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Review

A Review on Different State of Battery Charge Estimation Techniques and Management Systems for EV Applications

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Abstract: Electric vehicles (EVs) have acquired significant popularity in recent decades due to their performance and efficiency. EVs are already largely acknowledged as the most promising solutions to global environmental challenges and CO_2 emissions. Li-ion batteries are most frequently employed in EVs due to their various benefits. An effective Battery Management System (BMS) is essential to improve the battery performance, including charging–discharging control, precise monitoring, heat management, battery safety, and protection, and also an accurate estimation of the State of Charge (SOC). The SOC is required to provide the driver with a precise indication of the remaining range. At present, different types of estimation algorithms are available, but they still have several challenges due to their performance degradation, complex electrochemical reactions, and inaccuracy. The estimating techniques, average error, advantages, and disadvantages were examined methodically and independently for this paper. The article presents advanced SOC estimating techniques, such as LSTM, GRU, and CNN-LSMT, and hybrid techniques to estimate the average error of the SOC. A detailed comparison is presented with merits and demerits, which helped the researchers in the implementation of EV applications. This research also identified several factors, challenges, and potential recommendations for an enhanced BMS and efficient estimating approaches for future sustainable EV applications.

Keywords: electric vehicles; battery management system; Li-ion batteries; algorithms; SOC estimation of battery; accuracy

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Citation: T, G.; C, D. A Review on Different State of Battery Charge Estimation Techniques and Management Systems for EV Applications. *Electronics* **2022**, *11*, 1795. https://doi.org/10.3390/electronics11111795

Academic Editors: Calin Iclodean and Reinhard Tatschl

Received: 13 April 2022
Accepted: 28 May 2022
Published: 6 June 2022

1. Introduction

Nowadays, green environments and environmental hazards are the most significant concerns of researchers [1,2] The world is moving towards severe consequences such as GHG (Green House Gas) emission and global warming caused by the wide use of petrol and diesel in vehicles' operation, which produces lots of carbon dioxide every year [3–5]. The EVs are the most suitable solution to reduce this carbon emission [6–11]. The development of EVs generates massive employment in different sectors of EVs, such as battery manufacturing, powertrain modeling, highly efficient motor designing, etc. Batteries have been widely used at small and medium scales in electricity storage technologies due to their relatively high energy density, low noise levels, and low maintenance [12–15]. Li-ion and Ni-MH batteries are generally utilized in a spread of EV applications. Li-ion plays a vital role because of more advantages such as long life, high efficiency, and energy density, as shown in Table 1 [16–19]. The accuracy of SOC varies depending upon the type of lithium-ion battery, which is heavily impacted by the positive and negative electrode materials.

Commonly used Li-ion batteries for EV applications are lithium cobalt oxide (LCO), lithium titanium oxide (LTO), lithium nickel oxide (LNO), lithium iron phosphate (LFP), lithium manganese oxide (LMO), lithium nickel cobalt aluminum oxide (NCA), and lithium nickel manganese cobalt oxide (NMC). Table 2 depicts a performance comparison of various types of Li-ion batteries [15].

Table 1. Comparison of different energy storage devices [16–19].

Storage Devices	Nominal Voltage (V)	η (%)	Energy Density (Wh/L)	Life Cycle (hrs)	Depth of Discharge (%)	Cost Estimation (USD/kWh)
Lead Acid	2.0	85	50–80	1500	50	105–475
NaNiC1	-	84	160–275	3000	100	315–488
ZBFB	1.8	70	55–65	10,000	100	525–1680
Li-ion	4.3	96	200–400	10,000	95	200–1260

Table 2. Comparison of different Li-ion batteries and their characteristics [15].

Battery Name	Nominal Voltage (V)	Specific Energy (Wh/kg)	Charge (c)	Discharge (c)	Lifespan (hrs)
LCO	3.7~3.9	150~200	0.7~1	1	500~1000
LNO	3.6~3.7	150~200	0.7~1	1	>300
LMO	3.7~4.0	100~150	0.7~1	1	300~700
NMC	3.8~4.0	150~220	0.7~1	1	1000~2000
LFP	3.2~3.3	90~130	1	1	1000~2000
NCA	3.6~3.65	200~260	0.7	1	500
LTO	2.3~2.5	70~85	1	10	3000~7000

An effective BMS can work reliably and safely. It is also essential for updating data, controlling the voltage equalizing of a battery, and sensing faults that are substantial influences for attaining a better precision of SOC. The SOC in a BMS is taken into account together with severe and significant issues, which have been investigated in current years. With a gasoline-powered automobile, the SOC of the battery organizes the fuel indicator's similar action, which specifies the quantity of remaining energy in the battery. An accurate estimation of battery states not only provides information about the current and remaining performance of the battery but also ensures the EV's reliable and safe operation. However, estimating battery SOC is one of the most difficult challenges for the successful operation of EVs. Battery SOC cannot be directly observed due to nonlinear, time-varying characteristics and electrochemical reactions [20].

Furthermore, the battery's performance is heavily influenced by temperature variation, aging, and charged–discharge cycles, making estimating an accurate SOC challenging [21]. Very little literature provides a detailed explanation of all methods for SOC estimation for EVs [22–26]. The battery-accurate SOC estimation problem has not been efficiently solved [27,28]. References [29–32] provided a detailed SOC estimation in terms of overall research progress, future development trends, and the source of SOC estimation. However, there is no systematic explanation of the SOC calculation process and algorithm selection and how to deal with uncertain environmental conditions and battery pack grouping in EVs. The literature has illustrated some standard methods for estimating SOC; however, each technique has gaps in terms of accuracy and data availability. Furthermore, complex calculations and high computation costs are two concerns that make the estimation process difficult.

As a result, academics, researchers, and scientists have conducted extensive research to improve the accuracy of battery SOC. Nonetheless, the issues with estimating an accurate SOC have not been resolved. Furthermore, the challenges in estimating the SOC have not been identified. Figure 1 shows the number of research articles on Li-ion battery SOC estimation that have been published, which describes the growing interest in Li-ion battery SOC estimations in recent years. These published research articles were discovered using the Web of Science database and other journals also. From 2006 to 2022, the search criterion was "state of charge", followed by "Li-ion battery". Table 3 summarizes the recently reported studies covered and also presents the review articles' covered aspects.

Figure 1. The number of research articles on Li-ion battery SOC estimation per year.

Table 3. Summary of recently reported studies covered and review articles covered.

Concentrated Parameters	Recently Reported Studies Covered			Present Review Article Covered
	[10]	[11]	[12]	
Conventional Algorithms	√	√	√	√
Adaptive Filter	√	√	√	√
Learning Algorithms	√	√	√	√
Advanced Techniques	X	x	√	√
Hybrid	√	x	√	√
Advantages	X	√	x	√
Disadvantages	X	√	x	√
Applications	X	x	√	√
Average Error	X	x	x	√
Factors, Challenges, and Recommendations	X	√	x	√
Future Scope	X	√	x	√

Note: √ = yes and x = no.

As a result, this research paper fills the gap by investigating various existing methodologies and addressing the key issues and challenges associated with SOC estimation. This study will benefit automobile manufacturers and engineers by determining the best method and identifying the challenges.

The main contributions of the paper are summarized below.

- This review thoroughly examined the classification of conventional and advanced SOC estimation techniques.
- The estimation techniques were reviewed, focusing on the estimation algorithm, estimation error, advantages, and disadvantages.
- The various challenges, issues, and recommendations for monitoring SOC estimation were thoroughly discussed.
- Finally, the review provides valuable recommendations for developing an advanced BMS and efficient estimation methods for future sustainable EV applications.

The remaining paper is divided into six sections. Section 2 describes the framework of BMS. Section 3 describes the SOC estimation algorithms for estimating a battery SOC.

Section 4 describes the comparison of different SOC estimation methods. Section 5 describes the factors, challenges, and recommendations for a BMS. Finally, Section 6 depicts the concluding remarks.

2. Framework of BMS

Currently, a BMS is commonly employed by several vehicle companies, universities, and colleges. BMS goods have been advanced by several corporations such as EV Power Australia, the British REAP organization, American Edition Company, Beijing Significant Power Technology, and Harbin Guantuo Power Equipment Company [30]. The application of a BMS in EVs remains at the initial point. The base is that the quantity of batteries is 100 times above that of transportable devices in EVs [33–36]. Additionally, EVs are planned to supply high currents, voltage, and power. This process makes a BMS extra tricky compared to portable electronics.

The general role of a BMS is shown in Figure 2 [37], which shows the general function of a BMS, which consists of various kinds of actuators, sensors, signal lines, and controllers. The sample circuit measures temperature, voltage, and current, affording the gating sign achieved from the controller circuit. The vital work of the controller circuit is to estimate the SOC, state of health (SOH), state of energy (SOE), and state of power (SOP) of batteries over progressive algorithms and analog signals. The battery measurements of voltage, temperature, and currents are changed. After that, the data will be communicated to the vehicular controller and supply significant choice issues for vehicular and power distribution [38–41]. The BMS analyzes the EV power distribution and energy storage faults. Many researchers have proposed battery models in various ways. From [42], Figure 3 shows the BMS section divided into software and hardware assemblies.

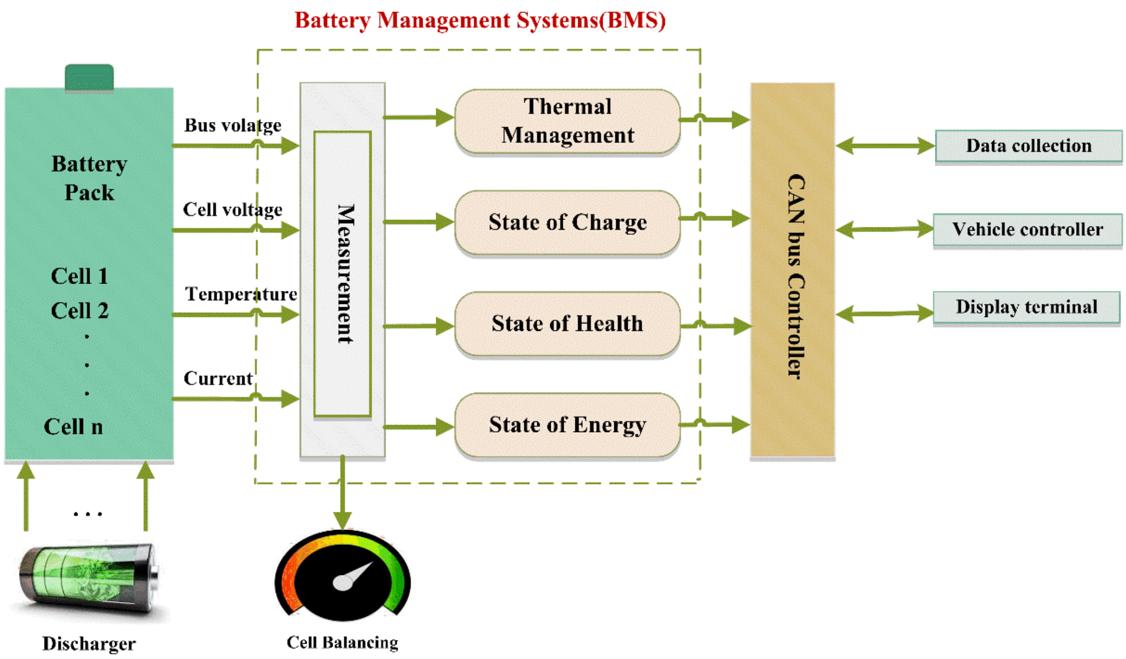

Figure 2. The general role of a BMS [37].

2.1. BMS Hardware

BMS uses various sensor frameworks to screen and measure battery parameters such as current, temperature, and voltage. Some researchers propose EIS (electrochemical impedance spectroscopy) to screen battery cell impedance [43]. High-cost devices and space limits make high-accuracy information outside the lab difficult to obtain. To stop overheating, charging, and discharging, a protection system must be developed. Constant voltage/current is used to charge batteries, and a galvanostat and potentiostat may be needed. Balance cells may also need a variable rheostat. Balancing cells is a key strategy for improving battery pack stability and estimating battery life. Temperature affects cell reliability, performance, and imbalance. Thus, some authors [44] have acknowledged that reducing temperature differences between cells is important and should be observed and worked on. A BMS unit works independently after data/information transfer. A controlled transceiver is required to send data inside the BMS. With wireless telecommunication and smart batteries, the charger and battery can share a wealth of information [45].

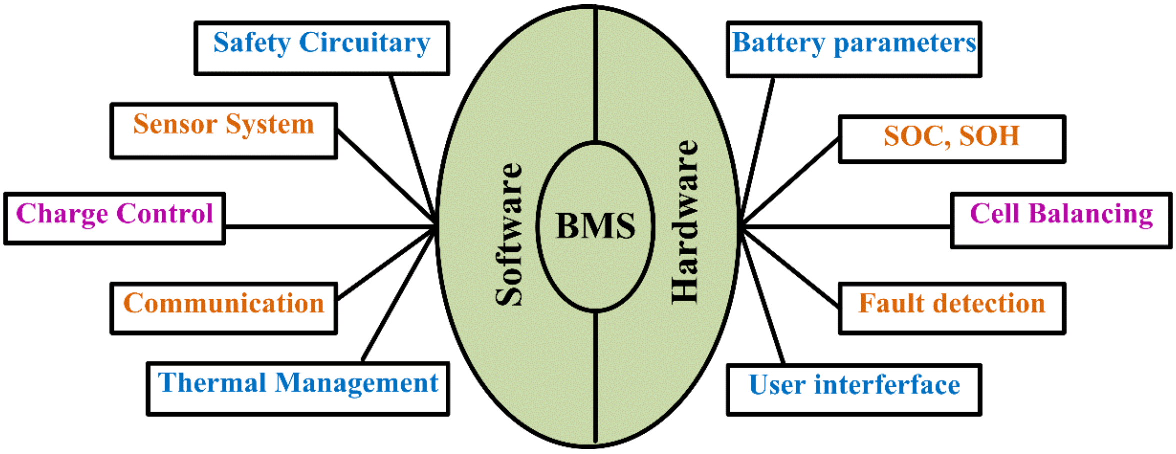

Figure 3. The basic outline of a BMS in an EV.

2.2. BMS Software

BMS software is the arrangement's midpoint. It controls sensor data and hardware operations to create choices and state approximations. BMS software must include a sample rate, switch control checking in the cell balancing controller, a sensor scheme, and a uniform active security circuit strategy. Online processing and research are required to inform and regulate battery functions. Robust automated information analysis and reliability may be key because the study handles state assessment and fault finding. This information will be presented to the operator in an easy-to-use interface. Below are BMS-specific roles. Total cell voltage, current, separate cell voltage measurement, temperature, impedance, and smoke detection are battery parameters.

Battery state estimation includes SOH and SOC, which group working situations supported by state–space representations, NN (neural networks), symbolic/fuzzy logic, etc. [46]. Cell balancing without over-discharging/charging maximizes battery performance. It aligns with SOC cell stages. The controller can control charging based on each cell's SOC. Thus, a precise estimation of the SOC of each cell is required to improve cell balancing. Online processing will expose sensitive issues. Data analysis is needed to determine battery faults and out-of-tolerance conditions. Before potential problems, important information will be noted. The BMS interface must display vital data. On the control panel, the battery SOC shows the range. Additionally, irregular, disturbing, and extra ideas are wanted to inform the operators of the battery estimate and calculation [47–49].

