Journal of Energy Storage 87 (2024) 111435

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Review article

Review of battery state estimation methods for electric vehicles - Part I: SOC estimation

Osman Demirci [a,*], Sezai Taskin [b], Erik Schaltz [c], Burcu Acar Demirci [b]

[a] Department of Electronics & Automation, Manisa Vocational School of Technical Sciences, Manisa Celal Bayar University, 45140 Manisa, Turkey
[b] Department of Electrical & Electronics Engineering, Manisa Celal Bayar University, 45140 Manisa, Turkey
[c] Department of Energy, Aalborg University, 9220 Aalborg, Denmark

ARTICLE INFO

Keywords:
Battery management system (BMS)
State of charge (SOC) estimation
Lithium-ion
Electric vehicles (EVs)

ABSTRACT

This study presents a comprehensive review of State of Charge (SOC) estimation methods for Lithium-Ion (Li-Ion) batteries, with a specific focus on Electric Vehicles (EVs). The growing interest in EVs and the need for efficient battery management have driven advancements in SOC estimation techniques. Various approaches, including data-driven techniques, advanced filtering methods, and machine learning algorithms have been explored to enhance SOC estimation accuracy. The integration of artificial intelligence and hybrid models has shown promising results in improving SOC estimation performance. However, challenges remain in dealing with non-linear battery behavior, temperature variations, and diverse operating conditions. Researchers are continuously studying to improve the robustness and adaptability of SOC estimation methods to address these challenges. The primary objective of this study is to provide an up-to-date summary of the latest advancements in SOC estimation, offering insights into innovative approaches and developments in this field. All existing SOC methods, their advantages, challenges, and usage rates have been comprehensively examined with a specific focus on EV battery management systems. As the EV market continues to expand, accurate SOC estimation will remain essential for optimal battery management and overall EV performance. Future research will focus on refining existing algorithms, exploring new data-driven techniques, and integrating advanced sensor technologies to achieve real-time and reliable SOC estimation in EVs.

1. Introduction

Global warming, the adverse environmental effects of fossil fuels, sustainability policies, environmental concerns, zero carbon emission goals, and advancements in battery technologies have been driving increased interest in EVs. In the early 2000s, EVs were still in the development stage. Limited progress in battery technologies resulted in low range capacities and high battery pack costs, which, in turn, led to low interest in EVs [1]. However, since the 2010s, advancements in battery technologies, longer-range capabilities, and fast charging technologies have further boosted the appeal of EVs. From the 2020s onwards, especially with the increase in range capacities, EVs have become a strategic target for automotive manufacturers. Many automotive companies have started to focus on EV models, leading to accelerated infrastructure development and an increase in the number of charging stations. According to the "Global EV Outlook 2023" report published by the International Energy Agency, there has been a notable increase in the total number of EVs worldwide between 2010 and 2022 [2].

EVs offer a cleaner and more sustainable transportation option, but ensuring the safe operation of the batteries, their reliability, and driving safety are of extreme importance [3]. Li-Ion batteries, a type of rechargeable battery that relies on the movement of lithium ions between electrodes, have gained popularity due to their high energy density, lightweight, and fast charging and discharging capabilities [4]. As the EV market has grown and developed, the cost of Li-Ion batteries has decreased while their efficiency has increased. As a result, Li-Ion batteries have become a widespread and effective energy storage solution for EVs. EV manufacturers can produce vehicles with higher performance, longer range, and better driving experiences by using Li-Ion batteries. Based on data extracted from the Global Electric Vehicle Battery Market for the year 2022, the market's dimensions in this domain stood at $50.5 billion. Projections suggest notable growth, with an anticipated substantial rise to $500 billion by 2032 [5].

* Corresponding author.
E-mail addresses: osman.demirci@cbu.edu.tr (O. Demirci), sezai.taskin@cbu.edu.tr (S. Taskin), esc@energy.aau.dk (E. Schaltz), burcu.acar@cbu.edu.tr (B. Acar Demirci).

https://doi.org/10.1016/j.est.2024.111435
Received 26 October 2023; Received in revised form 1 February 2024; Accepted 20 March 2024
Available online 2 April 2024

Nomenclature

BMS	Battery Management System
SOC	State of Charge
Li-Ion	Lithium-Ion
EVs	Electric Vehicles
SOH	State of Health
CC	Coulomb Counting
OCV	Open-Circuit Voltage
EIS	Electrochemical Impedance Spectroscopy
ECM	Electrical Circuit Model
EChM	Electrochemical Model
KF	Kalman Filter
RLS	Recursive Least Squares Method
H∞	H-Infinity
EKF	Extended Kalman Filter
AEKF	Adaptive Extended Kalman Filter
SCKF	Square Root Variant of the Cubature Kalman Filter
IEKF	Invariant Extended Kalman Filter
ANFIS	Adaptive Neuro-Fuzzy Inference System
GA	Genetic Algorithm
ANN	Artificial Neural Networks
DL	Deep Learning
FL	Fuzzy Logic
SVM	Support Vector Machine
FNN	Feedforward Neural Networks
BPANN	Backpropagation Artificial Neural Network
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
RBFNN	Radial Basis Function Neural Networks
DNN	Deep Neural Network
TL	Transfer Learning
TCN	Temporal Convolutional Network
CNN	Convolutional Neural Network
BWGRU	Bidirectional Weighted Gated Recurrent Unit
MARS	Multivariate Adaptive Regression Splines
PSO	Particle Swarm Optimization
SVSF	Smooth Variable Structure Filter
SMO	Sliding Mode Observer
MGLO	Multi-Gain Luenberger-Based Observer
HCOAG	Hybridizing Coyote Optimization Algorithm
SMC	Sequential Monte Carlo
PF	Particle Filter
SOT	State of Temperature
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
BESS	Battery Energy Storage System

Li-Ion batteries require electronic control systems known as Battery Management System (BMS) to operate efficiently and safely. BMS continuously monitors important parameters such as voltage, current, temperature, and capacity to assess the battery's charging and health status [6]. It prevents the battery from encountering harmful conditions such as overcharging, over-discharging, extreme temperatures, and overcurrent, which could lead to physical damage and premature end of life. In systems where multiple cells/batteries are connected in series and/or parallel, ensuring that the batteries can charge, and discharge equally is crucial for effective energy usage and extended battery life [7]. BMS performs various functions, including disabling the battery system and activating the cooling system when thermal and electrical limits are exceeded to protect the safety of drivers and equipment's [8]. It also balances the charge among batteries/cells within the system [9]. Additionally, BMS communicates with other vehicle systems (e.g., vehicle control units) through communication protocols such as CAN-Bus to transfer data about battery status, performance, and potential errors [10].

Battery state estimation, also known as battery SOC and State of Health (SOH) estimation, refers to the process of predicting a battery's current state and its future performance [11]. Determining critical parameters like the battery's charge level, capacity, voltage, internal resistance, and remaining life is crucial for safe and efficient battery use, extending its lifespan, and preventing undesirable situations [12]. SOC is defined as the amount of energy stored in the battery and shows the current charge level of the battery. SOC estimation is a critical indicator used to determine when to charge or discharge the battery by monitoring its voltage, current, temperature, and other parameters [13]. SOH estimation is used to predict the battery's current capacity or energy storage capability [14]. Capacity estimation involves determining the actual capacity of the battery and assessing factors such as capacity degradation or changes, which are important for evaluating the battery's lifespan, performance, and reliability [15]. Battery state estimation is typically achieved using statistical or mathematical models [16], filtering techniques [17], and data-driven methods [18]. It involves making predictions at both the cell and pack levels based on previous usage data, calibration data, and cell characteristics [19]. Data-driven estimation methods offer higher accuracy in battery state estimation than traditional methods [20]. Undoubtedly, the growth of the EV market will result in a significant increase in demand for Li-Ion-based battery systems. Consequently, the utilization of BMSs, crucial for Li-Ion battery packs, is expected to enhance performance standards.

As the EV market continues to growth, there will be a greater emphasis on developing more advanced and efficient BMS to guarantee the safe and optimal operation of Li-Ion battery packs. In the forthcoming years, advancements in battery state estimation accuracy, real-time monitoring capabilities, thermal management, and overall system reliability will be realized in the market. It is imperative to meet these elevated performance expectations, as it plays a pivotal role in facilitating the widespread adoption and success of EVs.

Accurate SOC estimation holds significant importance for several reasons: (i) it directly influences range estimation, (ii) it is essential for optimizing energy management, ensuring efficient power distribution and utilization, and (iii) it is crucial for the health of the battery, preventing conditions such as overcharging or deep discharging. In summary, precise SOC estimation is paramount for range prediction, energy optimization, battery health, and overall safety, making it a central focus within the multifaceted functions of the BMS in EVs.

The main objective of this study is to present the latest assessments related to SOC estimation methods. This review incorporates recent studies and comprehensive literature on battery SOC estimation, emphasizing the latest approaches and advancements in this field. Considering existing studies in the literature, the primary contribution of this review is the specific evaluation of battery SOC methods in BMSs, particularly in the context of EV systems. In line with this objective, all existing SOC methods have been examined, and their advantages and challenges in the context of EVs have been compared. This study establishes a foundation for refining existing algorithms and developing new data-driven techniques, shaping the trajectory of real-time SOC estimation advancements in the expanding EV market.

The organization of the remaining part of the study is as follows: Section 2 details BMS functions and challenges, Section 3 systematically elaborates on different SOC estimation methods and their associated challenges, and Section 4 provides various comparisons of SOC estimations. Section 5 includes concluding remarks and outlines future work.

2. Battery management systems

BMS controls the battery's charge and discharge processes [21]. The primary task of a BMS is to continuously monitor parameters such as current, voltage, temperature, and capacity of the battery to assess its SOC and SOH [22]. These functions ensure safe charging, protection from over-discharging, optimum performance, and safe, efficient, and long-lasting operation of batteries [23]. The fundamental functions of BMSs in EVs and the challenges in this field are outlined below.

