues.

5.2. Recommendations

Recommendations and highlights are provided for future research and development scopes in the sustainable electric vehicle (EV) domain based on identified concerns and obstacles. Future advancements in lithium-ion batteries (LIBs) production and BMS technology have been achieved in the following manner:

- Enhancing Safety and Reliability: Use interlock circuits and insulation monitoring to improve battery safety and dependability, following ISO 26262 PCB-to-connector lengths.
- Algorithm Hybridization and Advanced Prognostic: Hybrid algorithms need enhanced prognostics and health management to monitor temperature, charge/discharge rate, depth of discharge (DOD), vibrations, system safety, dependability and longevity.
- Advanced Thermal Management: Sensor-less sensing, electrochemical impedance spectroscopy, and innovative internal and external temperature management technologies can be implemented to enhance battery temperature control.
- Life Cycle Assessment and Aging Effect: LIBs should avoid rare, costly, poisonous, and hard-to-recycle materials because of their complicated aging dynamics.
- Enhancing LIBs Capacity and Fast Charging: Hidden variables affect LIB capacity; anomaly detection and different driving methods increase efficiency. Fast-charging and overcharging electric vehicles require advanced battery management technologies.

Table 21
Performances studies among various BMS components.

BMS components	Functions	Algorithm/methods	Target	Outcomes
Monitoring [109]	• Cell monitoring • Voltage and current monitoring	• Voltage and current measurement • Voltage divider technique	• Current, voltage, and temperature monitoring	• BMS performance is improved.
Communication [109]	• Monitor and protect • the battery	• Microcontroller unit, Debugger, and CAN bus.	• To control the battery data and monitoring	• Monitoring of the battery status using wired or wireless approach.
Fault diagnosis and protection [106–108]	• Battery protection • Unbalance • Undercharge • Overcharge • Overcurrent	• Knowledge-based methods, and data-driven methods	• Protection of battery	• Increased battery lifetime • Protection from temperature obtained • Detection of faulty locations.
State estimation [110]	• SOC • SOH • SOF	• Ampere-hour (Ah) • OCV • FLA	• To minimize estimation error • To reduce the computational cost	• Enhanced Vehicle • Performance • Accurate estimation
Control operation [101]	• Charge and discharge control • Power/energy management • Temperature control	• CC • CV • CC-CV • MCC • PEM	• To enhance performance • To improve durability • To control energy flow	• Controlled operation can be obtained.
Data acquisition [111]	• Data processing	• CAN bus • SCI	• Communication	• BMS performance is improved.