Figure 4 shows the BMS block diagram. The working detail is broken down. The battery's measurement block converts current, temperature, and voltage into digital signals at each point.

These constraints are used to evaluate the battery's SOH and SOC. A capability estimation block is used to control the max charging/discharging current. The cell balance block uses the capability estimation results to limit over-discharge/charge irregularities. Ground fault-finding improves system safety. The thermal management lump monitors the temperature to ensure battery safety. An input- and the output-controlled transceiver is used. To receive and transmit massive amounts of data, a high-speed, controlled transceiver is required.

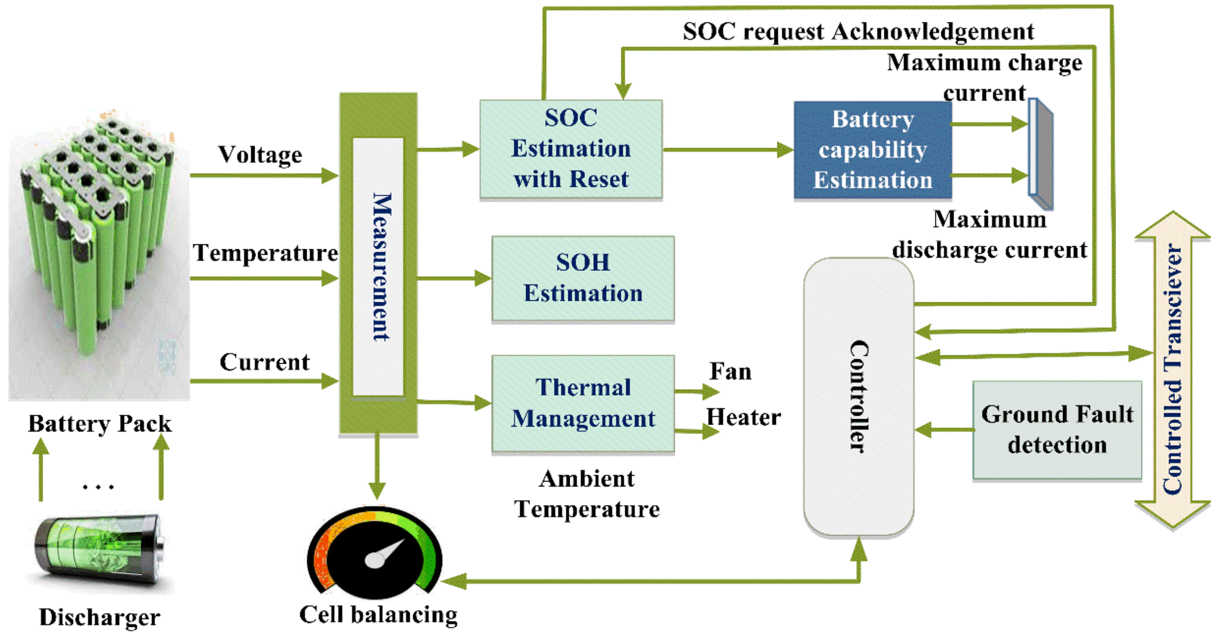

Figure 4. Block diagram of the BMS.

The various currently promoted BMS separately play out the elemental capacities in an unpredicted mode. Table 4 shows the comparative analyses of different BMS products.

Table 4. Comparative analyses among various BMS products.

Parameters	Maxim DS2726 [50]	TI BQ78PL114 [51]	OZ890 [52]
Cell constraints measured	Voltage as well as current	Voltage, temperature, impedance, and current	Current and voltage
Pack constraints measured	Not available	Not available	temperature
Safety protection	• Short circuit current • Over current • Over voltage	• Three power field-effect transistors • One secondary safety output fuse	• Short circuit current • Over current
Estimation of SOH/SOC	None	SOC	SOC
Data logging	No	On PC-based GUI only	EEPROM
Dissipative equalization of cell	Charge shifting	Not available	External resistance stable
Communication	Unknown	Power LAN, SMBus	CAN
Non-dissipative equalization of cell	Not available	Inductive charge shuttle	Not available

Disadvantages of the other referenced BMSs incorporate the following:

- Restricted information working performances: The knowledge of working function plays a crucial part in database formation and stores the driving design. It can support developing as well as updating the SOC model.
- Absence of SOH and SOC estimations: SOH and SOC are utilized to define the present health standing and, therefore, the outstanding practice of the battery that may ensure the reliable and planned support operation of the battery substitution.

Apprehensions about today's BMS vehicles

Because of the growing hydrocarbon charges and ongoing revolutions in the technology of batteries, HEVs and EVs were introduced in the early 1990s and typically developed in the 2000s. While the development of BMSs has been insufficient and slow in such cases, Li-ion batteries have been widely employed in the past decade for EVs because of their favorable properties such as high efficiency, life cycle, and energy density. The recent developments in BMSs for Li-ion batteries in EVs are discussed in [53].

Figure 5 shows the overview of a few works of literature that studied different SOC estimation methods.

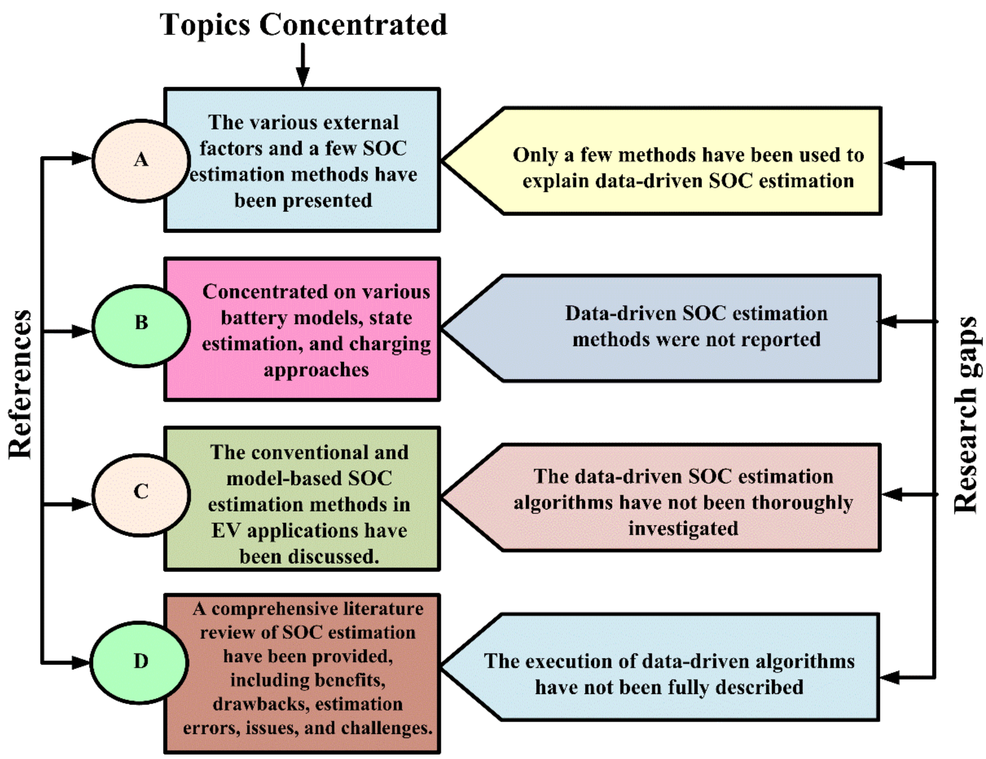

Figure 5. Overview of a few literature studies on different SOC estimation methods. "A" is referred to as [23], "B" is referred to as [34], "C" is referred to as [37] and "D" is referred to as [49].

3. State of Charge (SOC)

There has been a significant worry for all energy-storing devices for SOC estimation. SOC estimation gives us data and estimates the reliability of batteries with high precision. Since the 1980s, numerous methods have been introduced to estimate SOC. Although SOC estimation is a crucial challenge in EV batteries, it cannot be measured directly. It requires a specific algorithm for describing the battery's remaining capacity. The general architecture of the SOC system is shown in Figure 6. For SOC estimation, the current integration is the most traditional technique. The ratio of the available capacity to the battery's total capacity is shown in Equation (1).

$$\mathrm{SOC} = 1 - \frac{\int \mathrm{i}\,\mathrm{dt}}{\mathrm{c_m}} \tag{1}$$

where i indicates the current of the battery and c_m indicates the total capacity.

The battery's total capacity decreases gradually due to its internal reaction and external load, leading to its nonlinear and non-stationary degradation characteristics. The categorization of SOC estimation methods is shown in Figure 7. Different kinds of literature have been presented in various manners. Every technique has its unique advantages along with disadvantages. In this review, SOC estimation methods were divided into five types: conventional, adaptive filter, learning algorithms, nonlinear observers, and others. Again, each process was classified into sub-methods [54], described as follows.

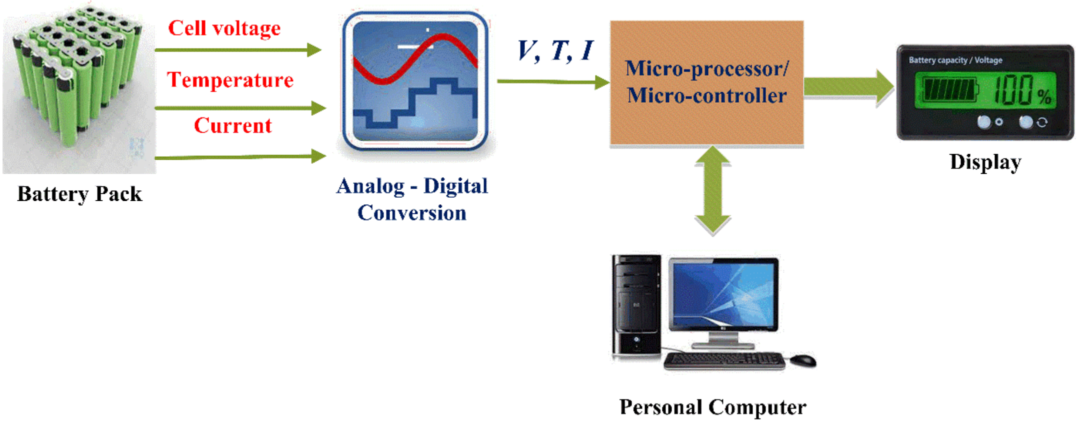

Figure 6. The general architecture of the SOC system.

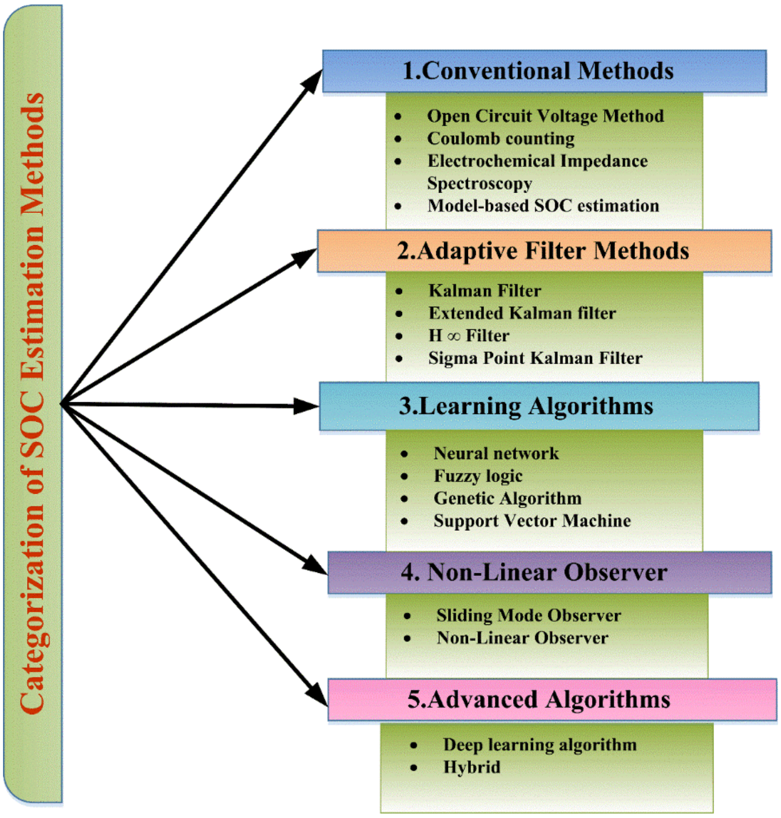

Figure 7. Categorization of methods for estimation of SOC.

3.1. Conventional Methods

3.1.1. Open-Circuit Voltage Method

The open-circuit voltage method has high accuracy, is easy to implement, and is a straightforward method, but its main disadvantage is that it takes more time to reach an equilibrium position. Therefore, online estimation of SOC is not an appropriate method. Therefore, this method is applicable only for low power consumption applications. Moreover, some observations are required to measure the discharge and charge voltage. For example, at high OCV, the battery is charged, and it is discharged at small OCV because of the hysteresis characteristics in batteries [55–58], as shown in Figure 8.

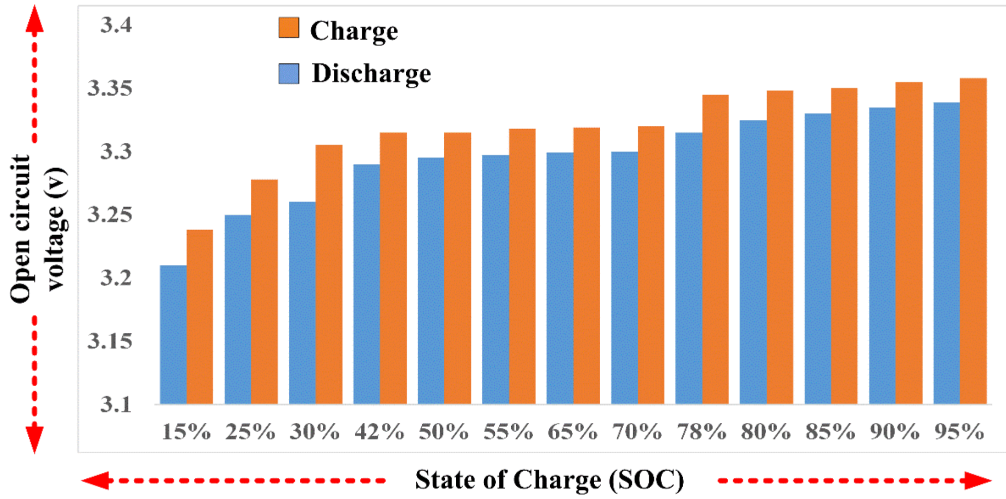

Figure 8. OCV vs. SOC was tested at 25 °C.

3.1.2. Coulomb Counting (CC) Method

The CC technique is the easiest one to estimate the SOC of the battery, and it can be implemented very quickly with low power calculation. The charging/discharging of the battery depends upon the integration of the current concerning time. It is expressed in Equation (2).

$$\mathrm{SOC} = 1 - \frac{\int \mathrm{i}.\eta \mathrm{dt}}{\mathrm{c_m}} \tag{2}$$

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

However, due to its uncertain disturbances, noise, temperature, and current, its results could be inaccurate. Furthermore, more difficulties exist in determining the SOC initial values, which might cause a cumulative error [59]. Additionally, to attain the maximum capacity, this method needs periodic capacity and complete cell discharge, which shortens the battery's lifespan [60].