2.1. Functions of a BMS

The BMS plays a significant role in overseeing and optimizing the performance of battery systems. By monitoring various parameters and ensuring safe operation, it is essential for the efficient functioning and longevity of batteries in a wide range of applications [24]. Furthermore, the BMS is responsible for estimating the SOC, SOH, and managing the overall safety of the battery pack [25].

The BMS takes measures for overcharging, over-discharging, and abnormal temperature changes in the battery pack. Its aim is to mitigate dangers such as short circuit and overcurrent, ensuring battery safety. By closely supervising and controlling, the BMS acts as a protective measure, reducing risks and maintaining battery integrity effectively [26]. The BMS is instrumental in facilitating efficient charging and discharging processes, thereby enabling optimal performance, extended battery life, and improved energy efficiency [27]. Additionally, the BMS is required to balance the charge and discharge of series or parallel-connected cells evenly, minimizing voltage differences between cells to ensure cell voltage balance. It achieves cell balancing through various techniques such as active and passive balancing or hybrid methods [28]. Passive balancing involves dissipating excess charge from higher voltage cells as heat, utilizing resistors or other electronic components. Active balancing transfers charge between cells using switching circuits to achieve a balanced condition [29].

The BMS should continuously monitors the some parameters including temperature, current, and voltage of each cell, conducting necessary evaluations for the healthy operation of cells [30]. The BMS also should monitor the battery's temperature and activate cooling systems, such as air or liquid cooling, to protect the battery from excessive heat [31]. The BMS should possess the capability to communicate with other systems, such as the vehicle control system, allowing bidirectional data transfer [32]. Its remote access and diagnostics feature allows monitor the battery's status in real-time [33]. When issues are detected, remote intervention can prevent overcharging, disable faulty cells, or plan maintenance and repairs [34]. The design of the BMS can be customized based on specific application requirements, priorities, and the inclusion of additional features. An example of a BMS functions for EVs is illustrated in Fig. 1.

2.2. Challenges in BMS

The BMS plays a crucial role in ensuring the safe and efficient operation of batteries. However, it also encounters several challenges that need to be addressed for optimal performance [26]. Achieving accurate and reliable state estimation is a challenging task due to battery characteristics' variations, aging, and environmental conditions [35]. Balancing the charge across individual battery cells to prevent overcharging or undercharging can be a complex task, particularly in large battery packs with varying cell characteristics [36].

Overcharging can damage cells, leading to improper functioning or failure. If certain cells in the setup have lower capacity than others, they may experience overcharging, ultimately resulting in system failure [37]. Fast charging generates a significant amount of heat, which can degrade the battery if not managed properly. BMS must regulate the charging rate and temperature to maximize charging speed while maintaining safety and longevity [38]. Establishing reliable

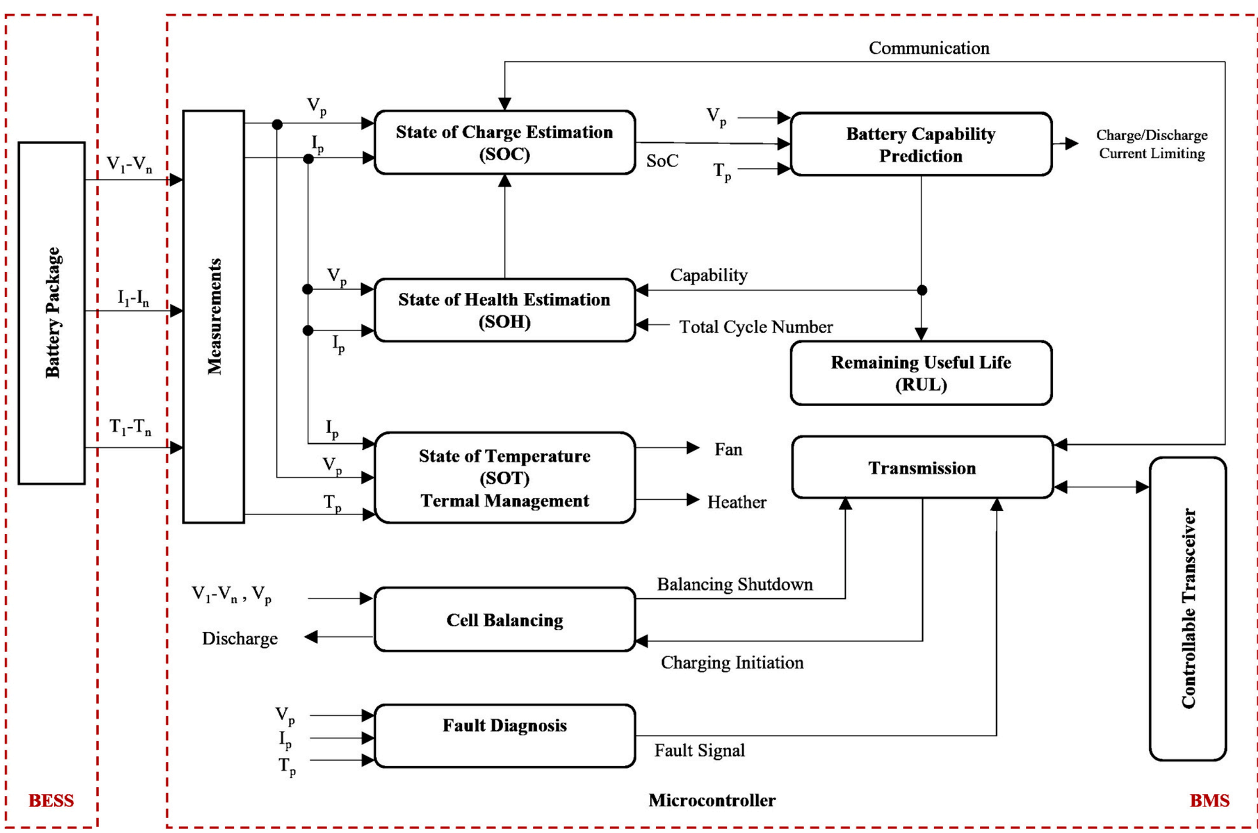

Fig. 1. An example of a BMS functions for a Battery Energy Storage System (BESS).

communication between the BMS and other vehicle systems or external devices may pose challenges, especially in complex and interconnected architectures. The BMS must seamlessly integrate with other vehicle systems, including the motor controller and regenerative braking system. Effective communication ensures smooth operation and energy recovery [39].

The BMS should estimate for battery aging and degradation over time, ensuring accurate monitoring and compensation for reduced capacity [40]. Addressing these challenges is important in the development of resilient and reliable BMSs. The most significant challenges related to BMS are summarized in Fig. 2.

The enumerated functions in the Fig. 2 collectively constitute integral facets of the BMS for EVs. *State estimation accuracy* serves as the foundational cornerstone, facilitating precise energy monitoring, while strategies pertaining to *aging mechanisms* significantly contribute to the extension of battery lifespan. The imperative function of *cell balancing* lies in ensuring the uniform distribution of energy, while steadfast adherence to *regulatory and standards* ensures not only safety but also compliance with industry benchmarks. *Thermal management* meticulously optimizes temperature conditions, and the seamless facilitation of *communication and networking* enhances interaction. *Remote access and diagnostics* elevate monitoring and troubleshooting capabilities, while *scalability and flexibility* accommodate diverse configurations. *Safety and fault management* proactively address potential hazards, with *energy management* standing as the overarching function orchestrating efficient power utilization. Accurate SOC estimation is crucial for BMS development, ensuring optimal energy management and overall battery health.

3. State of charge estimation methods

SOC represents the maximum discharge capacity of a battery under specific temperature and discharge rate conditions, ensuring the battery remains undamaged. Typically, it is expressed as a percentage (%), indicating the remaining capacity relative to the rated capacity [41].

$$SOC\ (t) = \frac{Q_r\ (t)}{Q_{max}(t)} \times 100\ [\%] \tag{1}$$

where Q_r is the remaining capacity of a battery, and Q_{max} is the maximum possible discharge capacity at rated temperature and C-rate. This capacity decreases as the battery ages. Due to the influence of factors such as charge rate, discharge rate, temperature, self-discharge, efficiency factor, and battery aging, the definition of SOC requires adjustments in practical applications. Based on this definition, the SOC equation is derived as follows:

$$SOC(t) = SOC_0 - \frac{\eta\ \int_{t_0}^{t} i\ (t)dt}{Q_n} \tag{2}$$

In the Eq. (2), SOC_0 represents the initial value of $SOC(t)$, and $i(t)$ denotes the real-time current. The symbol η represents the efficiency factor, accounting for the energy losses during charging and discharging processes in a battery. It is a dimensionless parameter typically ranging from 0 to 1, where 1 represents perfect efficiency (no energy losses). Values below 1 account for the actual efficiency of the battery system, considering factors such as heat dissipation and internal resistances. The Eq. (2) shows that the SOC estimation method relies on idealized estimations grounded in ampere-hour measurements. However, obtaining the precise initial value of SOC in this method proves challenging, causing inconvenience in its practical application [42]. Accurate SOC estimation is one of the most critical components of a BMS, as it performs tasks such as informing the user about the expected usage until the next charge, keeping the battery within a safe operating range, implementing control strategies, and ensuring efficient utilization of battery life [41,43,44]. The determination of battery SOC is a complicated procedure influenced by both the battery's type and its application context [45]. In recent years, numerous research and development efforts have been conducted to improve the accuracy of SOC prediction [46–48]. The SOC estimation in the literature can be categorized into two main groups: (i) direct measurement, and (ii) indirect analysis methods. SOC estimation methods for EVs are given in Fig. 3.

3.1. Direct measurement methods

Direct battery SOC estimation aims to determine the charge level of the battery using its physical properties or characteristics [49]. In this approach, SOC is estimated by using measurable factors, including voltage, current, and temperature. There are three main methods for direct SOC estimation: (i) Coulomb Counting (CC), (ii) Open-Circuit Voltage (OCV), and (iii) Electrochemical Impedance Spectroscopy (EIS).