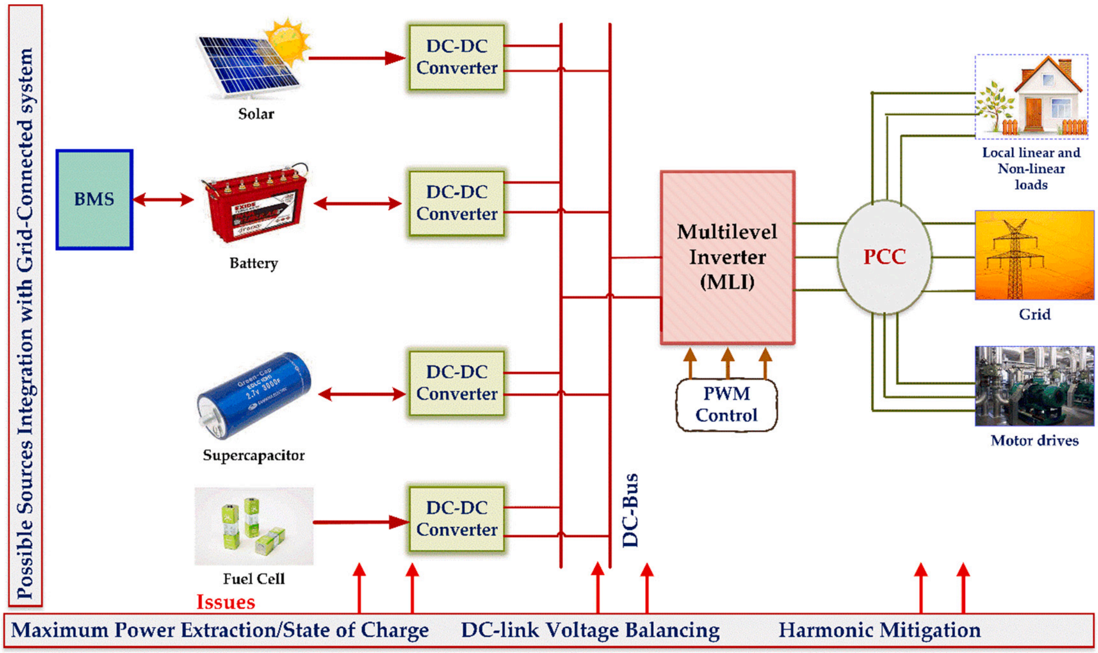

Fig. 25. BMS Grid-Integrated with different possible sources for Power Electronics converter applications.

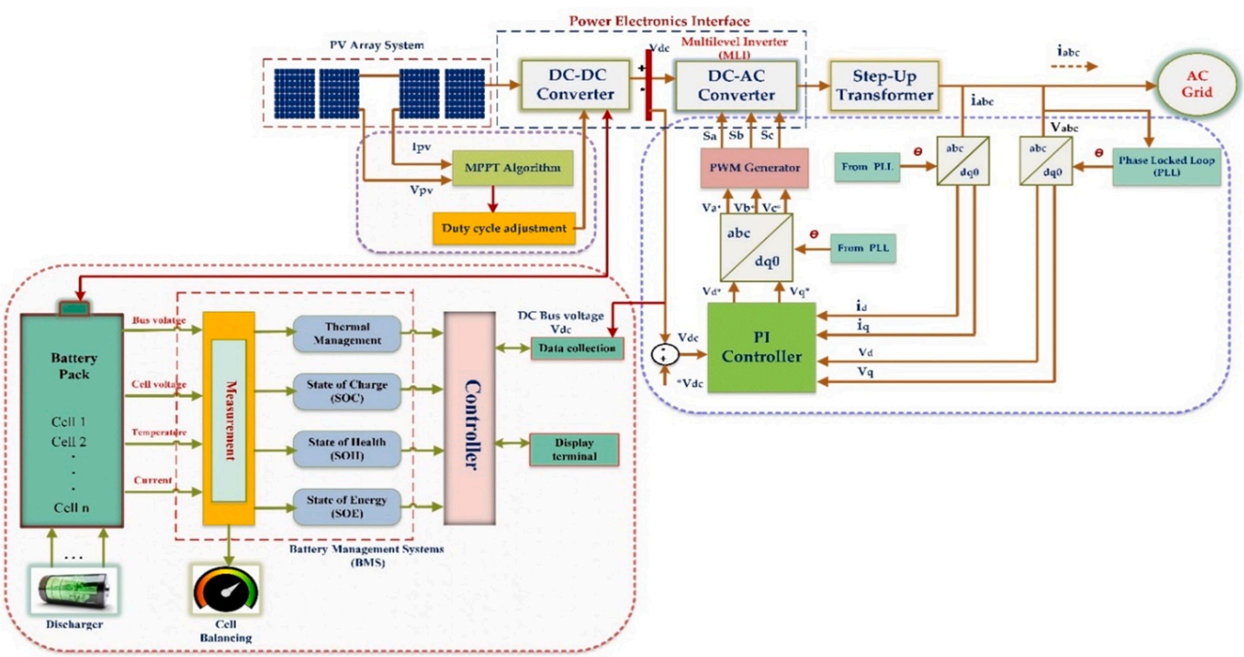

Fig. 26. PV-Battery Integration to grid.