3.1.3. Electrochemical Impedance Spectroscopy (EIS)

To implement the EIS, an appropriate electrochemical model is needed. Then, it evaluates the battery impedance by using capacitances and inductances over an extensive range of frequencies [61–63] that are recognized in an equivalent circuit model that includes two capacitive arcs and an inductive arc operated at low and high frequencies. Under various SOC values, a nonlinear LSF technique is utilized for computing the model impedances. If the system is not functioning in stable conditions, the EIS outcomes are difficult to reproduce. It has the advantages of low cost, operating online, and attaining good accuracy. From the actual values, the effect of battery temperature and the aging difference could vary the estimated outcomes, resulting in a deficiency of precision.

3.1.4. Model-Based SOC Estimation

Since the open-circuit voltage scheme cannot execute online, it needs appropriate rest time to monitor the SOC, which means it cannot be applied while the vehicle moves. Therefore, for online SOC, battery model development is essential. The most used battery models include the electrochemical [64–68] and equivalent circuit models [69,70]. An electrochemical model is used to study the battery's performance, which relates to the internal materials and considers the chemical thermodynamics and the electrodynamics effect. It can be expressed as:

$$\mathrm{V} = \mathrm{VOC} - \mathrm{VR} - \mathrm{VP} \tag{3}$$

where V denotes the terminal voltage, VOC means open-circuit voltage, VR indicates the potential difference across resistance, and VP represents the electric potential.

The RC networks have been used for the equivalent circuit model by considering dynamic and polarization characteristics. Using RLS (recursive least square) algorithm, the online OCV is executed and, for various RC networks, the outcome of the RLS algorithm is compared with experimental results. A model-based estimation is used online, and it has high precision. The drawback of this method for the specific battery is that a complete explanation of the electrochemical reactions is required, and it highly depends on the model's accuracy. Table 5 shows the analysis of the different conventional SOC estimation methods.

Table 5. Analysis of the different conventional SOC estimation methods.

Technique	Pros	Cons
OCV [55–58]	• Very simple method • High accuracy • Cost-effective • Easily implemented	• Not suitable for online • Reaching an equilibrium state requires a long time.
CC [59,60]	• Low power consumption • Easily implemented • Simple method	• Inaccurate outcomes • Difficulties in defining the SOC initial values
EIS [61–63]	• Operates online • Low cost • If the impedance value is stabilized, it attains good accuracy.	• The effect of battery temperature and the aging difference could vary the estimated outcomes.
Model-based [64–71]	• Operates online • High precision	• It highly depends on the accuracy of the model.

3.2. Adaptive Filter (AF) Algorithm

3.2.1. Kalman Filter (KF) Algorithm

KF is a well-designed and intelligent tool commonly used in automobiles, navigator tracking, and aerospace applications. The striking feature of the Kalman filter is it has a self-correcting nature. A Kalman filter linear model contains a state equation, which predicts the current state, and a measurement equation, which updates the current state [72], which are expressed as follows:

$$\text{State equation}\ : x_{m+1} = A_m x_m + B_m u_m + f_m \tag{4}$$

$$\text{Measurement equation}\ :\ y_m = C_m x_m + D_m u_m + z_m \tag{5}$$

where A, B, C, and D represent the covariance matrices, x is the system state, f represents the process noise, u represents the control input, y represents the measurement input, and z represents measurement noise. Ting et al. [73] developed an RC battery model, which is used for modeling a Kalman filter. To explain the dynamic battery characteristics, the RC model mathematical equations remain converted into a state–space model to describe the dynamic battery characteristics. The outcome indicates that the estimated RMS error of the SOC using the Kalman filter is minor compared to the measured error. The authors of [74] also used the same method on the electrical equivalent model of a Li-ion battery with the help of the dSPACE real-time card and Matlab/Simulink software. The estimated SOC error was less than 5%. Yatsui [75] combined the results of a Kalman filter with two methods, the OCV, and the CC methods, to ameliorate the non-ideal factors. After executing the Kalman filter, the SOC precision was improved, with an error of ±1.76%. However, the Kalman filter cannot be used directly. It needs a complex calculation and is profoundly dependable with great strength to various working conditions and battery aging. On the other hand, MI-UKF is impervious to unanticipated operational requirements and can improve UKF accuracy by more than 1% [76–78].

3.2.2. Extended Kalman Filter (EKF)

EKF has been applied to work the framework in nonlinear applications. It uses first-order Taylor series expansion and partial derivatives to linearize the battery model. At every instant of time, the state-space model is linearized and equates the predicted value of the battery with the measured voltage to precisely approximate the constraints for the SOC. If the scheme is exceptionally nonlinear, a linearization blunder might still happen. In any case, the linearization blunder could happen when the framework is profoundly nonlinear since the first-order Taylor series experiences an absence of precision in an exceptionally nonlinear state. Finally, the improved dual AEKF algorithm was applied, and the SOH and SOC estimation errors were within 1% [79–86].

3.2.3. H ∞ Filter

This is a very simple method in the designed model, and it does not have to know any details and measurement characteristics of noise. It considers only the time-varying parameters of the battery to carry out the system under the specific condition, which has robust strength. The precision of the model is deviated due to hysteresis, aging, and temperature effects [87–90]. In [91], this method was introduced to estimate battery SOC. The time-varying parameters are current, SOH, and temperature for second-order RC filter circuit design. An HPPC (hybrid pulse power characterization) experiment was performed to extract the voltage, resistance, and present characteristics. The projected model was tested using six Urban Dynamometer Driving Schedule tests and attained a good accuracy. In [92], the adaptive H∞ filter was introduced to estimate SOC. In this method, a polynomial function is helpful to evaluate the system functions, and the performance is examined and then compared with the adaptive extended Kalman filter (AEKF). The AHF performed better in accuracy and computational cost than other methods.

3.2.4. Sigma Point Kalman Filter

This is another nonlinear technique for the calculation of states, and it achieves more precise outcomes than the extended Kalman filter. The sigma-point Kalman filter (SPKF) algorithm is subjected to a numerical approximation. The algorithm selects sets of sigma points that are identical to the mean and covariance values of the developed model. The SPKF has the advantage of having a similar calculation. Furthermore, without taking Jacobian matrices into account, the complexity of the EKF is reduced [93,94]. The SPKF can demonstrate more accuracy while using less memory and performing fewer computational calculations. However, the estimated SOC was compared with the SPKF, Luenberger observer, and EKF algorithms, and the drawbacks are heavy and complicated calculations [95,96].

3.3. Learning Algorithms

3.3.1. Neural Network (NN) Algorithm

An NN is a self-learning algorithm and also an intelligent tool. It uses trained data to estimate the state of the charge without knowing the initial data of the SOC. It consists of input, hidden, and output layers to form an NN structure, as shown in Figure 9 [97]. Building the NN structure takes discharge current, temperature, and voltage as inputs and the SOC as the output. The benefit of an NN is that it has a talent for being employed in nonlinear battery circumstances. The drawbacks are that training requires a large amount of data and a big memory to store the information [98,99]. Table 6 shows the analysis of the different adaptive filter SOC estimation methods.

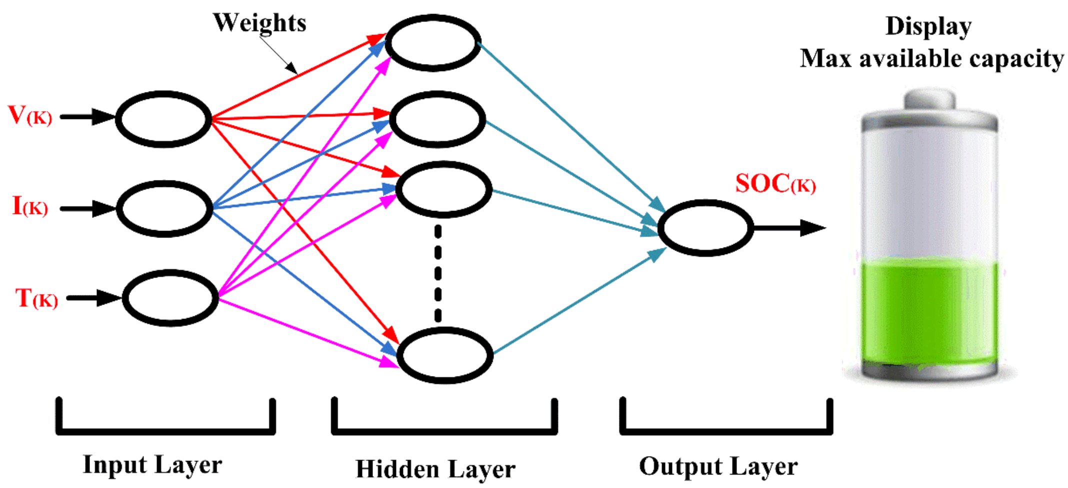

Figure 9. The comprehensive structure of neural network for SOC estimation [97].

Table 6. Analysis of the different adaptive filter SOC estimation methods.

Technique	Pros	Cons
Kalman Filter [72–78]	• Self-correcting nature • Intelligent tool • Accurately estimates	• It cannot be used directly for SOC estimation. • Needs complex calculations.
Extended Kalman Filter [79–86]	• Predicts nonlinear dynamic errors • Improves accuracy	• Limited robustness • Linearization error occurs
H ∞ Filter [87–92]	• Computational cost • Satisfactory performance in precision	• Deviates the precision values due to aging and temperature
Sigma-Point Kalman Filter [93–96]	• Robustness • Improvement in precision	• Heavy calculations • Complicated

3.3.2. Fuzzy Logic Algorithm

FL is the most influential algorithm for extending nonlinear, complex prototypes by using the training data. The employment of fuzzy logic includes rule-based inputs and outputs, a reasoning membership function, and defuzzification. However, estimating a nonlinear model is a powerful function. It needs an intricate calculation, dispensation unit, and large memory storage. Salkind et al. [46] applied FL for the estimation of SOC by using CC method data. This method uses three inputs at different frequencies, including impedances and SOC. It predicts the SOC with a max ±5% of error. The advanced ANFIS is most effective for estimating the SOC in Li-ion batteries; it was studied and applied in [100–105].

3.3.3. Genetic Algorithm (GA)

A genetic algorithm is mainly used for finding the optimum parameter. The primary function of a GA is to alter the constraint's trendy active method to improve the efficacy of the arrangement. It has been applied in mathematics, physics, and engineering for identifying nonlinear optimal parameters. Zheng et al. [106] used a genetic algorithm to assess four LiFePO4 battery cells, which were allied on a sequence. In addition, the outcome of this method was under 1% of the estimated SOC error. Xu et al. [107] applied a genetic algorithm for finding the parameters. By using various driving cycles, the method was validated; the outcome of this method had better accuracy, with below 1% error.

3.3.4. Support Vector Machine Algorithm

The SVM algorithm practices regression algorithm and works on kernel function, which is intended for converting the nonlinear type in an inferior measurement into a linear variety in an extreme measurement. In [108], the SVM technique was used for SOC estimation. The independent variables current, temperature, and voltage were obtained to excerpt the model constraints even though the batteries were discharging/charging. This method was authenticated, and an approved extreme SOC precision of 0.97 estimated quantity was determined. The benefits of SVM are performing in high-dimension models and nonlinear forms. By using training data, the SOC is estimated quickly and accurately. The drawback of this method is that trial and process errors are needed and require a long time [109]. Table 7 shows the analysis of the different learning SOC estimation algorithms.

Table 7. Analysis of the different learning SOC estimation algorithms.

Technique	Pros	Cons
Neural Network [97,98]	• Accomplished work of batteries in nonlinear circumstances	• For storing the trained information, it needs a bulky memory unit.
Fuzzy Logic [100–105]	• Performs well • It is very effective.	• Complex computation • Large memory storage is needed. • Costly
Genetic Algorithm [106,107]	• High accuracy • Robust	• Heavy computation • Good tuning parameters are needed to obtain effective outcomes.
Support Vector Machine [108,109]	• Performs outstandingly in nonlinear models • Performs well in high-dimension models	• Heavy computation • Requires trial along with process error to alter the parameters.

3.4. Nonlinear Observer (NLO)

3.4.1. Sliding Mode Observer (SMO)

SMO is an improved training controller for ensuring robustness and constancy of the system alongside model uncertainties as well as ecological disturbances. SMO is established by using the state equation in the next stage, which is decayed to the observer questions. In [110], a developed SMO was introduced to balance the nonlinear battery dynamic characteristics by using an RC circuit. This method can provide a controller for the conjunction period at the sophisticated discharge/charge value rate. The UDDS is situated to justify the method, and outcome details showed under 3% of the SOC error. In [111], the adaptive gain sliding mode observer (AGSMO) algorithm estimated the battery SOC on a combined equivalent circuit model. To extract the constraints, a battery pulse was used, and, by using the circuit model as well as terminal voltage, the state equations were developed. Experiments were performed to assess the recommended archetype, and outcomes proved that the model has an advantage in regulating the toughness derived when affecting all sound-on wrinkles.

3.4.2. Nonlinear Observer (NLO)

Several observers have been applied, including both a linear observer [112–114] as well as a nonlinear [115] observer, to estimate the SOC. In [116], the NLO-dependent SOC estimation was introduced via a first-order corresponding RC circuit. This model was performed by using a driving cycle as well as a discharge test, and the outcomes were improved compared to extended KF and SMO in standings of speed and precision as well as cost. They are still discovering an appropriate gain matrix to decrease the error. Table 8 shows the analysis of the different nonlinear observer SOC estimation algorithms.

Table 8. Analysis of the different nonlinear observer SOC estimation algorithms.

Technique	Pros	Cons
Sliding Mode Observer [110,111]	• Robustness • It enhances sstability.	• Difficult to alter switching gain
Nonlinear Observer [112–116]	• Improved accuracy • Improved convergence speed • Robustness	• To reduce the error, it is problematic to find the appropriate gain matrix.

3.5. Advanced SOC Estimation Techniques

3.5.1. Deep Learning Algorithm (DLA)

Deep learning (DL) algorithms have contributed to a better understanding of SOC estimation. Among the most notable are the long short-term memory (LSTM) network, deep neural networks (DNN), gated recurrent unit (GRU), and convolutional neural networks (CNN). The LSTM network [117] provides a strong SOC estimation performance because of its strong self-learning ability. The SOC of a battery is estimated using an LSTM network based on measured voltage, current, and temperature. Furthermore, DNN [118] exploits the battery's dependent behaviors on ambient temperatures and encodes them into DNN weights, resulting in a competitive estimation performance over a wide range of temperatures. GRU [119] is used to estimate the battery SOC at different temperatures and to evaluate the performance of two common lithium-ion batteries. Unlike a traditional feedforward neural network, the RNN employs hidden nodes to store information about previous inputs, allowing the SOC estimation to incorporate this information. LSTM and GRU are RNN variants that extend the original RNN's ability for long-term dependency. Another successful architecture in deep learning research is CNN. While the LSTM defines long-term dependency and is capable of handling time series data, the CNN employs convolutional behavior in a certain way to extract interconnections among input data. To model the complex battery dynamics, a combined CNN–LSTM network was proposed [120]. The CNN was specifically used to obtain advanced spatial features from the original data, while the LSTM was used to model relationships between the current SOC and past and present inputs. Both CNN and LSTM networks capture both spatial and temporal features of battery data. Table 9 shows the analysis of the different deep learning SOC estimation algorithms.

Table 9. Analysis of the different deep learning SOC estimation algorithms.