3.1.1. Coulomb Counting (CC)

In this method, the SOC of a battery is estimated by counting the amount of electric charge (coulombs) entering or leaving the battery. In the CC method, while the battery is being charged, the total incoming current is accumulated, leading to an increase in the battery's SOC. Similarly, during discharging, the total outgoing current is accumulated, resulting in a decrease in the battery's SOC. The SOC value is then calculated by integrating the charge or discharge current over time. For accurate predictions using this method, the initial SOC of the battery needs to be known [50]. The estimation equation using the Coulomb Counting method can be expressed as:

$$SOC(t) = SOC(t_0) + \frac{1}{C_n} \times \int_{t_0}^{t_0+t} i_{bat}(dt) \times 100\% \tag{3}$$

The SOC(t) represents the estimated SOC, SOC (t_0) is the initial SOC, C_n denotes the nominal capacity, and i_{bat} represents the charge/discharge current of the battery. The CC method is a commonly preferred approach for SOC estimation due to its low cost and ease of

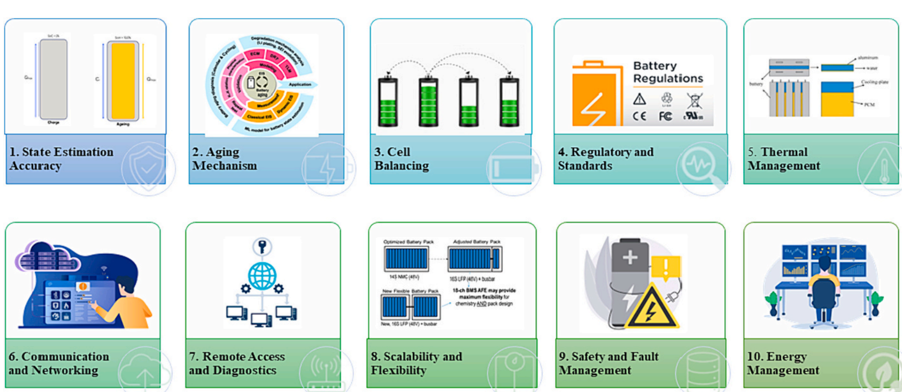

Fig. 2. The important challenges in BMS for EVs.

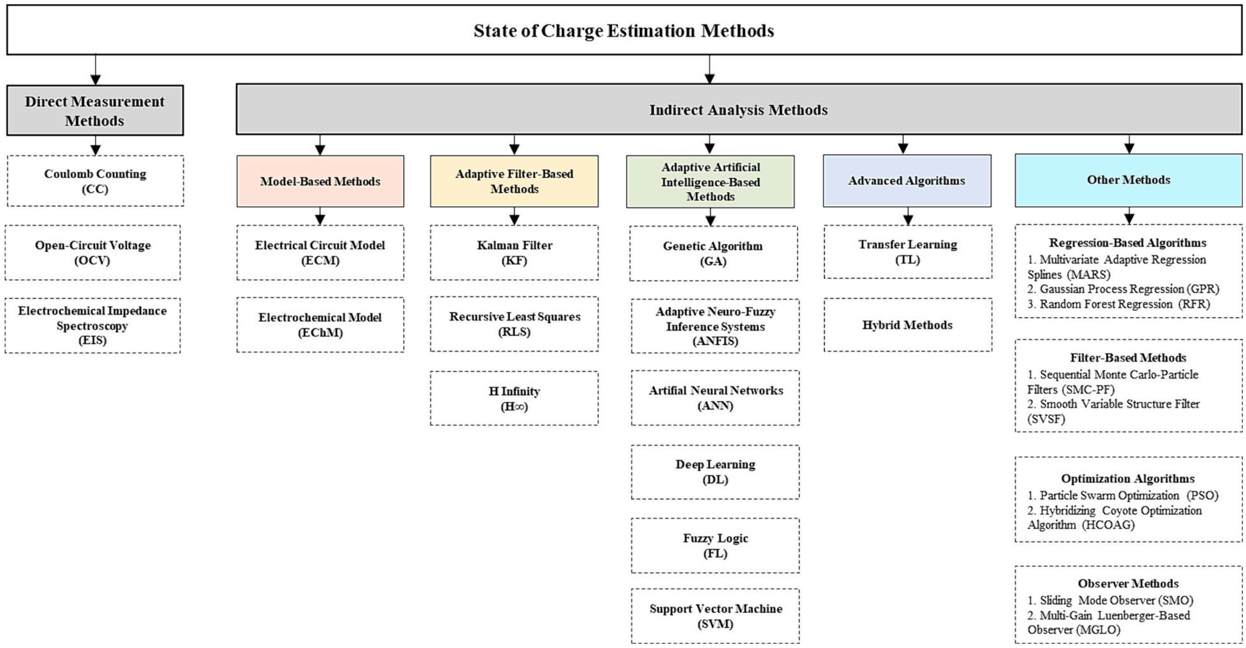

Fig. 3. SOC estimation methods for EVs.

implementation [51,52]. However, one of the main challenges with the method is the requirement for high precision in current measurements. Small errors or measurement deviations can significantly impact the accuracy of the estimated value [53]. Additionally, this method does not consider the real health status of the battery, such as aging or performance degradation, leading to reduced prediction accuracy over time-based on usage. Therefore, in many studies, the prediction accuracy has been attempted to be improved using Enhanced Coulomb Counting (ECC) techniques [53–55]. In [53], the proposed ECC technique utilizes voltage thresholds to determine battery states, resetting SOC and Depth of Discharge (DOD) at specific points like cut-off and full charge. In [54], a novel SOC reset algorithm that utilizes estimated OCV during brief rest intervals is presented. The proposed method encompasses SOC error prediction, attenuate rest periods, and SOC reset error compensation, ensuring highly precise SOC estimation. Furthermore, the study integrates an ECC method with adaptive SOC reset time for estimating OCV, contributing to enhanced precision in the estimation process. In [56], ECC method for accurate SOC estimation in Lithium-Ion Batteries (LIBs) is developed. This method incorporates Peukert equation expansion, Coulombic efficiency, and accounts for the rate- and temperature-dependence of battery capacity. It also includes a SOC mapping strategy and frequency-adjustable current sampling solution, demonstrating its effectiveness and generalization ability through experiments conducted under various conditions and battery chemistries.

3.1.2. Open-Circuit Voltage (OCV)

In this method, the battery's OCV is measured for different states of charge, and the measurements are listed in a lookup table. The measured OCV is used to determine the corresponding SOC based on its position on the OCV-SOC curve [57,58]. Fig. 4 illustrates a graphical representation of the relationship between OCV and SOC. The correlation between SOC and OCV may vary depending on the inherent characteristics and type of the battery. However, Eq. (4) provides a comprehensive expression to understand the relationship between a battery's SOC and OCV. The equation serves as a practical mathematical tool for determining the SOC of a battery based on its OCV. Battery manufacturers commonly

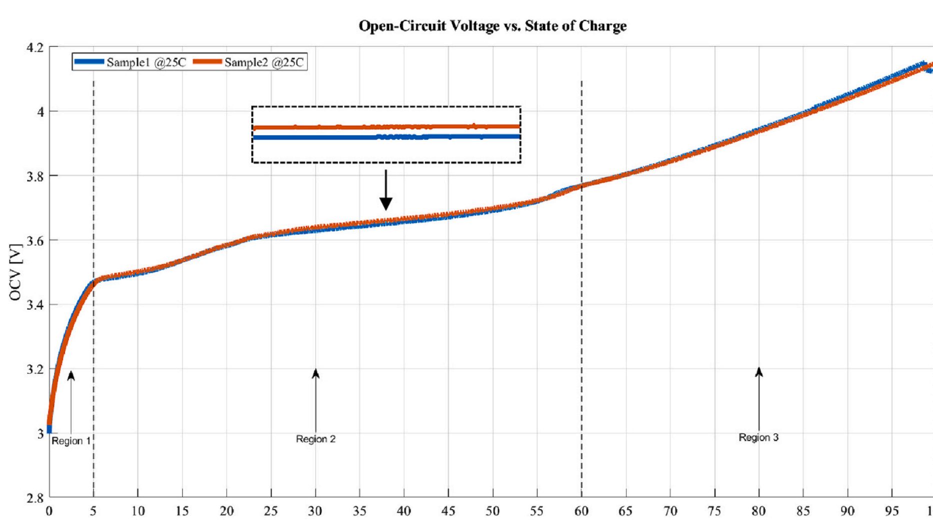

Fig. 4. Fitting function curve for OCV-SOC.

establish and distribute such equations, offering users mathematical models that can be applied to calculate the SOC for a specific battery.

$$SOC = f(OCV) \tag{4}$$

This method is popular due to its simplicity and low cost. It can also be applied to various battery types since there is a general correlation between the battery's nominal voltage and SOC. In [58], three methods are suggested to improve the accuracy of battery SOC estimation for Li-Ion batteries. (i) A new parameter backtracking strategy using the Recursive Least Square (RLS) algorithm is proposed for constant OCV identification, reducing jitters in OCV results. (ii) An Extended Kalman Filter (EKF) is employed as a state observer, using historical experimental data to estimate SOC for batteries that have not been evaluated. (iii) The OCV-SOC curve is analyzed using a cumulative online parameter identification and SOC estimation approach. This reconstruction remains effective even when data is available for only a limited SOC range, rendering it applicable for EV operational scenarios. However, factors such as battery aging and temperature variations can impact the linear relationship between OCV and SOC, thereby reducing the accuracy of the estimation [57].

3.1.3. Electrochemical Impedance Spectroscopy (EIS)

In this approach, the estimation of SOC is accomplished through the measurement of electrochemical impedance at various frequencies. A sinusoidal AC voltage is applied to the battery, and the resulting current responses are recorded to acquire the electrochemical impedance spectrum. This spectrum represents the voltage and current responses of the battery as a function of frequency [59]. EIS is a technique used to examine and characterize the electrochemical behavior of the battery. EIS analysis can be utilized to estimate the battery's SOC by measuring its impedance spectrum [60]. However, this method is not very practical as it requires laboratory settings and involves calibration and modeling procedures.