- Reuse and Recycling: Battery reuse research is essential to saving energy, ensuring Earth's lithium-ion battery supply, and recovering power. Non-profits and governments should work together to create cost-effective, eco-friendly approaches.
- Wireless and Universal BMS: A universal open-source battery management system requires adaptive methods, manufacturer collaboration, and upgraded hardware and software to improve efficiency and lower costs.
- Battery state estimation: Advanced technologies and methodologies for EV state estimation necessitate the inclusion of three key parameters: SoC, SoH, and RUL.

6. Conclusions and future scope

This review presented a comprehensive analysis of several battery storage technologies, materials, properties, and performances. This article also provided a detailed explanation of the advanced techniques, algorithms, controllers, and optimization methodologies utilized in electric vehicles (EVs). This research work comprehensively investigated the categorization of traditional and sophisticated SoC and SoH estimation methodologies as well as the associated advantages and drawbacks. This review article acknowledged that traditional methods are simple and easy to implement. The learning algorithm (LA) improves the performance of a nonlinear dynamic modelling setup. The NLO

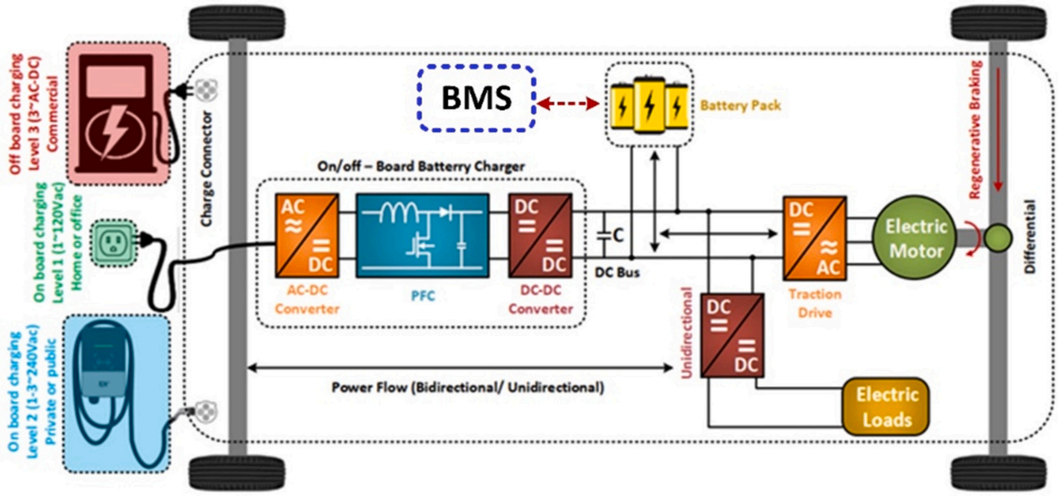

Fig. 27. BMS-EV Integration.