Technique	Pros	Cons
LSTM [117]	• Has a track record of success in the face of long-term dependencies. • During the online stage, computation is less intensive.	• Complex training execution requires the use of an expensive device to enhance training.
GRU [118]	• Long-term sequential dependencies are captured. • LSTM gating mechanism issues are addressed.	• It necessitates a large amount of training data as well as a large storage device.
CNN–LSMT [120]	• Improved tracking precision • It has a strong nonlinear fitting ability.	• The structure is complex, with a hidden layer and a visible layer.

3.5.2. Hybrid Methodologies

The mixing of two or more algorithms is known as a hybrid, which improves the accuracy and efficiency of the battery. It requires a large memory unit because of its complex mathematical computations. However, a hybrid methodology accomplishes consistent as well as operative outcomes and then, likewise, decreases the BMS price. In [121], the multi-state and extended Kalman filter methods were proposed, using the equivalent circuit model. The prototype is situated to move for a discrete state space that can provide supplementary data as opposed to linearized data by utilizing a Jacobian matrix. The simulation outcomes provided better accuracy, with a 2.7% average error. In [122], the CC, KF, and OCV methods were reviewed for SOC estimation. First, by using the OCV and CC methods, the SOC was estimated, which decreased the estimated error of CC. Then, the Kalman filter was utilized to enhance the precision value of the SOC.

In [123], a hybrid methodology was introduced; it included the CC and EKF methods for a time-changing dynamic estimation. The first open-circuit voltage method was applied for the SOC. The EKF was applied for the corrected SOC values, and this process was continued until the battery was fully discharged. The accuracy of the model was under 6.5%.

In [124], SOC was estimated based on AUKF utilizing RBF, and it was utilized to alter the particulars of the system. The AUKF stayed employed for evaluating the SOC. Then, united, both methods were equated by adaptive KF. The results of the AUKF were superior to the adaptive KF from the perspective of error. In [125], the H ∞ filter and discrete-time KF were applied to the nonlinear model of the Li-ion battery. The outcomes of this method were compared with adaptive Luenberger as well as SMO-based estimation models, and the accuracy of this method was improved, with <1% of error. In [126], the SOC of the lithium-ion cell was adaptively estimated using the multiple model adaptive estimation (MMAE) technique using a modified enhanced self-correcting (ESC) cell model. When compared to the EKF result, the SOC estimation converged more quickly. In [127], this study designed an enhanced Kalman filter (KF)-based adaptive observer by approximating the electrochemical model. The estimator's predictions were compared against the experimental data in simulations. The simulation outcomes were more precise and efficient than those of the KF. The accuracy of this method was improved, with <2% of error.

In [128], EKF paired with an adaptive neuro-fuzzy inference system (ANFIS) reduced error and improved accuracy over EKF alone. The root mean square error (RMSE) compared the EKF with the EKF-assisted ANFIS. In this way, the hybrid technology improved precision and accuracy while reducing expenses. In [129], for Li-ion batteries with uncertain noise circumstances, a new noise adaptive moving horizon estimating (NAMHE) approach was suggested. The simulation outcomes showed that the suggested technique reduced the SOC estimate error compared to the classic moving horizon estimating (MHE) method. The RMSE of the suggested technique and MHE were 0.7543% and 1.3026%, respectively. In [130], different OCV test methodologies impacted the correlation of the OCV and SOC; an effective OCV–SOC relationship may increase SOC online convergence speed and accuracy. The AEKF SOC estimate technique was more accurate and reliable than EKF during driving cycles, with a 0.5481% mean error of the proposed system. Hybrid methods give accurate outcomes and are cost effective. Table 10 shows the analysis of hybrid SOC estimation algorithms.

Table 10. Analysis of hybrid SOC estimation algorithms.

Technique	Pros	Cons
CC and KF [122]	• CC has low power consumption. • KF has a self-correcting nature and is an intelligent tool.	• Inaccurate outcomes by CC and KF need complex calculations.
EKF and multi-state [121]	• Predicts nonlinear dynamic errors. • Improves accuracy.	• Limited robustness • Linearization error occurs.
H ∞ filter and discrete-time KF [125]	• High accuracy • Robustness • It enhances the stability.	• Deviates the precision values due to aging and temperature.

Table 10. *Cont.*

Technique	Pros	Cons
NAMHE [129]	• Worked in conditions with unknown noise levels. • More stability and precision	• The program's computational complexity and memory use will rise as it runs.

4. Comparisons

A comparison of different SOC methods is shown in Table 11. The table consists of different types: conventional methods, adaptive filter, learning algorithms, nonlinear observers, and hybrid. Again, each type can be subdivided into different methods and algorithms. First, the conventional methodologies [131–134] use a battery's physical properties involving resistance, impedance, voltage, and discharge current. The methods are very simple, very cost effective, and have high accuracy. Compared to the remaining methods, the average error is between $\leq\pm4$ to $\leq\pm5\%$. It is moderate, as shown in Figure 10. Second, the adaptive filter methodologies [75,91,135,136] use different algorithms and models to estimate the SOC; these methods have a self-correcting nature, are intelligent tools, and their estimates are but need complex calculations. The average accuracy error is $\leq\pm1$ to $\leq\pm2.19\%$, which is very low; the best method for SOC estimation is as shown in Figure 11. Third, learning methodologies [46,106,137,138] need heavy computation as well as a large amount of training data to define the Li-ion nonlinear characteristics for SOC estimation. Nevertheless, the advantages are efficiency, high accuracy, and robustness, but the average error is between $\leq\pm2$ to $\leq\pm6\%$, which is very high compared to filter algorithms, as shown in Figure 12. Fourth, nonlinear observer methodologies [110,131] are handled with highly nonlinear schemes, and the benefits are robustness and enhanced stability. However, the drawback is that it is difficult to alter the switching gain. The average error is between $\leq\pm3$ to $\leq\pm4.5\%$, higher than KF; they are less related to a conventional methodology, as shown in Figure 13. Fifth, in the deep learning [117–120] and hybrid methodology [121,123,139], the average accuracy error of deep learning is $\leq\pm1.33$ to $\leq\pm1.88\%$, as shown in Figure 14. The mixing of two or more algorithms is known as a hybrid, which improves the accuracy and efficiency of the battery. It requires a large memory unit because of its complex mathematical computations, and the average error is between $\leq\pm2.7$ to $\leq\pm6.5\%$, as shown in Figure 15. Table 12 summarizes the different SOC estimation methods for Li-ion batteries.

Table 11. Comparisons of average error (%) on different SOC estimation methods.

Type	Methodology	Average Error (%)	Application in EVs
Conventional Method	OCV [131]	Unspecified	No
	CC [132]	$\leq\pm4$	Yes
	EIS [133]	Unspecified	No
	Model-based [134]	$\leq\pm5$	Yes
Adaptive Filter	KF [75]	$\leq\pm1.76$	Yes
	EKF [135]	$\leq\pm1$	Yes
	H ∞ F [91]	$\leq\pm2.49$	Yes
	SPKF [136]	$\leq\pm2$	Yes
Learning Algorithms	NN [137]	$\leq\pm4.6$	Yes
	FL [46]	$\leq\pm5$	Yes
	GA [106]	$\leq\pm2$	Yes
	SVM [138]	$\leq\pm6$	Yes
Nonlinear Observer	SMO [110]	$\leq\pm3$	Yes
	NLO [125]	$\leq\pm4.5$	Yes

Table 11. *Cont.*

Type	Methodology	Average Error (%)	Application in EVs
Deep Learning Algorithms	LSTM [117]	≤±1.40	Yes
	GRU [119]	≤±1.33	Yes
	CNN [120]	≤±1.88	Yes
Hybrid	Hybrid [121]	≤±2.7	Yes
	Hybrid [123]	≤±6.5	Yes
	Hybrid [139]	≤±3.5	Yes

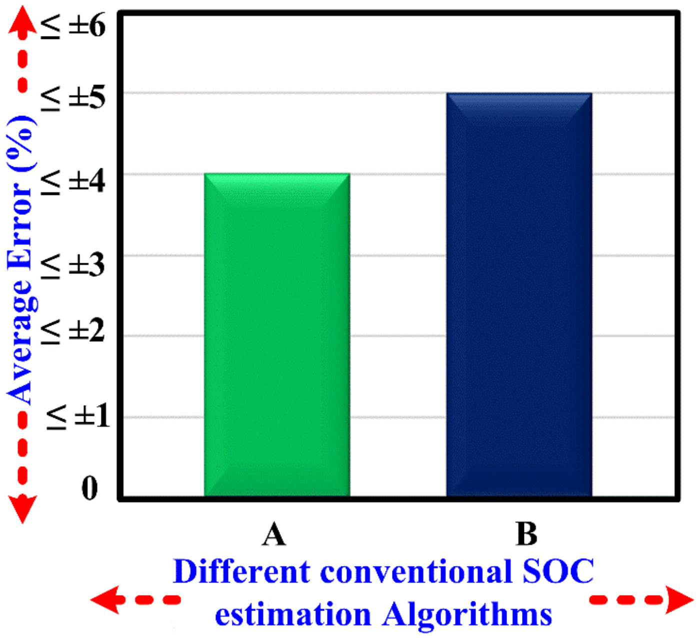

Figure 10. Comparison between the different conventional SOC estimation methods. "A" is referred to as [59], and "B" is referred to as [135].

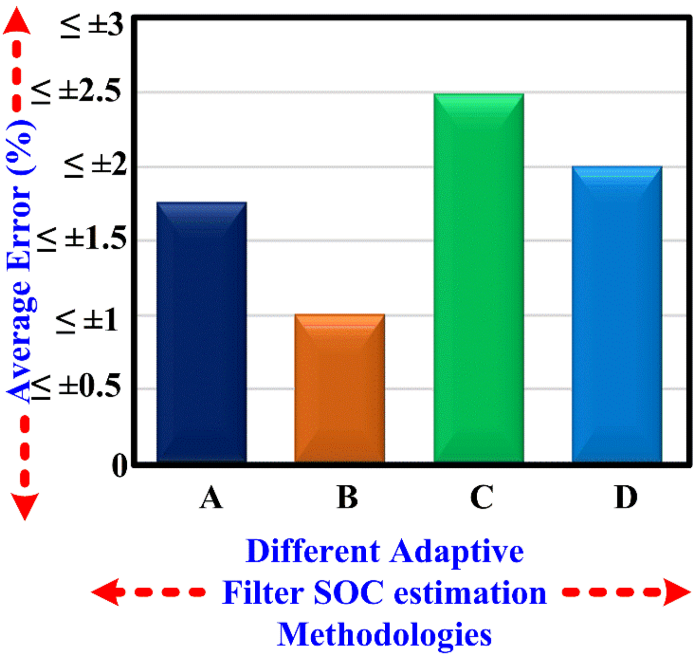

Figure 11. Comparison between the different adaptive filter SOC estimation methods. "A" is referred to as [75], "B" is referred to as [135], "C" is referred to as [91] and "D" is referred to as [136].

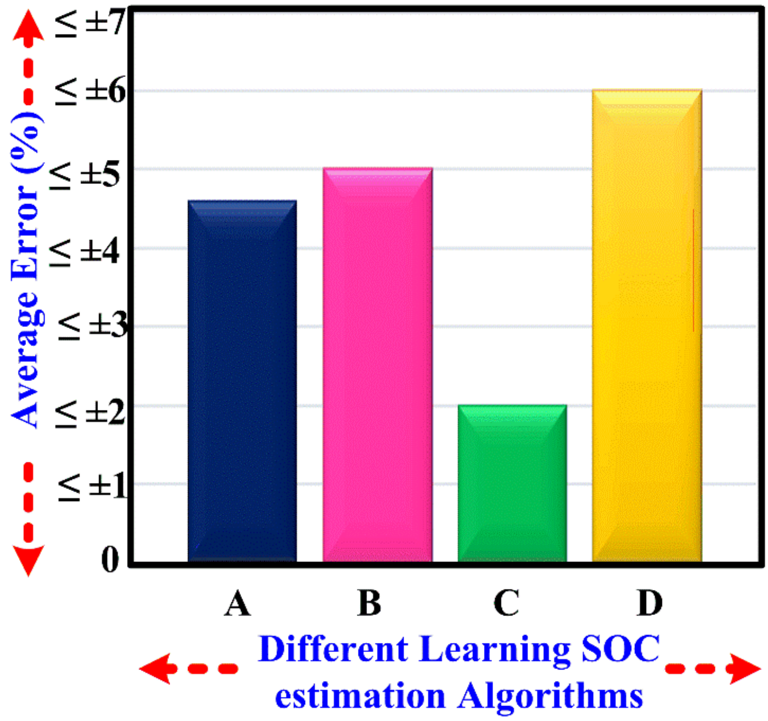

Figure 12. Comparison between the different learning SOC estimation algorithms. "A" is referred to as [137], "B" is referred to as [46], "C" is referred to as [106] and "D" is referred to as [138].

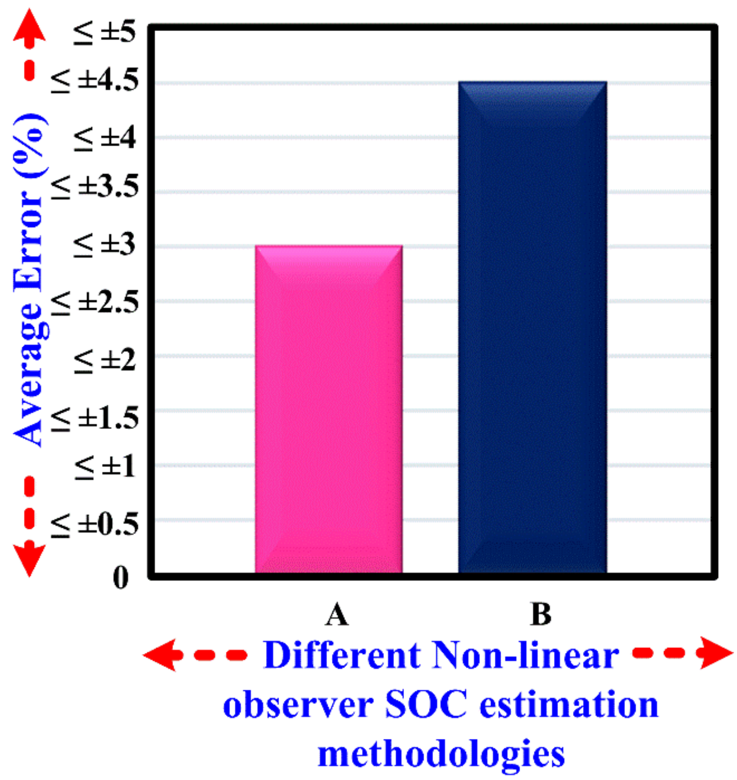

Figure 13. Comparison between the different nonlinear observer SOC estimation methods. "A" is referred to as [110], and "B" is referred to as [131].