In [61], a method is introduced that explicitly characterizes the nonlinear relationship between circuit parameters and SOC through analytical polynomial functions. The impact of polynomial order on the prediction accuracy is systematically investigated, and the proposed model's effectivity is demonstrated through EIS measurements of 20 Ah commercial LIBs. The results indicate that a seventh-order polynomial function effectively captures the nonlinear impact of SOC on circuit parameters. Furthermore, the proposed polynomial function-based equivalent circuit model surpasses the performance of a common interpolation-based model in leave-one-out cross-validation predictions.

3.2. Indirect analysis methods

Indirect estimation methods are techniques where the battery's SOC value is predicted using mathematical models and algorithms [62]. Indirect analysis methods can be categorized into five subgroups: model-based, adaptive filter-based, adaptive artificial intelligence-based, advanced algorithms, and other methods. In indirect analysis methods, the estimation accuracy is higher compared to direct measurement-based methods [50].

3.2.1. Model-based methods

Model-based methods are based on sophisticated algorithms to create a mathematical representation of the battery's electrical behavior and its characteristics [63]. The Electrical Circuit Model (ECM) and the Electrochemical Model (EChM) are widely popular models used for SOC estimation and serve as the basis for various other battery modeling techniques.

3.2.1.1. Electrical Circuit Model (ECM). The ECM is based on a mathematical model that defines the electrical behavior of batteries and represents the battery using components found in electrical circuits. For lithium-ion batteries, considering their dynamic performance, first-order, and second-order Thevenin models are commonly used. Fig. 5, presents the equivalent circuits for battery models [50].

Continuous-time analysis of the first-order Thevenin equivalent circuit is given by Eqs. (5) and (6), where the circuit consists of a voltage source V_{OCV}, internal resistance R_o, and transient responses during charging and discharging represented by R_1 and C_1, respectively. The variable V_1 represents the voltage across a circuit component, presumably linked to a capacitor. The mathematical expression formulates a first-order linear ordinary differential equation, describing the dynamic response of the voltage across specified component. On the other hand, discrete-time analysis of the same circuit is presented in Eqs. (7) and (8), where i_1 represents the battery current acquired from measurements, V_t denotes the measured battery voltage, T_s is the sampling period, and τ_p represents the time constant.

$$V_1 = \frac{-1}{R_1 \times C_1} V_1 + \frac{1}{C_1} i_1 \tag{5}$$

$$V_t = V_{ocv} - V_1 - R_0 i_1 \tag{6}$$

$$V_{1,k+1} = V_{1,k} e^{\frac{-T_s}{\tau_p}} + R_1 \left(1 - e^{\frac{-T_s}{\tau_p}}\right) i_{1,k} \tag{7}$$

$$V_{t,k} = V_{ocv}(SOC) - V_{1,k} - R_0 i_{1,k} \tag{8}$$

By using a simple ECM, such as the Thevenin ECM, SOC can be directly calculated through the transformation of model equations. Utilizing a simplified ECM like the Thevenin model involves a systematic process of voltage transformation and current integration. During charging and discharging cycles, the ECM equations capture the battery's behavior, considering energy storage and release dynamics. By integrating the current over time, the total charge passing through the battery is calculated, providing a measure of the utilized capacity. The relationship between voltage and SOC is established through calibration processes, allowing for a direct mapping of voltage levels to SOC values. This relationship, combined with the integrated current information, enables precise real-time SOC calculation. Hence, the simplicity of the Thevenin ECM, coupled with accurate voltage-SOC calibration, facilitates direct SOC estimation by transforming model equations, providing a valuable tool for efficient battery management. The advantage of this approach lies in its simplicity, making it easy to implement on a low-cost target microcontroller.

3.2.1.2. Electrochemical Model (EChM). The EChM is a battery modeling method employed to depict the electrochemical processes occurring within batteries. In this modeling approach, the chemical reactions within the battery and the behavior of electrodes are mathematically defined. Parameters such as the electrochemical potential difference between electrodes and ion flows are computed in this model, and these parameters are then utilized to predict the battery's SOC, voltage, and current responses [64]. The EChM parameters are directly linked to specific degradation types, such as capacity fade and power fade, making it the preferred modeling choice [65]. The EChM enables the representation of more complex electrochemical behaviors and interactions within batteries, facilitating a more detailed analysis of battery performance. However, it is important to note that this modeling requires more computational power and data due to its complexity. Electrochemical modeling finds diverse applications in fields such as battery design, control, optimization, and lifetime prediction. Additionally, it serves as a vital tool for battery energy management systems, contributing to the enhancement of overall battery performance.

3.2.2. Adaptive filter-based methods

Adaptive techniques refer to systems that integrate both direct and model-based approaches, demonstrating the capability to autonomously adapt to changes within the system. These systems commonly utilize

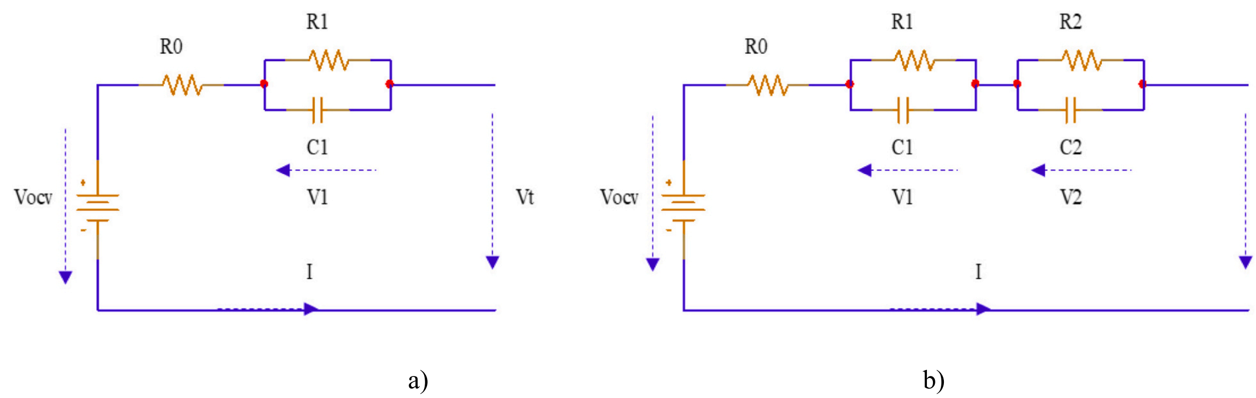

Fig. 5. a) First order and b) Second order Thevenin battery model [50].

feedback data to continuously update the current output in response to varying inputs. Noteworthy among the adaptive filter-based methods frequently employed in the literature are Kalman Filter (KF) Based Methods, Recursive Least Squares Method (RLS), and H-Infinity-Based Estimation (H∞).

3.2.2.1. Kalman Filter-Based Methods (KF). The KF is a widely used method for battery SOC estimation. It utilizes measurements of battery voltage, current, and temperature to estimate the SOC in real time. The KF statistically models the battery's internal state and the relationship between measurements to provide the best estimate [66]. The measured voltage and current values are used as state variables, and a system model is applied. Firstly, the KF uses the battery model and previous SOC estimations to predict the next SOC. Then, the differences between the real measurements and the predicted SOC are analyzed, and an update process adjusts the estimated SOC, taking measurement errors into account to obtain the best possible value [67].

The KF offers a real-time and adaptive approach for SOC estimation, effectively overseeing noise, errors, or uncertainties in the system measurements to yield a more dependable estimate. The fundamental mathematical equations for the battery model are presented in Eqs. (9) and (10), where u_k represents the system inputs (current, voltage, temperature, internal resistance, etc.) and n_{k+1} denotes the system output, which is the OCV. The state variable m_k represents the estimated SOC, while the functions f and g represent the nonlinear equations in the battery model [68].

$$m_{k+1} = f(m_k, u_k) + p_k \tag{9}$$

$$n_{k+1} = g(m_k, u_k) + v_k \tag{10}$$

The KF algorithm is expressed using the electrical equivalent model, as shown below, utilizing the PNGV model provided in Fig. 6. The state equations of the battery are given in Eqs. (11) and (12), where u_b represents the voltage across the capacity C_b, u_2 denotes the voltage across the circuit composed of $R_2//C_2$, R_1 is the internal resistance, and U_{ocv} represents the open-circuit voltage.

$$\begin{bmatrix} u_b \\ u_2 \end{bmatrix} = \begin{bmatrix} 0\,0 \\ 0 - \dfrac{1}{R_2C_2} \end{bmatrix} \begin{bmatrix} u_b \\ u_2 \end{bmatrix} = \begin{bmatrix} \dfrac{1}{C_b} \\ \dfrac{1}{C_2} \end{bmatrix} I \tag{11}$$

$$U_{ocv} = [-1-1] \begin{bmatrix} u_b \\ u_2 \end{bmatrix} + (-R_1 I) + U_{ocv} \tag{12}$$

Various filters based on the KF algorithm, such as the Extended Kalman Filter (EKF) [69], Adaptive Extended Kalman Filter (AEKF) [70], Square Root Variant of the Cubature Kalman Filter (SCKF) [71], Invariant Extended Kalman Filter (IEKF) [72], and others, are utilized for SOC estimation in research studies. The EKF stands out as the most employed filter, and many other filters have been developed with the EKF serving as a reference. The EKF is an advanced estimation algorithm used to predict and refine parameters in dynamic systems, particularly in situations where the system's behavior is not linear. The EKF basic algorithm is given in Fig. 7.

3.2.2.2. Recursive Least Squares Method (RLS). The Least Squares method functions based on the assumption that the system is affected by white noise. It calculates the parameter values of the system in a way that minimizes the least squares error between the observed output signal and the expected output signal. The RLS method is used to find filter coefficients in adaptive filters, aiming to minimize the least squares error of the error signal, characterized as the variance between the desired signal and the output of the filter [74]. The RLS algorithm performs this process iteratively, updating the estimated parameter values by combining existing information at each sample time. Fig. 8, illustrates the RLS method algorithm, where e_k represents the prediction error, λ is the targeted forgetting factor, P_k is the prediction error for the covariance matrix and K_k denotes the RLS gain [50].