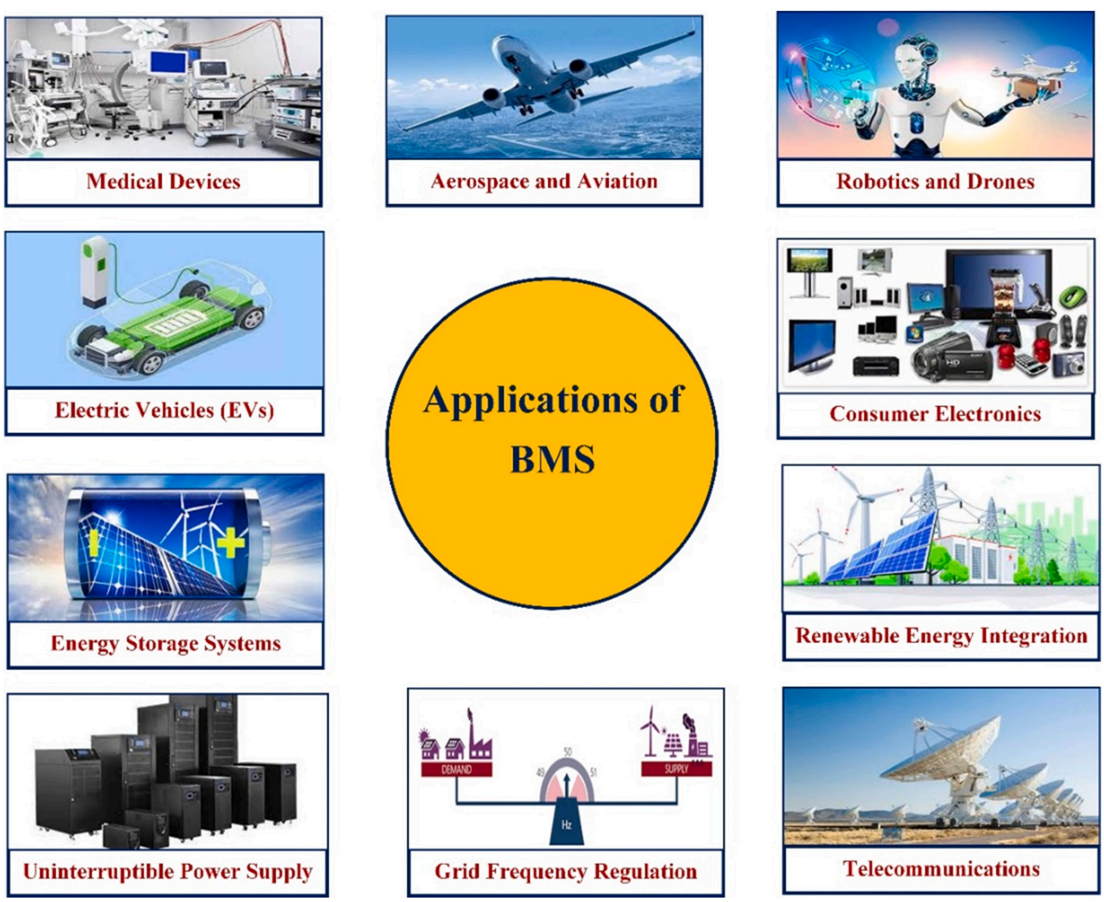

Fig. 28. Different applications of BMS.

technique is faster, cheaper to compute, more accurate, and more reliable than its predecessors. This review analysis demonstrated that BMS continues to confront several challenges despite the use of a wide range of appropriate algorithms and sophisticated approaches and models. Battery management systems (BMSs) are discussed in depth, as are their applications in EVs and renewable energy storage systems. This review covered topics ranging from voltage and current monitoring to the estimation of charge and discharge, protection, equalization of cells, thermal management, and actuation of stored battery data. This review demonstrated the difficulty of EV adoption by addressing existing problems and developing superior BMSs. This comprehensive resource offers valuable insights for engineers, researchers, and EV manufacturers and presents detailed analyses, applications, challenges, and recommendations relevant to the field.