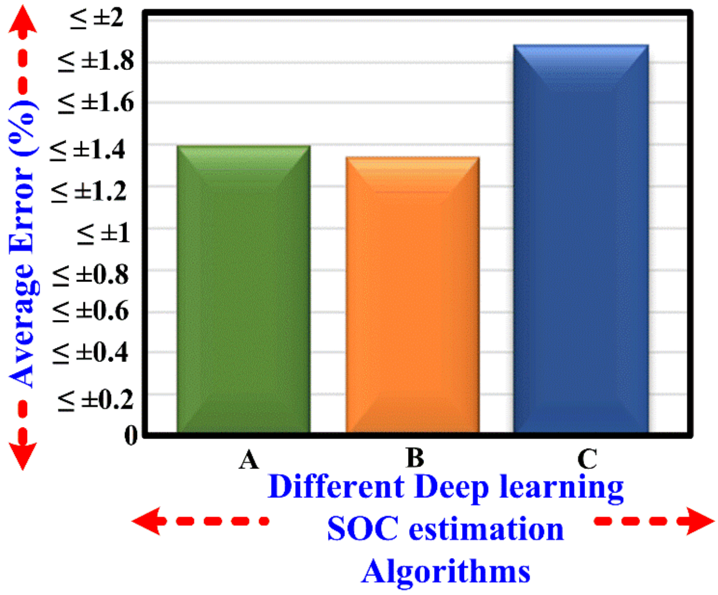

Figure 14. Comparison between the different deep learning SOC estimation algorithms. "A" is referred to as [117], "B" is referred to as [119], and "C" is referred to as [120].

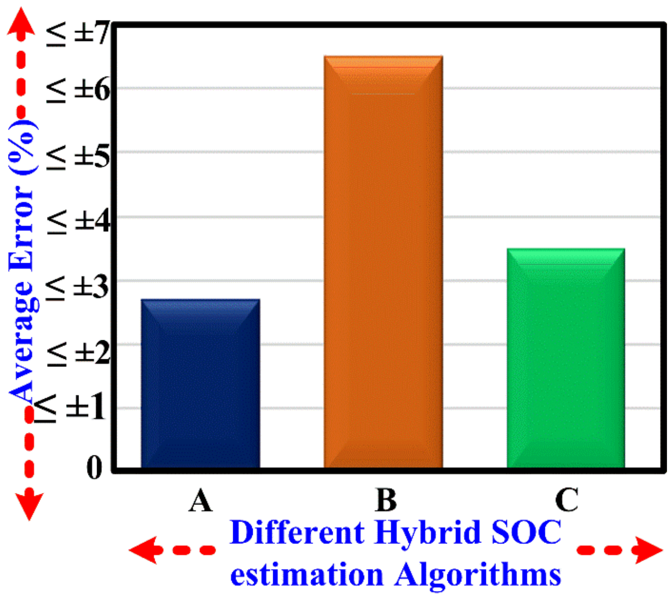

Figure 15. Comparison between the different hybrid SOC estimation algorithms. "A" is referred to as [131], "B" is referred to as [123], and "C" is referred to as [139].

Table 12. Summary of the different SOC estimation methods for Li-ion batteries.

Type	Major Benefits	Major Limitations
Conventional Method [132–134]	• Easy implementation • Low power consumption • High accuracy • Easy to understand	• Not suitable for online • It highly depends on the accuracy of the model. • Susceptible to aging and temperature
Adaptive Filter [75,91,135,136]	• High accuracy • Excellent filtering effect • Insensitive to initial SOC • High robustness	• High computation complexity • Large computation cost • Unfit for large noise measurement

Table 12. *Cont.*

Type	Major Benefits	Major Limitations
Learning Algorithms [46,106,137,138]	• Independent models • Great accuracy • Rule-based inference • Nonlinear mapping ability	• Requires a large amount of training data • Requires large memory units • Costly processing unit • Time-consuming process
Nonlinear Observer [110,131]	• Robustness • Powerful tracking performance • The excellent nonlinear processing capability	• Inaccurate • Difficult to find proper gain matrix • Insufficient stability
Hybrid [121,123,139]	• More effective • Reliable • High precision	• Requires longer computation time • High complex computation

5. Factors, Challenges, and Recommendations

Due to performance degradation and complex electrochemical reactions, developing and arranging a Li-ion battery organization system for EVs is a top priority. Moreover, most well-defined battery experiments are performed in a controlled laboratory environment with constant current, voltage, and temperature. Few analyses exist on battery performance in severe, hot, wet, and rainy conditions. External mass affects battery capacity. Unmodeled consequences add to unconsidered algorithms and models. Temperature, aging, cell unbalancing, hysteresis characteristics, battery modeling, self-discharge, charge/discharge rate, etc. are also factors in battery performance decline. The work summarizes the key findings by applying aging modeling to four different Li-ion battery capacity loss datasets [58]. Figure 16 shows Li-ion battery cycle life versus temperature at different charge rates. Many researchers have proposed battery SOC models. Every model suffers from missing data for real-world EV applications. To accurately estimate battery states, complex calculations, high cost, and accuracy are issues. Table 13 lists SOC monitoring challenges, causes, and recommendations. Figure 17 explains battery anode aging.

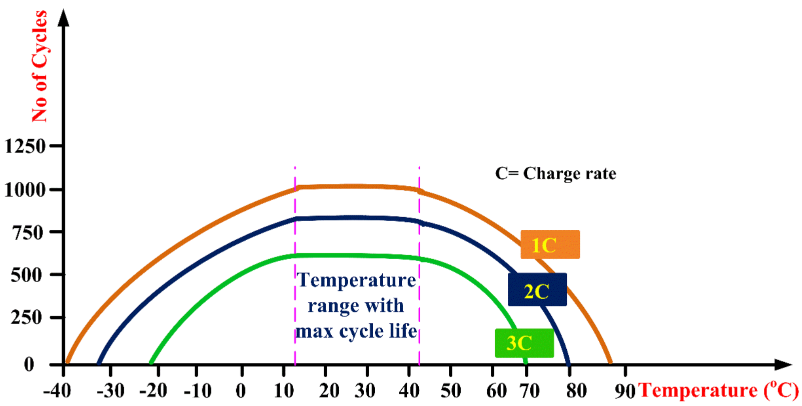

Figure 16. Battery cycle life vs. temperature at a dissimilar charge rate of Li-ion battery [58].

Table 13. Challenges, causes, and recommendations to monitor the SOC.

Ref. No.	Challenges	Causes	Recommendations
[140–144]	Temperature	• It is caused by an increase in inconsistency and an increment in the electrolyte's development, which can support the movement consequence and particle diffusion.	• The finest temperature range and battery cycle charging rate are acknowledged in [144].

Table 13. *Cont.*

Ref. No.	Challenges	Causes	Recommendations
[145,146]	Aging	• It is caused by capacitance degradation as well as internal resistance.	• An OCV curve model to evaluate the battery SOH is planned by enhancing one only constraint, the aging of batteries [146].
[147–156]	Cell unbalancing	• Due to the manufacturing and chemical characteristics of the battery, which might vary while discharging and charging	• An active cell balancing mechanism is separated into two types, passive and active, which were proposed in [153].
[156–160]	Hysteresis characteristics	• Ohmic resistance, electro-chemical issues, and concentration polarization are the key causing issues along with it being produced by scattering of energy in the development.	• Hysteresis assessment of Li-ion cells is established for improving the precision in contradiction of the impact of hysteresis [156].
[161–164]	Battery modelling	• Due to the complex dynamics and electro-chemical environment, it is challenging to create a battery model.	• ESC model along with higher-order RC model was proposed in [70].
[165,166]	Self-discharge	• Lithium species loss and SEI formation are accountable for causing self-discharge.	• ECN model for estimation of SOC by using prediction error minimization method was proposed in [166].
[167–170]	Charge and discharge rate	• Phase dispersion is the key warning factor for high discharge current in plastic Li-ion batteries.	• The discharge as well charges in a current range of the Li-ion battery were acknowledged in [170].
[171–174]	Communication method	• Due to the non-uniform charging mechanism, developing an advanced, even charger is problematic.	• Wireless expertise was employed to transfer the data between charger and battery in [173].

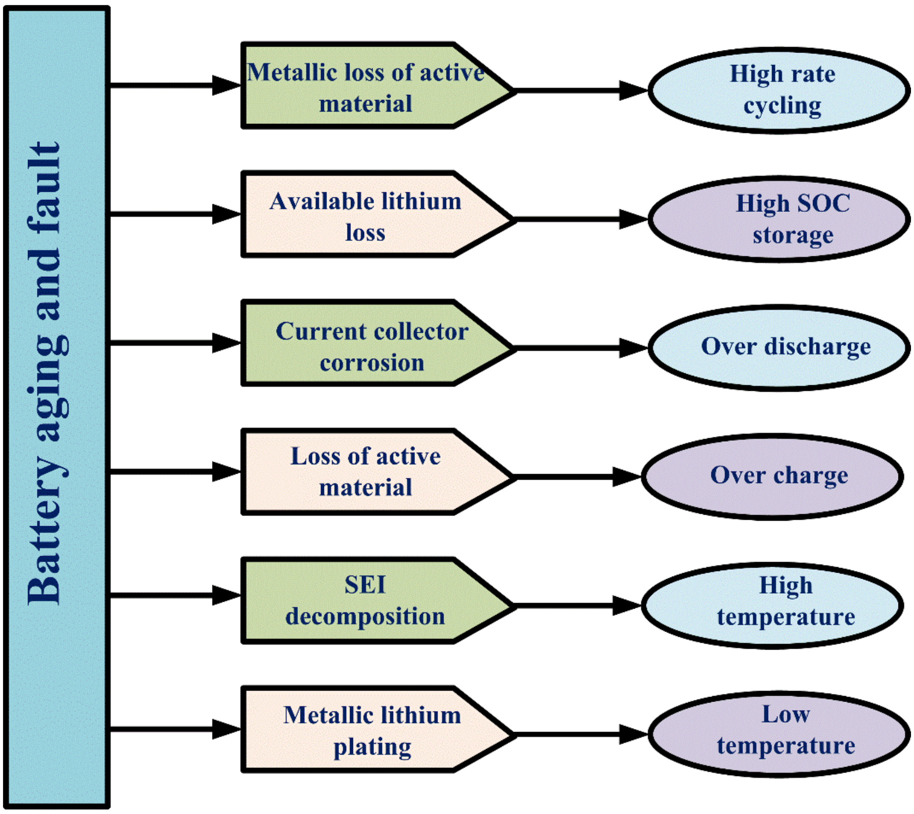

Figure 17. Explanations for the aging of a battery at the anode [145].

6. Conclusions

This paper critically reviewed BMS with attention to several methods for estimating the SOC. A Li-ion battery is recommended for complex in-vehicle operation due to having benefits such as high efficiency, energy density, voltage-generating capability, and long-life cycle span. The importance of a BMS to achieve reliable and safe operating of Li-ion batteries was described in detail. A BMS includes both hardware and software, which were discussed briefly. This analysis mainly explored several algorithms in addition to estimation methods of SOC. From the various literature reviewed, a complete explanation including method drawbacks, benefits, and estimation errors was broadly studied.

This review paper recognizes that the conventional techniques are simple, and implementation is also easy. Nevertheless, they are highly affected by temperature, aging, and external disturbances. Similarly, the situation was observed that an AF algorithm can calculate the nonlinear dynamic condition utilizing better accuracy, high efficiency, and low computational cost. Nevertheless, this method suffers from poor robustness and a heavy burden. Regarding the learning algorithm (LA), it executes a nonlinear dynamic modeling arrangement better by bearing in mind the temperature, aging, and noises. However, it requires composite computation and large memory storage parts. The nonlinear observer (NLO) method has improved robustness, accuracy, computation costs, and coverage speed. However, this method could provide inaccurate outcomes if the device is not designed correctly. Estimating a precision SOC has become a significant challenge due to the electrochemical reactions of several external and internal factors of Li-ion batteries.

7. Future Scope

Based on a comprehensive review of existing analyses on SOC estimation, this review makes several important recommendations for future research, as shown in Figure 18.

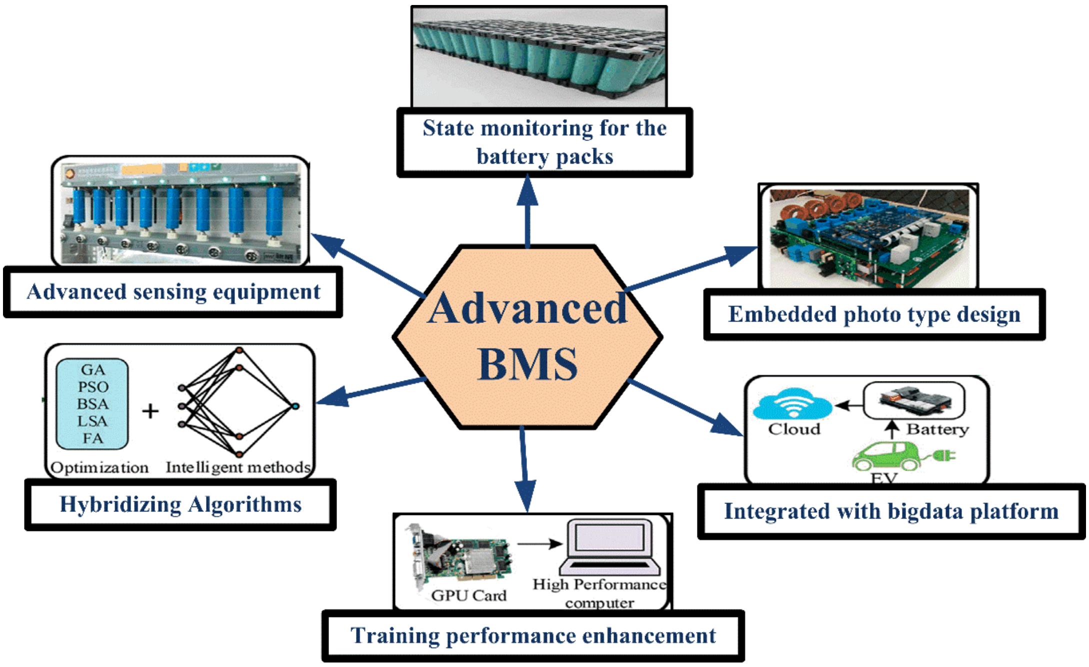

Figure 18. Future trends in advanced BMS for EV applications.

- **Hybridizing algorithms:** To achieve satisfactory SOC estimation performance, hybrid methods are highly recommended, in which multiple methods enhance each other.
- **Advanced sensing equipment:** It is essential in developing high-precision sensors to improve current and voltage measurement accuracy for accurate SOC estimation.

- **Cloud computing technology:** The real-time operation of intelligent algorithms and BMS controller schemes can be enhanced further with proper monitoring and analysis via the cloud storage and big data platform.
- **Embedded systems:** Additional research is needed to create an embedded prototype with a low computational cost and small memory units.
- **High-performance processors:** To accelerate the training operation, a GPU-based high-performance processor and appropriate activation functions, excitable parameters, and training algorithms are necessary.
- **State monitoring for the battery packs**: State estimation and fault diagnosis for battery packs must be evaluated to reduce cost, power loss, size, and voltage stress, and improve equalization time and efficiency.
- It is necessary to have a generalized validation and benchmark method for SOC estimation.

In conclusion, key information and the critical analysis obtained from this review will be useful for automobile engineers and the EV-related industries to develop and implement advanced BMSs for EV applications. Thus, further research on BMSs using advanced intelligent algorithms will improve battery performance and lifespan and ensure the safe and reliable operation of EVs, resulting in significant growth of the battery and EV markets. Furthermore, the battery-related market and expansion of the EV market can help achieve long-term development goals such as emission reduction, clean energy, economic development, and job creation. As a result, long-term future innovation is required to improve EV performance in terms of accurate battery monitoring and control strategy development, global collaboration, and sustainable development.