While RLS algorithm is not commonly used alone for SOC estimation,

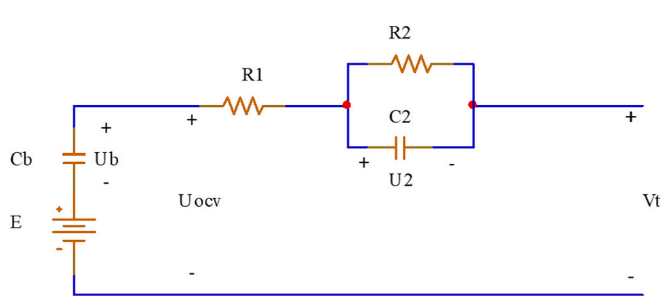

Fig. 6. Partnership for a New Generation of Vehicles (PNGV) equivalent circuit model [67].

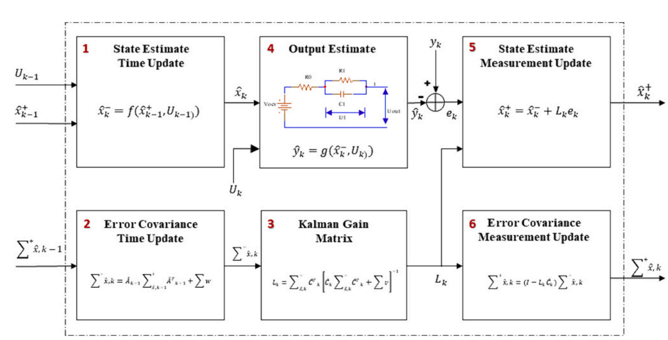

Fig. 7. Extended Kalman Filter (EKF) algorithm [73].

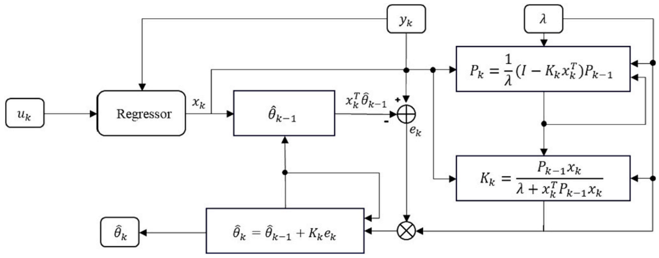

Fig. 8. Recursive least squares algorithm [50].

it can be integrated into a broader estimation framework. Typically, this integration involves selecting or developing a battery model capturing the battery's behavior, collecting data including voltage and current measurements, initializing model parameters, and iteratively updating them using RLS based on incoming data. The RLS-estimated parameters are then utilized within the battery model to estimate the SOC, allowing for real-time adaptation and integration into BMS for monitoring and optimization purposes. This comprehensive approach facilitates accurate SOC estimation, contributing to enhanced performance and longevity of BESS. RLS techniques have been widely employed for estimating circuit parameters in BMSs. In [75,76], RLS are utilized to estimate the parameters of a Thevenin ECM. Specifically, in [78], an RLS filter is dynamically employed in real-time to estimate the parameters of a Thevenin ECM. These model parameters are utilized to estimate the battery's OCV and subsequently its SOC using the fading KF method. In another approach utilized a single forgetting factor RLS method to obtain the second-order ECM parameters [77]. They applied an EKF for the final SOC estimation procedure.

3.2.2.3. H Infinity-Based Estimation (H∞). In H-Infinity-based estimation, a mathematical model representing the battery's real behavior is created using the battery model and measurement data. This method involves an optimized filtering process that utilizes the battery model and measurement data to estimate the true state of charge of the battery [78]. In [79], an enhanced SOC estimation algorithm based on $H\infty$ is introduced, integrating a sliding mode observer to achieve enhanced estimation stability and accuracy compared to traditional $H\infty$ approaches. The proposed algorithm capitalizes on the combined strengths of $H\infty$ and sliding mode observer, resulting in increased robustness against modeling errors and noises.

3.2.3. Adaptive artificial intelligence-based methods

Considering several studies in the literature [80–82], the most popular adaptive artificial intelligence-based SOC estimation methods are categorized into six groups: Genetic Algorithm (GA), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANN), Deep Learning (DL), Fuzzy Logic (FL), and Support Vector Machine (SVM). These methods have been widely explored and employed to enhance the accuracy and reliability of SOC estimation.

3.2.3.1. Genetic Algorithm-Based Estimation (GA). The GA is an optimization algorithm rooted in natural selection and genetic crossover principles. GA employs a population-based approach and evolves the genetic properties of individuals representing solutions [83]. In the realm of SOC estimation, genetic algorithms (GAs) serve as powerful optimization tools for refining parameters or models utilized in SOC estimation algorithms. Operating within a population-based framework, GAs initiate with a set of candidate solutions, each represented by chromosomes encoding parameters or models pertinent to SOC estimation. Through successive generations, GAs employ fitness functions to evaluate the performance of chromosomes in approximating the actual SOC values, favoring those yielding more accurate estimations [84]. By iteratively applying selection, crossover, mutation, and replacement operations, GAs facilitate the evolution of the population toward improved SOC estimation solutions. This process enables the adaptation and optimization of SOC estimation models, enhancing their accuracy and adaptability across diverse battery types and operating conditions [85]. When evaluating studies in the literature, GAs are not typically preferred as standalone methods for state of charge estimation. Instead, they serve as supportive algorithms for optimizing complex battery parameters and enhancing prediction accuracy within existing SOC methods.

The integration of GAs with the RLS method is widely adopted, particularly in fields such as system identification and parameter estimation. GAs are known for their ability to find optimal solutions in large search spaces, while the RLS method is a fast and effective system identification technique that can be adapted to real-time data. When used together, GAs enhance the predictive capabilities of RLS and can lead to better solutions [86]. This combination is considered an effective tool, particularly in modeling and controlling complex systems. In [77], a novel method for SOC estimation is introduced, utilizing the RLS algorithm with multiple fixed forgetting factors (SFFF-RLS and MFFF-RLS). The optimal values of the forgetting factors are determined using the GAs. By employing the GAs computer code for multiple objective optimizations, the proposed algorithm achieves a performance index of 1.0910^{-6} for SFFF-RLS and 2.1110^{-7} for MFFF-RLS. The results demonstrate that the proposed algorithm performs satisfactorily in estimating the SOC.

3.2.3.2. Adaptive Neuro-Fuzzy Inference Systems (ANFIS). Fuzzy Neural Networks is an artificial intelligence technique that integrates the concepts of fuzzy logic and artificial neural networks. This approach integrates the flexibility and ability to manage the uncertainty of fuzzy logic with the learning and modeling capabilities of artificial neural networks [87]. Fuzzy Neural Networks then input the data into the artificial neural network structure and adjust the network's weights and connections using learning algorithms. In this way, the most suitable model is created to predict the battery's state of charge [88]. When comparing the Backpropagation Artificial Neural Network (BPANN) model with the ANFIS, it is observed that ANFIS achieves superior prediction performance, especially when dealing with interpolation tasks. The study has revealed the potential of ANFIS in accurately modeling and predicting the behavior of complex nonlinear dynamic systems [89].

In [90], the input variables for the ANFIS model are selected through correlation analysis, considering the parameter options of nickel metal hydride battery (Ni-MH). The output characteristic of the Ni-MH batteries are generalized based on expert experience, and the ANFIS model is established, which involves selecting input variables and defining membership functions. Dai et al. present a study introducing an innovative online method for SOC estimation and validation in battery packs. The approach combines a traditional SOC estimator with an ANFIS. Initially, a KF based estimator determines the “averaged SOC,” which is then dynamically corrected by ANFIS, incorporating information about cell differences, and loading current. Experimental validation demonstrates that this method effectively mitigates drawbacks associated with traditional SOC estimators due to cell-to-cell variations, resulting in more accurate and reasonable corrected SOC values compared to traditional “averaged SOC” estimates [88].

3.2.3.3. Artificial Neural Networks (ANN). Artificial Neural Networks (ANNs) utilize measurements such as voltage, current, and temperature obtained from the battery as input data for SOC estimation. These data are fed into the input layer of the network and processed through connections between neurons. The output from the network's output layer represents the estimated SOC of the battery [91]. ANNs typically require a training process for SOC estimation, during which the network's weights and connections are adjusted using a training dataset. This dataset contains information based on real SOC values and measurements of the battery [92]. Throughout the training process, the ANN learns the optimal weight and connection values by working on this dataset. Fig. 9 illustrates the structure of a sample ANN [93].

The input signals vector is denoted as $X := [x_1, x_2, x_3 \ldots\ldots\ldots x_n]^t$ $n \in N = [1, |X|]$, the synaptic weights of the neurons are represented by $W_k := [W_{k1}, W_{k2}, W_{k3} \ldots\ldots\ldots W_{kn}]^t$ $n \in N = [1, |X|]$, u_k signifies the outcome of multiplying the weights with the input signals, while b_k denotes the bias a supplementary parameter of the neuron within the multiplication process. y_k represents the output response of the neuron, and φ(.) is the activation function [93]. Various ANN models can be used, including Feedforward Neural Networks (FNN) for simple relationships, Recurrent Neural Networks (RNN) for sequential data [94], Long Short-Term Memory (LSTM) for longer dependencies [95], Radial Basis Function Neural Networks (RBFNN) for interpolation tasks [93], and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) when dealing with uncertain data and linguistic terms [90]. The choice of the ANN model depends on the complexity of the SOC estimation problem and the characteristics of the battery data. Recent studies utilizing ANNs for SOC estimation can be summarized as follows.