6.1. Future scope

After surveying the literature on BMS and SoC estimation methods in

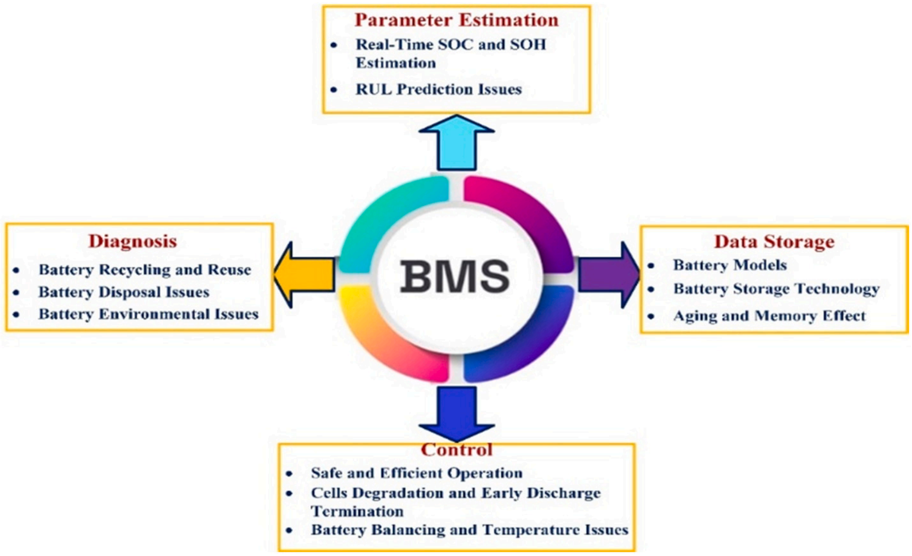

Fig. 29. An overview of BMS Challenges

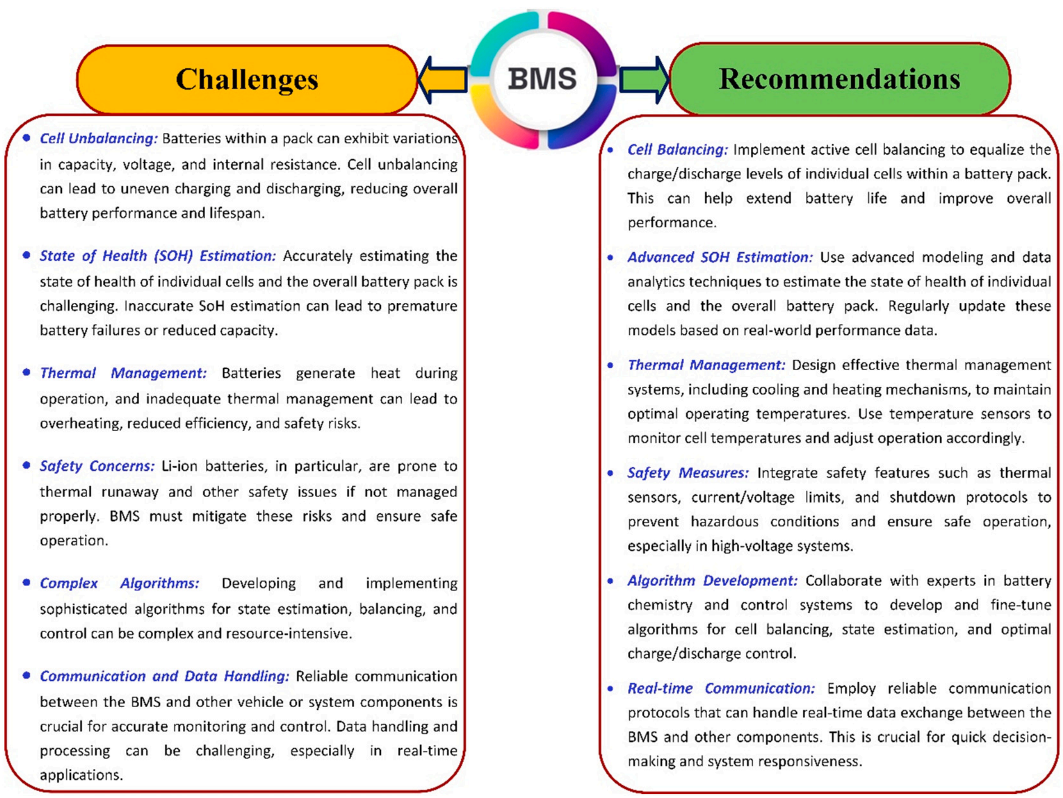

Fig. 30. Basic challenges and recommendations to BMS.

depth, this article proposes various directions for further study, as represented in Fig. 31.