Author Contributions: Conceptualization and methodology, G.T.; investigation, D.C.; resources, D.C.; data curation, G.T.; writing—original draft preparation, G.T.; writing—review & editing, G.T.; visualization, G.T.; and D.C.; supervision, D.C.; project administration, D.C.; funding acquisition, D.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Vellore institute of technology in Vellore, India, for conceding a SEED fund/12439 to subsidize this research.

Data Availability Statement: This review has no information related to it.

Acknowledgments: The authors are thankful to the Vellore institute of technology in Vellore, India, for conceding a SEED fund/12439 to subsidize this research. The authors, likewise, wish to thank the particular copyright holders for allowing approval to use the pictures, graphics, tables, and figures in this work.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AF	Adaptive Filter
AEKFANFIS	Adaptive Extended Kalman filterAdaptive Neuro Fuzzy Inference System
BMS	Battery Management System
CAN	Controller Area Network
CC	Coulomb Counting
CNN	Convolutional Neural Networks
DNN	Deep Neural Networks
EIS	Electrochemical Impedance Spectroscopy
EKF	Extended Kalman Filter
EV	Electric Vehicle
FL	Fuzzy Logic
GA	Genetic Algorithm
GHG	Greenhouse Gas
GRU	Gated Recurrent Unit
KF	Kalman Filter

ESC	Enhanced Self-Correcting
LA	Learning Algorithms
LSTM	Long Short-Term Memory
LCO	Lithium Cobalt Oxide
LTO	Lithium Titanium Oxide
LNO	Lithium Nickel Oxide
LFP	Lithium Iron Phosphate
LMOMHE	Lithium Manganese OxideMoving Horizon Estimation
MMAENAMHE	Multiple Model Adaptive EstimationNoise Adaptive Moving Horizon Estimation
NCA	Lithium Nickel Cobalt Aluminum Oxide
NMC	Lithium Nickel Manganese Cobalt Oxide
NLO	Nonlinear Observer
NN	Neural Network
OCVRMSE	Open-Circuit VoltageRoot Mean Square Error
SMO	Sliding Mode Observer
SOC	State of Charge
SOE	State of Energy
SOH	State of Health
SOP	State of Power
SPKF	Sigma-Point Kalman Filter
SVM	Support Vector Machine

References

1. Hu, X.; Jiang, J.; Egardt, B.; Cao, D. Advanced Power-Source Integration in Hybrid Electric Vehicles: Multicriteria Optimization Approach. *IEEE Trans. Ind. Electron.* **2015**, *62*, 7847–7858. [CrossRef]
2. Choi, W. A Study on State of Charge and State of Health Estimation in Consideration of Lithium-Ion Battery Aging. *Sustainability* **2020**, *12*, 10451. [CrossRef]
3. Narasipuram, R.P.; Mopidevi, S. A technological overview & design considerations for developing electric vehicle charging stations. *J. Energy Storage* **2021**, *43*, 103225. [CrossRef]
4. Birjandi, A.K.; Alavi, M.F.; Salem, M.; Assad, M.E.H.; Prabaharan, N. Modeling carbon dioxide emission of countries in southeast of Asia by applying artificial neural network. *Int. J. Low-Carbon Technol.* **2022**, *17*, 321–326. [CrossRef]
5. Javid, G.; Abdeslam, D.O.; Basset, M. Adaptive Online State of Charge Estimation of EVs Lithium-Ion Batteries with Deep Recurrent Neural Networks. *Energies* **2021**, *14*, 758. [CrossRef]
6. Hasan, M.K.; Mahmud; Habib, A.A.; Motakabber, S.; Islam, S. Review of electric vehicle energy storage and management system: Standards, issues, and challenges. *J. Energy Storage* **2021**, *41*, 102940. [CrossRef]
7. Hofmann, J.; Guan, D.; Chalvatzis, K.; Huo, H. Assessment of electrical vehicles as a successful driver for reducing CO_2 emissions in China. *Appl. Energy* **2016**, *184*, 995–1003. [CrossRef]
8. Abdul-Manan, A.F. Uncertainty and differences in GHG emissions between electric and conventional gasoline vehicles with implications for transport policy making. *Energy Policy* **2015**, *87*, 1–7. [CrossRef]
9. Casals, C.; Martinez-Laserna, L.; García, A.; Nieto, B. Sustainability analysis of the electric vehicle use in Europe for CO_2 emissions reduction. *J. Clean. Prod.* **2016**, *127*, 425–437. [CrossRef]
10. Singirikonda, S.; Obulesu, Y.P. Battery modelling and state of charge estimation methods for Energy Management in Electric Vehicle-A review. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *937*, 012046. [CrossRef]
11. Hu, X.; Feng, F.; Liu, K.; Zhang, L.; Xie, J.; Liu, B. State estimation for advanced battery management: Key challenges and future trends. Renew. Sustain. *Energy Rev.* **2019**, *114*, 109334. [CrossRef]
12. Wang, Z.; Feng, G.; Zhen, D.; Gu, F.; Ball, A. A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles. *Energy Rep.* **2021**, *7*, 5141–5161. [CrossRef]
13. Hannan, M.; Wali, S.; Ker, P.; Rahman, M.A.; Mansor, M.; Ramachandaramurthy, V.; Muttaqi, K.; Mahlia, T.; Dong, Z. Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues. *J. Energy Storage* **2021**, *42*, 103023. [CrossRef]
14. Daud, M.Z.; Mohamed, A.; Hannan, M.A. An improved control method of battery energy storage system for hourlydispatch of photovoltaic power sources. *Energy Convers. Manag.* **2013**, *73*, 256–270. [CrossRef]
15. Zhang, R.; Xia, B.; Li, B.; Cao, L.; Lai, Y.; Zheng, W.; Wang, H.; Wang, W. State of the Art of Lithium-Ion Battery SOC Estimation for Electrical Vehicles. *Energies* **2018**, *11*, 1820. [CrossRef]
16. Rao, Z.; Wang, S.; Zhang, G. Simulation and experiment of thermal energy management with phase change material forageing LiFePO4 power battery. *Energy Convers. Manag.* **2011**, *52*, 3408–3414. [CrossRef]
17. Scrosati, B.; Garche, J. Lithium batteries: Status, prospects and future. *J. Power Sources* **2010**, *195*, 2419–2430. [CrossRef]

18. Speirs, J.; Contestabile, M.; Houari, Y.; Gross, R. The future of lithium availability for electric vehicle batteries. *Renew. Sustain. Energy Rev.* **2014**, *35*, 183–193. [CrossRef]
19. Surya, S.; Rao, V.; Williamson, S. Comprehensive Review on Smart Techniques for Estimation of State of Health for Battery Management System Application. *Energies* **2021**, *14*, 4617. [CrossRef]
20. Watrin, N.; Blunier, B.; Miraoui, A. Review of adaptive systems for lithium batteries State-of-Charge and State-of-Healthestimation. In Proceedings of the 2012 IEEE Transportation Electrification Conference and Expo (ITEC), Dearborn, MI, USA, 18–20 June 2012.
21. Yang, N.; Zhang, X.; Shang, B.; Li, G. Unbalanced discharging and aging due to temperature differences among the cells in a lithium-ion battery pack with parallel combination. *J. Power Sources* **2016**, *306*, 733–741. [CrossRef]
22. Cuma, M.U.; Koroglu, T. A comprehensive review on estimation strategies used in hybrid and battery electric vehicles. *Renew. Sustain. Energy Rev.* **2015**, *42*, 517–531. [CrossRef]
23. Yanhui, Z.; Wenji, S.; Shili, L.; Jie, L.; Ziping, F. A critical review on state of charge of batteries. *J. Renew. Sustain. Energy* **2013**, *5*, 021403. [CrossRef]
24. Chang, W.-Y. The State of Charge Estimating Methods for Battery: A Review. *ISRN Appl. Math.* **2013**, *2013*, 953792. [CrossRef]
25. Wang, N.; Qin, Y. Research on state of charge estimation of batteries used in electric vehicle. In Proceedings of the Asia-Pacific Power and Energy Engineering Conference, Wuhan, China, 25–28 March 2011; pp. 1–4.
26. Fathima, A.H.; Prabaharan, N.; Palanisamy, K. Sizing of a VRB Battery Based on Max-Min Method of Power Dispatch in aWind-PV Hybrid System. In Proceedings of the 2015 IEEE Conference on Energy Conversion (CENCON), Johor Bahru, Malaysia, 19–20 October 2015.
27. Li, Z.; Huang, J.; Liaw, B.Y.; Zhang, J. On state-of-charge determination for lithium-ion batteries. *J. Power Sources* **2017**, *348*, 281–301. [CrossRef]
28. Kalawoun, J.; Biletska, K.; Suard, F.; Montaru, M. From a novel classi cation of the battery state of charge estimators towarda conception of an ideal one. *J. Power Sources* **2015**, *279*, 694–706. [CrossRef]
29. Hu, X.; Zou, C.; Zhang, C.; Li, Y. Technological developments in batteries:Asurvey of principal roles, types, and manament needs. *IEEE Power Energy Mag.* **2017**, *15*, 20–31. [CrossRef]
30. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. *J. Power Sources* **2013**, *226*, 272–288. [CrossRef]
31. Farag, M. *Lithium-Ion Batteries: Modelling and State of Charge Estimation*; McMaster University: Hamilton, ON, Canda, 2013.
32. Chen, S.; Wan, C.; Wang, Y. Thermal analysis of lithium-ion batteries. *J. Power Sources* **2005**, *140*, 111–124. [CrossRef]
33. Pattipati, B.; Pattipati, K.; Christopherson, J.P.; Namburu, S.M.; Prokhorov, D.V.; Qiao, L. Automotive battery management systems. In Proceedings of the 2008 IEEE AUTOTESTCON, Salt Lake City, UT, USA, 8–11 September 2008.
34. Liu, K.; Li, K.; Peng, Q.; Zhang, C. A brief review on key technologies in the battery management system of electric vehicles. *Front. Mech. Eng.* **2019**, *14*, 47–64. [CrossRef]
35. Saravanan, S.; Pandiyan, P.; Chinnadurai, T.; Ramji, T.; Prabaharan, N.; Kumar, R.S.; Pugalhanthi, P.L. Reconfigurable Battery Management System for Microgrid Application. *Microgrid Technol.* **2021**, *6*, 145–176. [CrossRef]
36. Velamuri, S.; Cherukuri, S.H.C.; Sudabattula, S.K.; Prabaharan, N.; Hossain, E. Combined Approach for Power Loss Minimization in Distribution Networks in the Presence of Gridable Electric Vehicles and Dispersed Generation. *IEEE Syst. J.* **2021**, *112*, 1–12. [CrossRef]
37. Xiong, R.; Cao, J.; Yu, Q.; He, H.; Sun, F. Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles. *IEEE Access* **2018**, *6*, 1832–1843. [CrossRef]
38. Hannan, M.A.; Hoque, M.D.M.; Hussain, A.; Yusof, Y.; Ker, A.P.J. State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations. *IEEE Access Spec. Sect. Adv. Energy Storage Technol. Appl.* **2018**, *6*, 19362–19378. [CrossRef]
39. Yang, R.; Xiong, R.; He, H.; Mu, H.; Wang, C. A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles. *Appl. Energy* **2017**, *207*, 336–345. [CrossRef]
40. Peng, S.; Chen, C.; Shi, H.; Yao, Z. State of Charge Estimation of Battery Energy Storage Systems Based on Adaptive Unscented Kalman Filter With a Noise Statistics Estimator. *IEEE Access* **2017**, *5*, 13202–13212. [CrossRef]
41. Hu, X.; Xiong, R.; Egardt, B. Model-based dynamic power assessment of lithium-ion batteries considering different opeating conditions. *IEEE Trans. Ind. Inform.* **2014**, *10*, 1948–1959. [CrossRef]
42. Xing, Y.; Ma, E.W.M.; Tsui, K.L.; Pecht, M. Battery Management Systems in Electric and Hybrid Vehicles. *Energies* **2011**, *4*, 1840–1857. [CrossRef]
43. Kozlowski, J.D. Electro-chemical cell prognostics using online impedance measurements and model-based data fusion tecniques. In Proceedings of the IEEE Aerospace Conference Proceedings (Cat. No. 03TH8652), Big Sky, MT, USA, 8–15 March 2003; pp. 3257–3270.
44. Pesaran, A.A. Battery thermal models for hybrid vehicle simulations. *J. Power Sources* **2002**, *110*, 377–382. [CrossRef]
45. Jossen, A.; Spath, V.; Döring, H.; Garche, J. Reliable battery operation—A challenge for the battery management system. *J. Power Sources* **1999**, *84*, 283–286. [CrossRef]
46. Salkind, A.J.; Fennie, C.; Singh, P.; Atwater, T.; Reisner, D.E. Determination of state-of charge and state-of-health of batteries by fuzzy logic methodology. *J. Power Sources* **1999**, *80*, 293–300. [CrossRef]