Chemali et al. introduced a new method for accurate SOC estimation in Li-ion batteries utilizing a RNN with LSTM. The paper highlights the LSTM-RNN's capacity to capture temporal dependencies, achieving accurate SOC estimation without the need for battery models, filters, or inference systems like KFs. The study underscores the machine-learning technique's generalization capability, enabling the LSTM-RNN to accurately estimate SOC across diverse ambient temperature conditions. Through training on datasets recorded at various temperatures, the single network achieves a low mean absolute error (MAE) of 0.573 % at a constant ambient temperature and 1.61 % on a dataset with temperature variations from 10 to 25 °C [95]. Yang et al. present a paper proposing a stacked LSTM network with multiple hidden layers to estimate the SOC in LFP batteries. The network utilizes current, voltage, and temperature data as inputs and is trained offline on dynamic stress, US06, and urban-driven schedule test data to capture the intricate dynamics of battery behavior. The study evaluates the performance of the proposed LSTM network by comparing it to the UKF method, considering aspects such as tracking accuracy, computation time, and robustness against unknown initial SOC. Additionally, the research explores how the LSTM network's performance varies with different training and testing datasets [96]. Jun et al. explore an online method for estimating the SOC in batteries of pure electric vehicles, utilizing a RBFNN to address the batteries' nonlinear characteristics. The study adopts the RBFNN for its effectiveness in handling nonlinear problems. With a simplified structure and a small number of input variables, the method is validated using data from pure electric buses equipped with LiFePO4 Li-ion batteries during the 2010 Shanghai World Expo. The contribution analysis method identifies four crucial factors for SOC estimation, enhancing real-time performance, as demonstrated by experimental results.

3.2.3.4. Deep Learning-Based Methods (DL). Deep Learning-Based Methods are advanced techniques used for predicting the SOC of batteries by employing artificial neural networks and deep learning algorithms. These methods enable high prediction accuracy by directly processing the data obtained from batteries and automatically learning complex relationships [97]. Typically, multi-layered artificial neural networks, known as Deep Neural Networks (DNNs), are employed in this approach. These networks process input data through layers, allowing them to learn intricate and high-level features [98]. Data from the battery, such as voltage, current, and temperature, are defined into the input layer of these artificial neural networks and automatically processed by nodes in consecutive layers. This process enables the automatic discovery of internal features for accurately estimating the battery's state of charge [99]. Deep learning-based methods generally have the capability to learn more complex battery models due to their training on large datasets [100]. Moreover, these methods are particularly effective in cases with nonlinear relationships and when modeling the intricate behavior of batteries compared to traditional approaches [101]. However, the effectiveness of DL-based methods relies on the size and quality of the training dataset. When there is insufficient training data that adequately reflects all battery characteristics or improper parameter settings are used, the prediction accuracy may decrease [102]. An example of deep neural network architecture is given in Fig. 10.

In [103], a novel approach is presented for SOC estimation utilizing a DNN. The method requires only 10-min charging voltage and current data as input, enabling rapid and precise SOC estimation with a remarkable accuracy rate of less than 2.03 % across the entire battery SOC range. In [104], they determined that a DNN with an adequate number of hidden layers exhibits the capability to accurately predict SOC for unseen drive cycles during the training process. To assess their performance across various drive cycles, they constructed multiple DNN models with different numbers of hidden layers and conducted training algorithms. Remarkably, increasing the number of hidden layers in the DNN, up to four hidden layers, led to a reduction in error rate and a significant enhancement in SOC estimation accuracy.

3.2.3.5. Fuzzy Logic (FL). In the fuzzy logic-based SOC estimation, the data obtained from the battery is represented using fuzzy sets, and these sets are processed based on a set of rules. Measurement data are expressed in fuzzy sets according to specific criteria [105]. It is evident from the literature that fuzzy logic alone may not achieve high success in estimation [45]. Therefore, this method is combined with other techniques to enhance estimation accuracy. In [106], the study is focused on the development of a model-less fuzzy logic-based control system to address the combined effects of aging state and SOC variations among battery cells. The proposed approach relies solely on real-time measurements of current and cell voltages, along with pre-identified ECM

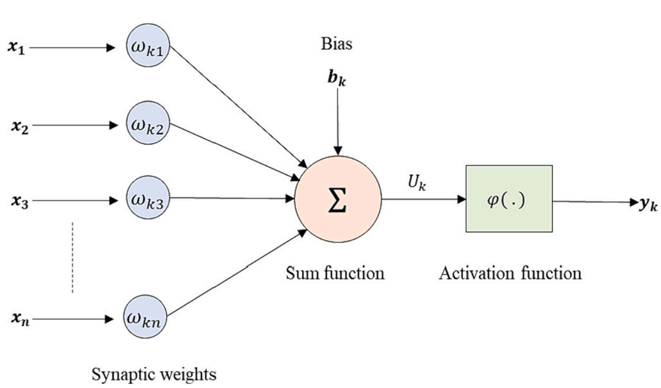

Fig. 9. Example neural network structure [93].

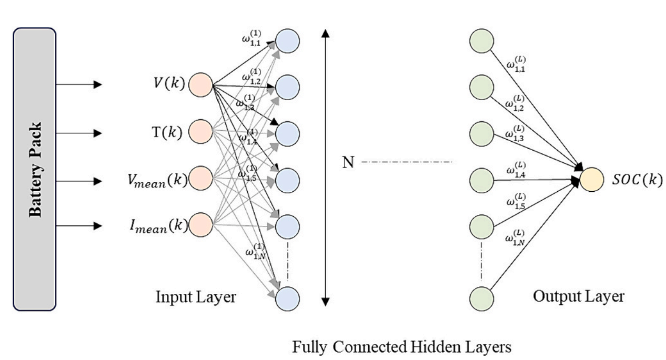

Fig. 10. Example deep neural network architecture [99].

parameters of the new cell obtained offline. By using this approach, the control system effectively compensates for differences in aging and SOC among cells, leading to improved battery performance and reliability.

3.2.3.6. Support Vector Machines (SVM). SVM is commonly used to achieve successful results in both classification and regression problems. Within the framework of estimating SOC, SVM is utilized to create a decision boundary or hyperplane to separate data points into different classes. To accurately predict the battery's state of charge, SVM undergoes a training process using pre-existing data. This training process involves using a training dataset that contains measurement data from the battery along with corresponding accurate state of charge labels [107]. In [108], the study proposes a SOC estimation method based on optimized SVM regression. The proposed method shows promising results in achieving high accuracy and reliability in SOC estimation for effective battery management. In [109], a novel approach called the improved barnacle mating optimizer-support vector machine (IBMO-SVM) model is introduced for the SOC estimation of Li-Ion batteries. The IBMO-SVM model combines the barnacle mating optimizer with the support vector machine technique to achieve enhanced accuracy and efficiency in SOC estimation.

3.2.4. Advanced algorithms

Advanced algorithms provide higher prediction accuracy in today's SOC estimation compared to traditional methods [110]. These advanced algorithms can be categorized into three main groups: Transfer Learning-Based Methods (TL), and Hybrid Methods.

3.2.4.1. Transfer Learning-Based Methods (TL). TL for SOC estimation involves transferring knowledge learned from a previous battery model or a similar battery to the target battery. This approach utilizes a pre-trained model or network to predict the state of charge of batteries, requiring less data for training the new battery. Consequently, less time and resources are needed to estimate the SOC for a new battery [111]. The method exhibits a notable capacity for generalization across diverse battery models or batteries displaying distinct characteristics. The learned knowledge can be effective in predicting the SOC for new batteries in areas where similarities and patterns are found [112]. However, the success of transfer learning methods relies on the appropriate selection of the source task and the adaptation of transferred knowledge to the target task. Additionally, some disparities may exist between different battery models or batteries with different features, so transfer learning methods should be appropriately configured and fine-tuned [113].

In [114], the authors demonstrate the application of the Temporal Convolutional Network (TCN) network to directly map voltage, current, and temperature data to the SOC of a lithium-ion battery. The network utilizes a specialized dilated causal convolution structure, which exhibits improved capability in processing battery timing data. Through a self-learning process during training, the model can update its parameters, resulting in accurate SOC estimation. Notably, the proposed method eliminates the need for manual battery model establishment and the determination and calculation of numerous parameters, making it more suitable for onboard systems. Transfer learning architecture is given in Fig. 11.

In reference [115], a novel approach for SOC estimation in lithium-ion batteries is proposed using a DNN with TL. Unlike traditional methods, this approach utilizes pre-trained DNN parameters to enhance accuracy and reduce training time and data needs. The results demonstrate up to 64 % better accuracy and improved performance with a reduced amount of training data. In their work [116], the authors present a data-driven SOC estimation framework for LIBs that considers varying ambient temperatures. The authors utilize TL to improve the precision of SOC estimation for novel temperature conditions, showcasing superior effectiveness when contrasted with alternative algorithms. The proposed method proves to be practical and effective, but it faces challenges when dealing with large-scale temperature variations.

3.2.4.2. Hybrid methods. Hybrid methods are an approach that combines multiple techniques to achieve higher prediction accuracy. The goal of current and future studies is to integrate the advantages of different prediction methods to attain improved accuracy in SOC estimation [117]. Hybrid methods aim to achieve more precise and reliable results in estimating the SOC by using the advantages of diverse estimation methods. In [118], the authors investigate the recent literature on lithium-ion battery SOC estimation using hybrid methods that combine neural networks with Kalman filtering (NN-KF). The methods are thoroughly examined and discussed, focusing on aspects such as battery model, algorithm structure, implementation process, suitable environment, parameter identification, advantages, disadvantages, and estimation errors.

In [119], a hybrid method called Convolutional Neural Network-Bidirectional Weighted Gated Recurrent Unit (CNN-BWGRU) network is proposed for SOC estimation. The method incorporates a “multi-moment input” structure and a bidirectional network to optimize the influence of battery information on the results. The CNN is employed to acquire feature parameters from the input data, and in tandem, the BWGRU enhances the fitting performance under lower temperatures through adaptive weight adjustments. The presented network showcases robust generalization capabilities, remarkable precision in estimation, and a high degree of resilience. The evaluation of SOC estimation spans diverse scenarios to verify the network's efficacy and dependability.