There will be substantial growth in the battery and EV sectors due to further research on BMSs employing cutting-edge intelligent algorithms to enhance battery performance and longevity and guarantee EVs' safe and dependable operation. Additionally, the battery-related industry may support long-term development objectives like pollution reduction, clean energy, economic expansion, job creation, and the growth of the EV sector. Therefore, further innovations are needed to increase EV performance in terms of developing precise battery monitoring and control strategies, collaborating across borders, and fostering sustainable growth.

CRediT authorship contribution statement

Shaik Nyamathulla: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **C. Dhanamjayulu:** Investigation, Project administration, Resources, Supervision, Validation, Writing – review & editing.

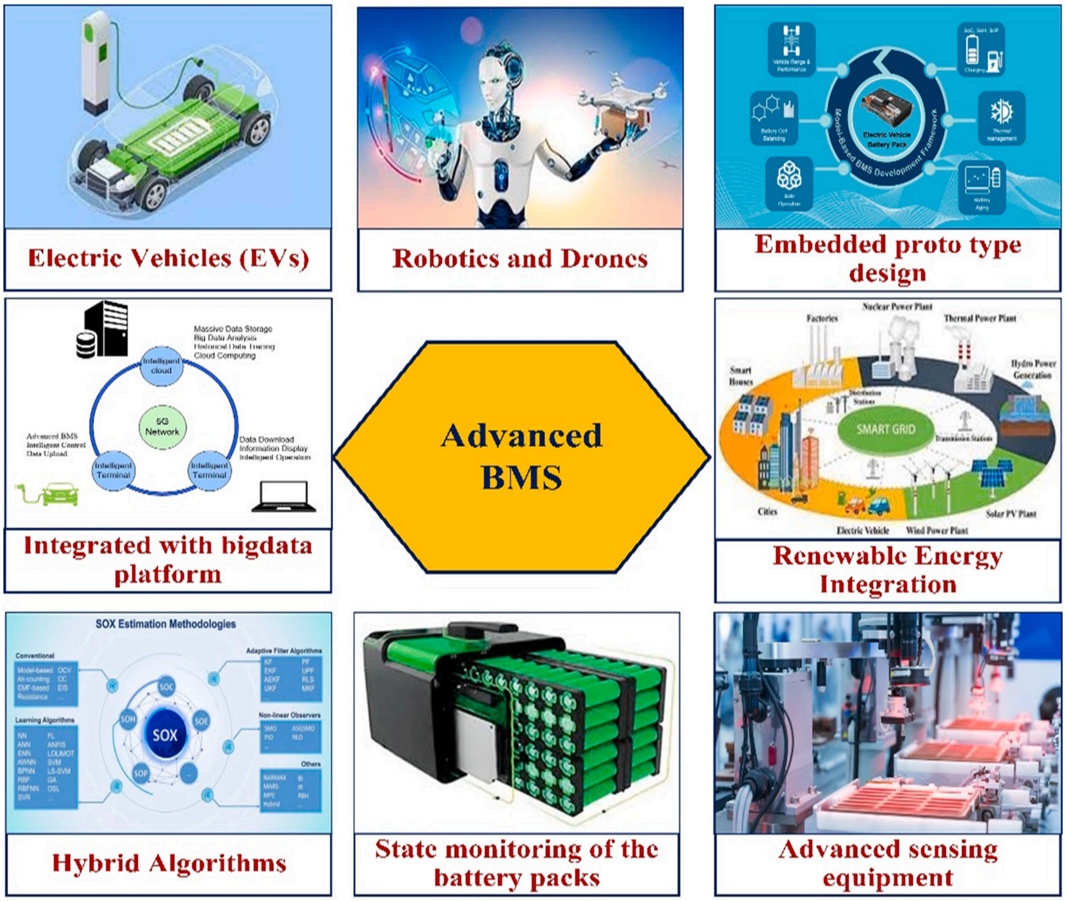

Fig. 31. Future trends in advanced BMS for EV applications.

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.

Data availability

No data was used for the research described in the article.

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