47. Shareef, H.; Islam, M.M.; Mohamed, A. A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. *Renew. Sustain. Energy Rev.* **2016**, *64*, 403–420. [CrossRef]
48. Meissner, E.; Richter, G. Battery monitoring and electrical energy management: Precondition for future vehicle electric power systems. *J. Power Sources* **2003**, *116*, 79–98. [CrossRef]
49. Hannan, M.A.; Lipu, M.S.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. *Renew. Sustain. Energy Rev.* **2017**, *78*, 834–854. [CrossRef]
50. *DS2726 Datasheet Rev 3. MAXIM 5-Cell to 10-Cell Li+ Protector with Cell Balancing*; Maxim Integrated Products, Inc.: Sunnyvale, CA, USA, 2010. Available online: http://datasheets.maxim-ic.com/en/ds/DS2726.pdf (accessed on 1 August 2011).
51. *BQ78PL114 Datasheet. PowerLAN Gateway Battery Management Controller with Power Pump Cell Balancing*; Texas Instruments Inc.: Dallas, TX, USA, 2009. Available online: http://www.ti.com/lit/ds/symlink/bq78pl114.pdf (accessed on 1 August 2011).
52. Intelligent Battery. *The PO2WER of CO2OL Battery Technology*; O2Micro International LTD: Cayman Islands, UK, 2010. Available online: http://www.o2micro.com/prods/o2m_intbattery_catalog.pdf (accessed on 1 August 2011).
53. Panwar, N.G.; Singh, S.; Garg, A.; Gupta, A.K.; Gao, L. Recent advancements in battery management system for Li-ion batteries of electric vehicles: Future role of digital twin, cyber-physical systems, battery swapping technology, and nondestructive testing. *Energy Technol.* **2021**, *9*, 2000984. [CrossRef]
54. Yang, B.; Wang, J.; Cao, P.; Zhu, T.; Shu, H.; Chen, J.; Zhang, J.; Zhu, J. Classification, summarization and perspectives on state-of-charge estimation of lithium-ion batteries used in electric vehicles: A critical comprehensive survey. *J. Energy Storage* **2021**, *39*, 102572. [CrossRef]
55. Snihir, I.; Rey, W.; Verbitskiy, E.; Belfadhel-Ayeb, A.; Notten, P.H. Battery open-circuit voltage estimation by a method of statistical analysis. *J. Power Sources* **2006**, *159*, 1484–1487. [CrossRef]
56. Tingting, D.; Jun, L.; Fuquan, Z.; Yi, Y.; Qiqian, J. Analysis on the influence of measurement error on state of charge estimtion of LiFePO4 power Battery. In Proceedings of the 2011 International Conference on Materials for Renewable Energy & Environment 2011, Shanghai, China, 20–22 May 2011.
57. Lee, S.J.; Kim, J.H.; Lee, J.M.; Cho, B.H. The state and parameter estimation of an Li-ion battery using a new OCV-SOCconcept. In Proceedings of the 2007 IEEE Power Electronics Specialists Conference, Orlando, FL, USA, 17–21 June 2007.
58. Roscher, M.A.; Sauer, D.U. Dynamic electric behavior and open-circuit-voltage modeling of LiFePO4-based lithium ion secondary batteries. *J. Power Sources* **2011**, *196*, 331–336. [CrossRef]
59. Zhang, Y.; Song, W.; Lin, S.; Feng, Z. A novel model of the initial state of charge estimation for LiFePO4 batteries. *J. Power Sources* **2014**, *248*, 1028–1033. [CrossRef]
60. Leng, F.; Tan, C.M.; Yazami, R.; Le, M.D. A practical framework of electrical based online state-of-charge estimation of lithium ion batteries. *J. Power Sources* **2014**, *255*, 423–430. [CrossRef]
61. Messing, M.; Shoa, T.; Ahmed, R.; Habibi, S. Battery SoC estimation from EIS using neural nets. In Proceedings of the 2020 IEEE Transportation Electrification Conference & Expo (ITEC), Chicago, IL, USA, 24–26 June 2020.
62. Li, M. Li-ion dynamics and state of charge estimation. *Renew. Energy* **2017**, *100*, 44–52. [CrossRef]
63. Ran, L.; Junfeng, W.; Haiying, W.; Gechen, L. Prediction of state of charge of Lithium-ion rechargeable battery with electrochemical impedance spectroscopy theory. In Proceedings of the 2010 5th IEEE Conference on Industrial Electronics and Applications 2010, Taichung, Taiwan, 15–17 June 2010.
64. Meng, J.; Stroe, D.-I.; Ricco, M.; Luo, G.; Teodorescu, R. A Simplified Model-Based State-of-Charge Estimation Approach for Lithium-Ion Battery With Dynamic Linear Model. *IEEE Trans. Ind. Electron.* **2019**, *66*, 7717–7727. [CrossRef]
65. Cho, S.; Jeong, H.; Han, C.; Jin, S.; Lim, J.H.; Oh, J. State-of-charge estimation for lithium-ion batteries under various opeating conditions using an equivalent circuit model. *Comput. Chem. Eng.* **2012**, *41*, 1–9. [CrossRef]
66. Rahman, A.; Anwar, S.; Izadian, A. Electrochemical model parameter identification of a lithium-ion battery using particle swarm optimization method. *J. Power Sources* **2016**, *307*, 86–97. [CrossRef]
67. Stetzel, K.D.; Aldrich, L.L.; Trimboli, M.; Plett, G.L. Electrochemical state and internal variables estimation using a reduced-order physics-based model of a lithium-ion cell and an extended Kalman filter. *J. Power Sources* **2015**, *278*, 490–505. [CrossRef]
68. Di Domenico, D.; Fiengo, G.; Stefanopoulou, A. Lithium-ion battery state of charge estimation with a Kalman Filter based on a electrochemical model. In Proceedings of the 2008 IEEE International Conference on Control Applications, San Antonio, TX, USA, 3–5 September 2008.
69. Bruen, T.; Marco, J. Modelling and experimental evaluation of parallel connected lithium ion cells for an electric vehicle battery system. *J. Power Sources* **2016**, *310*, 91–101. [CrossRef]
70. Lai, X.; Gao, W.; Zheng, Y.; Ouyang, M.; Li, J.; Han, X.; Zhou, L. A comparative study of global optimization methods for parameter identification of different equivalent circuit models for Li-ion batteries. *Electrochim. Acta* **2019**, *295*, 1057–1066. [CrossRef]
71. Tran, M.-K.; Mevawala, A.; Panchal, S.; Raahemifar, K.; Fowler, M.; Fraser, R. Effect of integrating the hysteresis component to the equivalent circuit model of Lithium-ion battery for dynamic and non-dynamic applications. *J. Energy Storage* **2020**, *32*, 101785. [CrossRef]
72. Xu, L.; Wang, J.; Chen, Q. Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model. *Energy Convers. Manag.* **2012**, *53*, 33–39. [CrossRef]

73. Ting, T.O.; Man, K.L.; Lim, E.; Leach, M. Tuning of Kalman Filter Parameters via Genetic Algorithm for State-of-Charge Estimation in Battery Management System. *Sci. World J.* **2014**, *2014*, 176052. [CrossRef]
74. Urbain, M.; Rael, S.; Davat, B.; Desprez, P. State Estimation of a Lithium-Ion Battery Through Kalman Filter. In Proceedings of the 2007 IEEE Power Electronics Specialists Conference 2007, Orlando, FL, USA, 17–21 June 2007. [CrossRef]
75. Yatsui, M.W.; Bai, H. Kalman filter-based state-of-charge estimation for lithium-ion batteries in hybrid electric vehicles using pulse charging. In Proceedings of the 2011 IEEE Vehicle Power and Propulsion Conference, Chicago, IL, USA, 6–9 September 2011.
76. Jokic, I.; Zecevic, Z.; Krstajic, B. State-of-charge estimation of lithium-ion batteries using extended Kalman filter and unscented Kalman filter. In Proceedings of the 2018 23rd International Scientific-Professional Conference on Information Technology (IT), Žabljak, Montenegro, 19–24 February 2018.
77. Plett, G.L. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. *J. Power Sources* **2004**, *134*, 277–292. [CrossRef]
78. Ben Sassi, H.; Errahimi, F.; Es-Sbai, N. State of charge estimation by multi-innovation unscented Kalman filter for vehicular applications. *J. Energy Storage* **2020**, *32*, 101978. [CrossRef]
79. Chen, Z.; Fu, Y.; Mi, C. State of Charge Estimation of Lithium-Ion Batteries in Electric Drive Vehicles Using Extended Kalman Filtering. *IEEE Trans. Veh. Technol.* **2013**, *62*, 1020–1030. [CrossRef]
80. Fang, Y.; Zhang, Q.; Zhang, H.; Xu, W.; Wang, L.; Shen, X.; Yun, F.; Cui, Y.; Wang, L.; Zhang, X. State-of-charge estimation technique for lithium-ion batteries by means of second-order extended Kalman filter and equivalent circuit model: Great temperature robustness state-of-charge estimation. *IET Power Electron.* **2021**, *14*, 1515–1528. [CrossRef]
81. Liu, X.; Li, K.; Wu, J.; He, Y.; Liu, X. An extended Kalman filter based data-driven method for state of charge estimation of Li-ion batteries. *J. Energy Storage* **2021**, *40*, 102655. [CrossRef]
82. Nian, P.; Shuzhi, Z.; Xiongwen, Z. Co-estimation for capacity and state of charge for lithium-ion batteries using improved adaptive extended Kalman filter. *J. Energy Storage* **2021**, *40*, 102559. [CrossRef]
83. Xiong, R.; He, H.; Sun, F.; Zhao, K. Evaluation on State of Charge Estimation of Batteries With Adaptive Extended Kalman Filter by Experiment Approach. *IEEE Trans. Veh. Technol.* **2013**, *62*, 108–117. [CrossRef]
84. Wang, S.; Fernandez, C.; Shang, L.; Li, Z.; Li, J. Online state of charge estimation for the aerial lithium-ion battery packs based on the improved extended Kalman filter method. *J. Energy Storage* **2017**, *9*, 69–83. [CrossRef]
85. Espedal, I.B.; Jinasena, A.; Burheim, O.S.; Lamb, J.J. Current Trends for State-of-Charge (SoC) Estimation in Lithium-Ion Battery Electric Vehicles. *Energies* **2021**, *14*, 3284. [CrossRef]
86. Wassiliadis, N.; Adermann, J.; Frericks, A.; Pak, M.; Reiter, C.; Lohmann, B.; Lienkamp, M. Revisiting the dual extended Kalman filter for battery state-of-charge and state-of-health estimation: A use-case life cycle analysis. *J. Energy Storage* **2018**, *19*, 73–87. [CrossRef]
87. Sangwan, V.; Kumar, R.; Rathore, A.K. State-of-Charge estimation of Li-ion battery at different temperatures using particle filter. *J. Eng.* **2019**, *2019*, 5320–5324. [CrossRef]
88. Gao, M.; Liu, Y.; He, Z. Battery state of charge online estimation based on particle filter. In Proceedings of the 2011 4th International Congress on Image and Signal Processing, Shanghai, China, 15–17 October 2011.
89. Schwunk, S.; Armbruster, N.; Straub, S.; Kehl, J.; Vetter, M. Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries. *J. Power Sources* **2013**, *239*, 705–710. [CrossRef]
90. He, Y.; Liu, X.; Zhang, C.; Chen, Z. A new model for State-of-Charge (SOC) estimation for high-power Li-ion batteries. *Appl. Energy* **2013**, *101*, 808–814. [CrossRef]
91. Zhang, Y.; Zhang, C.; Zhang, X. State-of-charge estimation of the lithium-ion battery system with time-varying parameter for hybrid electric vehicles. *IET Control Theory Appl.* **2014**, *8*, 160–167. [CrossRef]
92. Charkhgard, M.; Zarif, M.H. Design of adaptive H ∞ filter for implementing on state-of-charge estimation based on battery state-of-charge-varying modelling. *IET Power Electron.* **2015**, *8*, 1825–1833. [CrossRef]
93. Zhang, J. Battery state-of-charge estimation based on sigma point Kalman filter. In Proceedings of the 2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC), Zhengzhou, China, 8–10 August 2011.
94. Plett, G.L. Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 2: Simultaneous state and parameter estimation. *J. Power Sources* **2006**, *161*, 1369–1384. [CrossRef]
95. He, Z.; Liu, Y.; Gao, M.; Wang, C. A joint model and SOC estimation method for lithium battery based on the sigma point KF. In Proceedings of the 2012 IEEE Transportation Electrification Conference and Expo (ITEC), Dearborn, MI, USA, 17–20 June 2012.
96. He, Z.; Gao, M.; Xu, J.; Liu, Y. Battery Model Parameters Estimation with the Sigma Point Kalman Filter. In Proceedings of the 2009 International Conference on Artificial Intelligence and Computational Intelligence, Shanghai, China, 7–8 November 2009.
97. He, W.; Williard, N.; Chen, C.; Pecht, M. State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 783–791. [CrossRef]
98. Chen, Z.; Qiu, S.; Masrur, M.; Murphey, Y.L. Battery state of charge estimation based on a combined model of Extended Kalman Filter and neural networks. In Proceedings of the 2011 International Joint Conference on Neural Networks, San Jose, CA, USA, 31 July–5 August 2011.
99. Rui-Hao, L.; Yu-Kun, S.; Xiao-Fu, J. Battery state of charge estimation for electric vehicle based on neural network. In Proceedings of the 2011 IEEE 3rd International Conference on Communication Software and Networks, Xi'an, China, 27–29 May 2011.

100. Jamlouie, M.H.A. Accuracy improvement of SOC estimation in lithium-ion batteries by ANFIS vs. ANN modeling of nonlinear cell characteristics. *J. Energy Storage* **2021**, *6*, 95–104.
101. Singh, P.; Vinjamuri, R.; Wang, X.; Reisner, D. Design and implementation of a fuzzy logic-based state-of-charge meter for Li-ion batteries used in portable defibrillators. *J. Power Sources* **2006**, *162*, 829–836. [CrossRef]
102. Malkhandi, S. Fuzzy logic-based learning system and estimation of state-of-charge of lead-acid battery. *Eng. Appl. Artif. Intell.* **2006**, *19*, 479–485. [CrossRef]
103. Li, I.-H.; Wang, W.-Y.; Su, S.-F.; Lee, Y.-S. A Merged Fuzzy Neural Network and Its Applications in Battery State-of-Charge Estimation. *IEEE Trans. Energy Convers.* **2007**, *22*, 697–708. [CrossRef]
104. Cai, C.H.; Du, D.; Liu, Z.Y. Battery state-of-charge (SOC) estimation using adaptive neuro-fuzzy inference system (ANFIS). In Proceedings of the 12th IEEE International Conference on Fuzzy Systems, St. Louis, MO, USA, 25–28 May 2003.
105. Shen, W.; Chan, C.; Lo, E.; Chau, K.T. Adaptive neuro-fuzzy modeling of battery residual capacity for electric vehicles. *IEEE Trans. Ind. Electron.* **2002**, *49*, 677–684. [CrossRef]
106. Zheng, Y.; Lu, L.; Han, X.; Li, J.; Ouyang, M. LiFePO4 battery pack capacity estimation for electric vehicles based on charging cell voltage curve transformation. *J. Power Sources* **2013**, *226*, 33–41. [CrossRef]
107. Xu, J.; Cao, B.; Chen, Z.; Zou, Z. An online state of charge estimation method with reduced prior battery testing information. *Int. J. Electr. Power Energy Syst.* **2014**, *63*, 178–184. [CrossRef]
108. Antón, J.C.Á.; Nieto, P.J.G.; de Cos Juez, F.J.; Lasheras, F.S.; Vega, M.G.; Gutiérrez, M.N.R. Battery state-of-charge estimator using the SVM technique. *Appl. Math. Model.* **2013**, *37*, 6244–6253. [CrossRef]
109. Wu, X.; Mi, L.; Tan, W.; Qin, J.L.; Na Zhao, M. State of Charge (SOC) Estimation of Ni-MH Battery Based on Least Square Support Vector Machines. *Adv. Mater. Res.* **2011**, *211–212*, 1204–1209. [CrossRef]
110. Kim, I.-S. Nonlinear State of Charge Estimator for Hybrid Electric Vehicle Battery. *IEEE Trans. Power Electron.* **2008**, *23*, 2027–2034. [CrossRef]
111. Chen, X.; Shen, W.; Cao, Z.; Kapoor, A.; Hijazin, I. Adaptive gain sliding mode observer for state of charge estimation based on combined battery equivalent circuit model in electric vehicles. *Aust. J. Electr. Electron. Eng.* **2013**, *9*, 601–606. [CrossRef]
112. Boizot, N.; Busvelle, E.; Gauthier, J.-P. An adaptive high-gain observer for nonlinear systems. *Automatica* **2010**, *46*, 1483–1488. [CrossRef]
113. Xu, J.; Mi, C.; Cao, B.; Deng, J.; Chen, Z.; Li, S. The State of Charge Estimation of Lithium-Ion Batteries Based on a Proportional-Integral Observer. *IEEE Trans. Veh. Technol.* **2014**, *63*, 1614–1621. [CrossRef]
114. Xu, F.; Wang, Y.; Luo, X. Soft Sensor for Inputs and Parameters Using Nonlinear Singular State Observer in Chemical Processes. *Chin. J. Chem. Eng.* **2013**, *21*, 1038–1047. [CrossRef]
115. Kim, I.-S. The novel state of charge estimation method for lithium battery using sliding mode observer. *J. Power Sources* **2006**, *163*, 584–590. [CrossRef]
116. Xia, B.; Chen, C.; Tian, Y.; Sun, W.; Xu, Z.; Zheng, W. A novel method for state of charge estimation of lithium-ion batteries using a nonlinear observer. *J. Power Sources* **2014**, *270*, 359–366. [CrossRef]
117. Chemali, E.; Kollmeyer, P.J.; Preindl, M.; Ahmed, R.; Emadi, A.; Kollmeyer, P. Long Short-Term Memory Networks for Accurate State-of-Charge Estimation of Li-ion Batteries. *IEEE Trans. Ind. Electron.* **2018**, *65*, 6730–6739. [CrossRef]
118. How, D.N.; Hannan, M.; Lipu, M.H.; Sahari, K.S.; Ker, P.J.; Muttaqi, K.M. State-of-charge estimation of li-ion battery in electric vehicles: A deep neural network approach. *IEEE Trans. Ind. Appl.* **2020**, *56*, 5565–5574. [CrossRef]
119. Yang, F.; Li, W.; Li, C.; Miao, Q. State-of-charge estimation of lithium-ion batteries based on gated recurrent neural network. *Energy* **2019**, *175*, 66–75. [CrossRef]
120. Song, X.; Yang, F.; Wang, D.; Tsui, K.-L. Combined CNN-LSTM Network for State-of-Charge Estimation of Lithium-Ion Batteries. *IEEE Access* **2019**, *7*, 88894–88902. [CrossRef]
121. Li, Y.; Wang, L.; Liao, C.; Wang, L.; Xu, D.; Yong, L.; Lifang, W.; Chenglin, L.; Liye, W.; Dongping, X. State-of-Charge Estimation of Lithium-Ion Battery Using Multi-State Estimate Technic for Electric Vehicle Applications. In Proceedings of the 2013 IEEE Vehicle Power and Propulsion Conference (VPPC), Beijing, China, 15–18 October 2013.
122. Alfi, A.; Charkhgard, M.; Zarif, M.H. Hybrid state of charge estimation for lithium-ion batteries: Design and implementation. *IET Power Electron.* **2014**, *7*, 2758–2764. [CrossRef]
123. Xu, J.; Gao, M.; He, Z.; Han, Q.; Wang, X. State of Charge Estimation Online Based on EKF-Ah Method for Lithium-Ion Power Battery. In Proceedings of the 2009 2nd International Congress on Image and Signal Processing, Tianjin, China, 17–19 October 2009.
124. Liu, Z.; Wang, Y.; Du, J.; Chen, C. RBF network-aided adaptive unscented kalman filter for lithium-ion battery SOC estimation in electric vehicles. In Proceedings of the 2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA), Singapore, 18–20 July 2012.
125. Unterrieder, C.; Priewasser, R.; Marsili, S.; Huemer, M. Battery state estimation using mixed Kalman/hinfinity, adaptive luenberger and sliding mode observer. In Proceedings of the 2013 IEEE Vehicle Power and Propulsion Conference (VPPC), Beijing, China, 15–18 October 2013.
126. Su, J.; Schneider, S.; Yaz, E.; Josse, F. Online State of Charge Estimation of Lithium-ion Battery Cells: A Multiple Model Adaptive Estimation Approach. In Proceedings of the 2021 American Control Conference (ACC), New Orleans, LA, USA, 25–28 May 2021.