3.2.5. Other methods

The methods mentioned in the previous sections are widely used in battery SOC estimation. In addition to these methods, Regression-Based

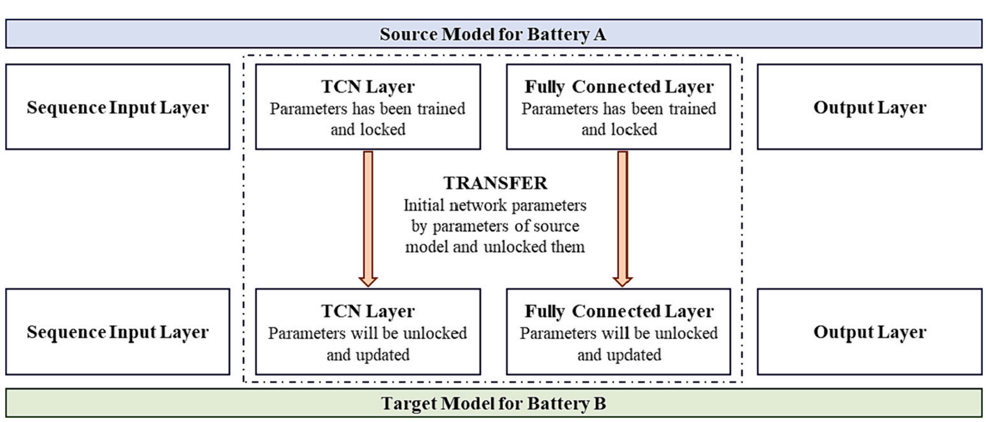

Fig. 11. Example transfer learning architecture [114].

Algorithms, Filter-Based Methods, Optimization Algorithms, and Observer Methods are also used directly for SOC estimation or as assisting methods/algorithms in improving traditional methods. Regression-Based Methods such as Multivariate Adaptive Regression Splines (MARS) [120], Gaussian Process Regression (GPR) [121], and Random Forest Regression (RFR) [122] are widely employed in battery SOC estimation. MARS, with its ability to fit piecewise linear regressions, is adept at capturing non-linear relationships within the data. GPR, a non-parametric approach utilizing Gaussian processes, offers flexibility, especially in scenarios with limited data or where uncertainty estimation is critical. On the other hand, RFR, an ensemble method leveraging multiple decision trees, excels in handling non-linearities and interactions between variables while remaining robust against overfitting. These methods play crucial roles in accurately predicting battery charge states and can significantly enhance existing estimation techniques.

Filter-Based Methods such as Sequential Monte Carlo-Particle Filters (SMC-PF) [111] and Smooth Variable Structure Filter (SVSF) [123] play pivotal roles in battery charge state estimation, addressing uncertainties and system complexities inherent in dynamic battery systems. SMC-PF, also known as the Particle Filter, employs a set of particles to represent the system state's posterior distribution, making it adept at handling nonlinear and non-Gaussian systems. Meanwhile, SVSF combines the benefits of variable structure systems with smooth transition properties, effectively managing uncertainties and disturbances in dynamic systems like batteries. These methods enhance the reliability and performance of battery management systems by accurately tracking state evolution and adapting to abrupt changes and noisy environments encountered during charge state estimation.

Optimization Algorithms like Particle Swarm Optimization (PSO) and Hybridizing Coyote Optimization Algorithm (HCOAG) are essential tools in battery charge state estimation. PSO mimics natural behaviors to efficiently search parameter spaces, enhancing model accuracy and convergence rates. On the other hand, HCOAG's hybrid nature combines diverse optimization strategies, empowering it to explore complex search spaces effectively [124]. The integration of ANN with Particle Swarm Optimization (PSO) leverages the collective intelligence and natural selection features of PSO to effectively optimize the parameters of the ANN. This methodology focuses on minimizing the predetermined objective function to identify the most suitable parameter set. The obtained optimized parameters are subsequently integrated into the ANN model, enhancing its performance, and ensuring better alignment with specific problem requirements. This strategy proves to be an effective optimization tool, particularly when dealing with the intricate parameter spaces inherent in ANN structures. PSO is an optimization algorithm inspired by the natural behavior of a group of particles. In this algorithm, a group of particles moves in a defined search space to find the best solution for an optimization problem [125]. When applied to optimization problems such as SOC estimation, the particles move within the solution space representing the battery's SOC. Each particle represents a solution point, and their velocities and positions are updated according to predefined rules during the optimization process. PSO aims to iteratively converge toward the optimal solution by exploiting the collective intelligence of the particles to find the best SOC estimation for the battery [126]. In [127], the PSO algorithm is employed to enhance the accuracy of the Radial Basis Function Neural Network (RBFNN) estimation model, resulting in the PSO-RBFNN method. Through verification, it has been demonstrated that the PSO-RBFNN method outperforms the conventional RBFNN approach in terms of estimation performance.

Observer Methods like Sliding Mode Observer (SMO) and Multi-Gain Luenberger-Based Observer (MGLO) are fundamental in battery charge state estimation, enabling the inference of system states based on available measurements. SMO, with its robustness against uncertainties and disturbances, utilizes a sliding surface to align system states with estimated states, making it apt for battery systems [128]. Meanwhile, MGLO, employing multiple gain matrices, enhances observer performance across diverse operating conditions, thus improving accuracy and adaptability in charge state estimation [111]. These methods play crucial roles in accurately assessing battery charge states by effectively utilizing measurements and addressing uncertainties and disturbances inherent in dynamic battery systems.

4. Comparison of SOC estimation methods

As the need to reduce carbon emissions in electric vehicles becomes essential for clean technology, Li-Ion batteries have emerged as a crucial energy storage system in electric vehicles due to their high energy density, long cycle life, and low self-discharge. When considering most studies conducted in recent years, the estimation of charge and health status in BMS has emerged as an important research area. The following paragraph provides a summary of important studies conducted in recent years.

Zhao et al. have developed a new TL method by considering the conditional probability distribution and achieved high accuracy in SOC estimation [129]. Xie et al. proposed a distributed spatial-temporal online correction algorithm for the joint estimation of SOC and state of temperature (SOT) in a three-dimensional (3D) battery temperature scenario. The joint estimation method achieved a 1.5 % improvement in prediction accuracy compared to traditional methods [130]. Wadi et al. proposed an EKF extension called the Invariant EKF (IEKF) for SOC estimation of lithium-ion battery cells. Unlike classical methods like EKF and existing methods like Square Root Cubic Kalman Filter's square root variant, IEKF can handle non-linear dynamics by reducing the complexity of measurement noise [72]. Shu et al. suggested a hybrid model that considers temperature and current variations and developed an advanced algorithm for high-accuracy SOC estimation. The method is based on reliable parameter identification and capacity recognition, and it uses an adaptive H-infinity filter to predict SOC while considering different temperature and current profiles and variations in operating conditions [131]. Mondal et al. conducted research on real-time SOC estimation errors of Li-Ion batteries using a combined predictive online parameter identification and adaptive extended KF based on a second-order equivalent circuit model. The diagnostic techniques formulated through the proposed model were seamlessly integrated into a cloud-based system, thereby facilitating uninterrupted and precise monitoring of battery status [132]. Tang et al. proposed an innovative digital twin-based SOC estimation system. Additionally, they proposed the conjugate H-Infinity Filter-Particle Filter (HIF-PF) online algorithm for SOC estimation under the Beijing Bus Dynamic Stress Test (BBDST) experimental conditions and compared it with the traditional EKF, H-Infinity Filter (HIF), and Particle Filter (PF) methods [133].

Sylvestrin et al. developed an affordable adaptive open-source BMS prototype designed to oversee parameters within a multi-cell battery pack (consisting of 10 cells), including monitoring capabilities for the battery system. The verification of the proposed BMS involved tests with two different battery technologies, namely Li-Ion (18,650 type) and sodium nickel chloride. The flexibility of the BMS to work with these two technologies and its ability to perform state of charge estimation demonstrated the system's adaptive nature [134]. Li et al. proposed a new flexible and dependable BMS based on a big data platform and cyber-physical system technology. The proposed methodologies were validated using actual data collected from electric buses. The maximum SOC estimation error in the suggested feature-based battery modeling method was determined to be 2.47 % [135]. In their study, Song et al. proposed a unified CNN and LSTM network to estimate battery SOC. The results demonstrated that the suggested CNN-LSTM network effectively captured the nonlinear relationships between SOC and measurable variables, outperforming individual LSTM and CNN networks in tracking performance. Moreover, the proposed network accounted for the influence of ambient temperature in SOC estimation, achieving a maximum mean error below 1.5 % and a maximum root mean square

Table 1
Comparison of SOC estimation methods for different studies.

Ref No	Direct measurement methods		Indirect analysis methods					
	Open-Circuit Voltage (OCV)	Coulomb Counting (CC)	Equivalent Circuit Model (ECM)	Kalman Filter (KF)	Particle Filter (PF)	Deep Learning (DL)	Artificial Neural Networks (ANN)	Transfer Learning (TL)
[51]	✓	✓	.	.	.	.	.	.
[57]	✓	.	.	✓	.	.	.	.
[66]	.	.	.	✓	.	.	.	.
[69]	.	.	.	✓	.	.	.	.
[70]	✓	.	✓	✓	.	.	.	.
[72]	.	.	✓	✓	.	.	.	.
[91]	✓	✓	.	.	.	.	✓	.
[93]	.	.	.	✓	.	.	✓	.
[99]	.	.	.	.	.	✓	.	.
[102]	✓	.	✓	.	.	✓	.	.
[113]	.	.	.	.	.	✓	.	✓
[114]	.	.	.	.	.	✓	✓	✓
[124]	.	.	.	.	.	.	✓	.
[129]	.	✓	.	.	.	✓	.	✓
[130]	.	✓	.	✓	.	.	.	.
[131]	.	.	✓	✓	.	.	.	.
[132]	.	.	✓	✓	.	.	.	.
[133]	.	.	✓	✓	✓	.	.	.
[134]	.	✓	.	✓	.	.	.	.
[135]	.	.	✓	.	.	✓	✓	.
[136]	.	.	.	.	.	✓	✓	.
[64]	✓	.	✓	.	.	.	.	.
[137]	✓	✓	.	✓	.	.	.	.
[138]	✓	✓	✓	✓	.	✓	✓	✓
[139]	✓	✓	✓	✓	.	✓	✓	✓
[140]	.	.	✓	.	✓	.	.	.
[141]	.	.	✓	✓	.	✓	✓	.
[142]	✓	✓	✓	.	.	.	.	.
[11]	✓	✓	✓	✓	✓	✓	✓	✓

error (RMSE) below 2 % [136]. Consequently, the studies demonstrate advancements in SOC estimation methodologies, with improved accuracy, efficiency, and adaptability, contributing to the development of more reliable BMSs for EVs and energy storage applications.