127. Afshar, S.; Morris, K.; Khajepour, A. State-of-Charge Estimation Using an EKF-Based Adaptive Observer. *IEEE Trans. Control Syst. Technol.* **2019**, *27*, 1907–1923. [CrossRef]
128. Shabarish, P.R.; Aditya, D.V.S.S.; Pavan, V.V.S.S.P.; Manitha, P.V. SOC estimation of battery in hybrid vehicle using adaptive neuro-fuzzy technique. In Proceedings of the 2020 International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 10–12 September 2020.
129. Zhang, Z.; Xue, B.; Fan, J. Noise Adaptive Moving Horizon Estimation for State-of-Charge Estimation of Li-Ion Battery. *IEEE Access* **2021**, *9*, 5250–5259. [CrossRef]
130. Li, Y.; Guo, H.; Qi, F.; Guo, Z.; Li, M. Comparative Study of the Influence of Open Circuit Voltage Tests on State of Charge Online Estimation for Lithium-Ion Batteries. *IEEE Access* **2020**, *8*, 17535–17547. [CrossRef]
131. Gholizadeh, M.; Yazdizadeh, A.; Rahmati, M.; Aliabadi, A. SOC estimation for a lithium-ion battery by designing a nonlinear observer based on an equivalent circuit model. In Proceedings of the 2017 IEEE 15th International Conference on Industrial Informatics (INDIN), Emden, Germany, 24–26 July 2017.
132. Truchot, C.; Dubarry, M.; Liaw, B.Y. State-of-charge estimation and uncertainty for lithium-ion battery strings. *Appl. Energy* **2014**, *119*, 218–227. [CrossRef]
133. Coleman, M.; Lee, C.K.; Zhu, C.; Hurley, W.G. State-of-Charge Determination From EMF Voltage Estimation: Using Impedance, Terminal Voltage, and Current for Lead-Acid and Lithium-Ion Batteries. *IEEE Trans. Ind. Electron.* **2007**, *54*, 2550–2557. [CrossRef]
134. He, H.; Zhang, X.; Xiong, R.; Xu, Y.; Guo, H. Online model-based estimation of state-of-charge and open-circuit voltage of lithium-ion batteries in electric vehicles. *Energy* **2012**, *39*, 310–318. [CrossRef]
135. Jiang, C.; Taylor, A.; Duan, C.; Bai, K. Extended Kalman Filter based battery state of charge(SOC) estimation for electric vehicles. In Proceedings of the 2013 IEEE Transportation Electrification Conference and Expo (ITEC), Metro Detroit, MI, USA, 16–19 June 2013.
136. Plett, G. Sigma-point Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 1: Introduction and state estimation. *J. Power Sources* **2006**, *161*, 1356–1368. [CrossRef]
137. Affanni, A.; Bellini, A.; Concari, C.; Franceschini, G.; Lorenzani, E.; Tassoni, C. EV battery state of charge: Neural network-based estimation. *IEEE Int. Electr. Mach. Drives Conf.* **2003**, *2*, 684–688.
138. Anton, J.C.A.; Nieto, P.J.G.; Viejo, C.B.; Vilan, J.A.V. Support Vector Machines Used to Estimate the Battery State of Charge. *IEEE Trans. Power Electron.* **2013**, *28*, 5919–5926. [CrossRef]
139. He, W.; Williard, N.; Chen, C.; Pecht, M. State of charge estimation for electric vehicle batteries using unscented kalman filtering. *Microelectron. Reliab.* **2013**, *53*, 840–847. [CrossRef]
140. Bonkile, M.P.; Ramadesigan, V. Physics-based models in PV-battery hybrid power systems: Thermal management and degradation analysis. *J. Energy Storage* **2020**, *31*, 101458. [CrossRef]
141. Wu, C.; Zhu, C.; Ge, Y.; Zhao, Y. A Review on Fault Mechanism and Diagnosis Approach for Li-Ion Batteries. *J. Nanomater.* **2015**, *2015*, 631263. [CrossRef]
142. Qian, K.; Zhou, C.; Yuan, Y.; Allan, M. Temperature effect on electric vehicle battery cycle life in Vehicle-to-grid applications, CICED. In Proceedings of the CICED 2010 Proceedings, Nanjing, China, 13–16 September 2010.
143. Wang, Y.; Liu, B.; Han, P.; Hao, C.; Li, S.; You, Z.; Wang, M. Optimization of an air-based thermal management system for lithium-ion battery packs. *J. Energy Storage* **2021**, *44*, 103314. [CrossRef]
144. Zhao, C.; Zhang, B.; Zheng, Y.; Huang, S.; Yan, T.; Liu, X. Hybrid Battery Thermal Management System in Electrical Vehicles: A Review. *Energies* **2020**, *13*, 6257. [CrossRef]
145. Danzer, M.A.; Liebau, V.; Maglia, F. Aging of lithium-ion batteries for electric vehicles. In *Advances in Battery Technologies for Electric Vehicles*; Elsevier: Amsterdam, The Netherlands, 2015; pp. 359–387.
146. Lavigne, L.; Sabatier, J.; Francisco, J.M.; Guillemard, F.; Noury, A. Lithium-ion Open Circuit Voltage (OCV) curve modelling and its ageing adjustment. *J. Power Sources* **2016**, *324*, 694–703. [CrossRef]
147. Shi, W.; Hu, X.; Jin, C.; Jiang, J.; Zhang, Y.; Yip, T. Effects of imbalanced currents on large-format LiFePO 4 /graphite batteries systems connected in parallel. *J. Power Sources* **2016**, *313*, 198–204. [CrossRef]
148. Pastor-Fernández, C.; Bruen, T.; Widanage, W.D.; Gama-Valdez, M.A.; Marco, J. A Study of Cell-to-Cell Interactions and Degradation in Parallel Strings: Implications for the Battery Management System. *J. Power Sources* **2016**, *329*, 574–585. [CrossRef]
149. Singirikonda, S.; Obulesu, Y. Active cell voltage balancing of Electric vehicle batteries by using an optimized switched capacitor strategy. *J. Energy Storage* **2021**, *38*, 102521. [CrossRef]
150. Hoque, M.M.; Hannan, M.A.; Mohamed, A. Voltage equalization control algorithm for monitoring and balancing of series connected lithium-ion battery. *J. Renew. Sustain. Energy* **2016**, *8*, 025703. [CrossRef]
151. Gallardo-Lozano, J.; Romero-Cadaval, E.; Milanes-Montero, M.I.; Guerrero-Martinez, M.A. Battery equalization active methods. *J. Power Sources* **2014**, *246*, 934–949. [CrossRef]
152. Kim, M.-Y.; Kim, C.-H.; Kim, J.-H.; Moon, G.-W. A Chain Structure of Switched Capacitor for Improved Cell Balancing Speed of Lithium-Ion Batteries. *IEEE Trans. Ind. Electron.* **2014**, *61*, 3989–3999. [CrossRef]
153. Lee, W.C.; Drury, D.; Mellor, P. Comparison of passive cell balancing and active cell balancing for automotive batteries. In Proceedings of the 2011 IEEE Vehicle Power and Propulsion Conference, Chicago, IL, USA, 6–8 September 2011; pp. 1–7. [CrossRef]
154. Wang, Y.-X.; Zhong, H.; Li, J.; Zhang, W. Adaptive estimation-based hierarchical model predictive control methodology for battery active equalization topologies: Part I–Balancing strategy. *J. Energy Storage* **2022**, *45*, 103235. [CrossRef]

155. Hoque, M.; Hannan, M.; Mohamed, A.; Ayob, A. Battery charge equalization controller in electric vehicle applications: A review. *Renew. Sustain. Energy Rev.* **2017**, *75*, 1363–1385. [CrossRef]
156. Ju, F.; Deng, W.; Li, J. Performance Evaluation of Modularized Global Equalization System for Lithium-Ion Battery Packs. *IEEE Trans. Autom. Sci. Eng.* **2016**, *13*, 986–996. [CrossRef]
157. Marongiu, A.; Nußbaum, F.G.W.; Waag, W.; Garmendia, M.; Sauer, D.U. Comprehensive study of the influence of aging on the hysteresis behavior of a lithium iron phosphate cathode-based lithium ion battery—An experimental investigation of the hysteresis. *Appl. Energy* **2016**, *171*, 629–645. [CrossRef]
158. Barai, A.; Widanage, W.D.; Marco, J.; McGordon, A.; Jennings, P. A study of the open circuit voltage characterization technique and hysteresis assessment of lithium-ion cells. *J. Power Sources* **2015**, *295*, 99–107. [CrossRef]
159. Zhu, L.; Sun, Z.; Dai, H.; Wei, X. A novel modeling methodology of open circuit voltage hysteresis for LiFePO 4 batteries based on an adaptive discrete Preisach model. *Appl. Energy* **2015**, *155*, 91–109. [CrossRef]
160. Dong, G.; Wei, J.; Zhang, C.; Chen, Z. Online state of charge estimation and open circuit voltage hysteresis modeling of LiFePO4 battery using invariant imbedding method. *Appl. Energy* **2016**, *162*, 163–171. [CrossRef]
161. Cao, Y.; Kroeze, R.C.; Krein, P.T. Multi-timescale Parametric Electrical Battery Model for Use in Dynamic Electric Vehicle Simulations. *IEEE Trans. Transp. Electrif.* **2016**, *2*, 432–442. [CrossRef]
162. Fathima, H.; Prabaharan, N.; Palanisamy, K.; Kalam, A.; Mekhilef, S.; Justo, J.J. (Eds.) *Hybrid-Renewable Energy Systems in Microgrids: Integration, Developments and Control*; Woodhead Publishing: Cambridge, UK, 2018; ISBN 9780081024935.
163. Chen, M.; Rincon-Mora, G.A. Accurate Electrical Battery Model Capable of Predicting Runtime and I–V Performance. *IEEE Trans. Energy Convers.* **2006**, *21*, 504–511. [CrossRef]
164. Kamruzzaman; Zhang, X.; Abdelmalak, M.; Shi, D.; Benidris, M. A data-driven accurate battery model to use in probabilistic analyses of power systems. *J. Energy Storage* **2021**, *44*, 103292. [CrossRef]
165. Helseth, L. The self-discharging of supercapacitors interpreted in terms of a distribution of rate constants. *J. Energy Storage* **2021**, *34*, 102199. [CrossRef]
166. Propp, K.; Marinescu, M.; Auger, D.J.; O'Neill, L.; Fotouhi, A.; Somasundaram, K.; Offer, G.; Minton, G.; Longo, S.; Wild, M.; et al. multi-temperature state-dependent equivalent circuit discharge model for lithium-sulfur batteries. *J. Power Sources* **2016**, *328*, 289–299. [CrossRef]
167. Ji, Y.; Chen, X.; Wang, T.; Ji, H.; Zhang, Y.; Yuan, Q.; Li, L. Coupled effects of charge–discharge cycles and rates on the mechanical behavior of electrodes in lithium–ion batteries. *J. Energy Storage* **2020**, *30*, 101577. [CrossRef]
168. Chuangfeng, H.; Pingan, L.; Xueyan, J. Measurement and analysis for lithium battery of high-rate discharge performance. *Procedia Eng.* **2011**, *15*, 2619–2623. [CrossRef]
169. Arora, P.; Doyle, M.; Gozdz, A.S.; White, R.E.; Newman, J. Comparison between computer simulations and experimental data for high-rate discharges of plastic lithium-ion batteries. *J. Power Sources* **2000**, *88*, 219–231. [CrossRef]
170. Yuan, X.; Liu, H.; Zhang, J. (Eds.) *Lithium-Ion Batteries*; CRC Press: Boca Raton, FL, USA, 2016.
171. Andrea, D. *Battery Management Systems for Large Lithium-Ion Battery Packs*; Artech House: Norwood, MA, USA, 2014.
172. Bi, Z.; Kan, T.; Mi, C.; Zhang, Y.; Zhao, Z.; Keoleian, G.A. A review of wireless power transfer for electric vehicles: Prospects to enhance sustainable mobility. *Appl. Energy* **2016**, *179*, 413–425. [CrossRef]
173. Zhang, J.; Lee, J. A review on prognostics and health monitoring of Li-ion battery. *J. Power Sources* **2011**, *196*, 6007–6014. [CrossRef]
174. Rajendran, G.; Vaithilingam, C.A.; Misron, N.; Naidu, K.; Ahmed, R. A comprehensive review on system architecture and international standards for electric vehicle charging stations. *J. Energy Storage* **2021**, *42*, 103099. [CrossRef]