Table 1 presents a comparison of the most popular methods (especially in EV BMSs) for SOC estimation. When reviewing the current studies in the literature regarding the direct measurement methods presented in Fig. 3, it becomes evident that the most preferred methods in BMSs of EV systems are OCV and CC methods. These methods are favored in electric vehicles due to their simplicity and cost-effectiveness. However, the accuracy of SOC estimation obtained through these methods is often not at the desired level. On the other hand, when indirect analysis methods are considered, it is generally observed that methods based on KF and ECM can more effectively determine the dynamic characteristics of the battery. These methods are commonly used in electric vehicles and are preferred due to their ability to analyze the dynamic properties of the battery more accurately. However, a disadvantage of these methods is their inability to identify the nonlinear characteristics of the battery and the complexity of the calculation process.

In recent years, artificial intelligence-based methods, particularly deep learning, artificial neural networks, and transfer learning, have gained significance in various studies. Artificial intelligence methods employed in battery state prediction stand out with their ability to analyze extensive datasets with high accuracy. These methods offer significant advantages in adapting to changes in battery performance, effectively evaluating complex datasets, and predicting charge status with high accuracy. However, drawbacks such as data dependency, model interpretability, computational power requirements, data quality, computational resources, ethical responsibilities, and long learning periods are also observed. It is anticipated that these methods will be more widely adopted in electric vehicle systems in the future.

The general advantages and disadvantages of the SOC estimation methods most frequently encountered in the literature are summarized in Tables 2 and 3, respectively. Table 4 provides a thorough evaluation of various SOC estimation methods for BMS in EVs. The assessment encompasses their broad application, merits, challenges, and respective ratings. The implementation of SOC estimation methods in BMS for EVs involves various approaches, each with its advantages and challenges. The CC method provides a real-time SOC estimation suitable for diverse applications, but issues like integration errors, initial calibration, and environmental sensitivity require meticulous consideration. On the other hand, the OCV method, characterized by simplicity and reduced sensitivity to integration errors, faces challenges related to nonlinearities, temperature dependencies, and precise voltage measurements. EIS offers valuable insights into battery electrochemical behavior, but challenges such as data interpretation complexity and potential intrusiveness must be carefully addressed for practical

Table 2
Advantages and disadvantages for direct measurement methods.

Category	Method	Advantages	Disadvantages
Direct measurement methods	Open-Circuit Voltage (OCV)	1. High estimation accuracy. 2. Easily applicable to different battery chemistries.	1. Online prediction is not possible. 2. The battery must be kept open-circuit for a certain period.
	Coulomb Counting (CC)	1. Easy to implement and does not require complex algorithms. 2. CC does not require a detailed battery model or complex calibration processes.	1. CC may not be suitable for all battery chemistries and may require calibration and adjustments for different battery types.

Table 3
Advantages and disadvantages for indirect analysis methods.

Category	Method	Advantages	Disadvantages
Indirect analysis methods	Kalman Filter (KF)	1. Ability to manage dynamic and changing conditions. 2. Effective in filtering noisy data and reducing measurement errors.	1. It is not suitable for non-linear systems. 2. As the number of state variables increases, the computation time also increases.
	Extended Kalman Filter (EKF)	1. High estimation accuracy. 2. Effective for nonlinear battery behavior and robust to noise and uncertainties. 3. Adaptable to various battery types and conditions.	1. Computationally expensive with many state variables. 2. Sensitive to initial parameter estimates, requiring careful tuning. 3. Requires a well-defined system model, challenging for complex battery systems.
	Recursive Least Squares (RLS)	1. RLS is computationally efficient and memory-friendly. 2. Provides real-time updates and continuous improvement. 3. Less sensitive to initial parameter estimates and flexible for different battery systems.	1. RLS can be computationally intensive compared to simple estimation methods. 2. It is sensitive to outliers in the data, which can lead to inaccurate results. 3. The performance of RLS can be affected by the choice of initial parameter values.
	H Infinity ($H\infty$)	1. Robustness against uncertainties and disturbances. 2. Stability in the presence of noise or measurement errors. 3. Effectiveness in handling non-linear and time-varying systems.	1. Increased computational complexity, leading to longer processing times. 2. Challenging requirement of accurate modeling and system identification. 3. Expertise and careful tuning are needed for $H\infty$ controller design.
	Deep Learning (DL)	1. High estimation accuracy. 2. Fast learning performance for non-linear systems. 3. Data-driven, generalizable, and adept with time-series measurements.	1. Large amount of data required for training. 2. DL models are often considered "black-box" models, making interpretation challenging. 3. Prone to overfitting with limited or noisy data, reducing generalization performance.
	Transfer Learning(TL)	1. Improved accuracy with less training data 2. Faster training time due to leveraging pre-trained models 3. Generalization across different battery models or characteristics	1. Need for a large and diverse dataset during pre-training. 2. Potential overfitting if not properly adapted to the target domain. 3. Performance limitations in scenarios with different battery models.
	Genetic Algorithm (GA)	1. High accuracy in state-of-charge estimation is achieved. 2. Global search capability. 3. Suitable for large solution spaces and no gradient information required.	1. Computationally expensive. 2. Parameter sensitivity and premature convergence. 3. Lack of domain-specific knowledge.
	Artificial Neural Networks (ANN)	1. Can adapt and update their models with new data, allowing for continuous learning. 2. Generalization capability across different battery models and operating conditions. 3. High accuracy in SOC estimation when trained.	1. May require a large amount of training data and computation time for complex models. 2. Susceptible to overfitting, especially with limited data or excessive model complexity. 3. Initial training and parameter tuning can be time-consuming and resource-intensive.
	Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	1. Flexible modeling of complex nonlinear battery behaviors. 2. Handling uncertainty and noisy data effectively. 3. Hybrid approach combining human expertise and data-driven learning.	1. Challenging rule and membership function design. 2. Increased computational complexity with high-dimensional data. 3. Performance dependent on training data quality.

implementation. ECM provide real-time capability with lower computational complexity, yet challenges encompass accuracy, aging effects, dynamics, generalization, and temperature sensitivity. Electrochemical models boast high accuracy but demand careful attention to computational complexity, model calibration, generalization, sensitivity to uncertainties, and substantial data requirements. Kalman Filters enable real-time estimation and integration of multiple data sources, but challenges arise from model complexity, sensor errors, initialization sensitivity, computational load, and assumptions of linearity. RLS methods offer real-time adaptability and robustness to initialization, but challenges encompass model complexity, memory requirements, parameter tuning, measurement quality, and computational intensity. H-Infinity methods, known for robustness and optimal control features, face challenges regarding complexity, computational intensity, parameter tuning, modeling requirements, and adaptability to nonlinearities. TL, although efficient in data usage and improved generalization, requires careful management of challenges such as domain adaptation, model overfitting, source domain selection, transferability, and fine-tuning. Hybrid methods, combining advantages in robustness, accuracy, adaptability, and flexibility, necessitate addressing challenges related to complexity, model fusion, parameter tuning, computational load, and interpretability.

Genetic algorithms, offering global optimization and adaptability to nonlinearity, pose challenges in computational intensity, parameter tuning, convergence, dependence on the initial population, and scalability. ANFIS present advantages in nonlinear approximation and adaptability to uncertainty but face challenges in complex parameter tuning, data requirements, overfitting, interpretability trade-off, and computational intensity. ANN and deep learning methods share advantages in nonlinear approximation, adaptability, and parallel processing but confront challenges related to data requirements, overfitting, parameter tuning, lack of interpretability, and computational intensity. Fuzzy logic methods provide interpretability and adaptability but face challenges in subjectivity in rule formulation, limited learning capability, handling nonlinearities, sensitivity to rule parameters, and limited generalization. SVMs excel in high-dimensional modeling and versatility with the kernel trick but encounter challenges in parameter tuning, memory intensity, limited interpretability, sensitivity to noisy data, and adaptability to changing conditions. In summary, the choice of SOC estimation method for electric vehicles necessitates a careful consideration of these advantages and challenges in order to achieve effective and reliable outcomes in practical applications.

Table 4
Advantages, disadvantages, and rating of SOC methods in EV BMSs.

	Method	Rating for BMSs in EVs	Advantages	Challenges	Ref.
Direct measurement methods	CC	✓✓✓	Simplicity, low cost, real-time performance	Accumulated error, calibration requirements, limited accuracy	[56]
	OCV	✓✓	Model Simplicity, low sensitivity to integration errors, applicability during rest periods	Nonlinearity and hysteresis, dependency on battery model, limited dynamic response	[57]
	EIS	X	Non-destructive characterization, comprehensive information, high sensitivity	Complex interpretation, data processing requirements, limited accuracy at high frequencies, dependency on initial conditions	[61]
Model-based methods	ECM	✓✓✓✓	Real-time capability, low computational complexity, less dependency on calibration	Limited accuracy, aging effects, limited dynamics, sensitivity to temperature variations	[50]
	EChM	X	Incorporation of aging effects, high accuracy, adaptability to different conditions, dynamic response	Computational complexity, model calibration, limited generalization	[65]
Adaptive filter-based methods	KF	✓✓✓✓	Real-time estimation, integration of multiple data sources, adaptability to system dynamics,	Model complexity, sensor noise and errors, initialization sensitivity, assumption of linearity	[73]
	RLS	✓	Low sensitivity to initialization, adaptability to nonlinearities, ability to handle noisy measurements	Model complexity, memory requirements, dependency on measurement quality	[71]
	H∞	✓	Robustness, adaptability to uncertainties, performance under disturbances	Complexity, computational intensity, modeling requirements, limited adaptability to nonlinearities	[79]
Adaptive artificial intelligence-based methods	GA	✓	Global optimization, parallel processing, adaptability to nonlinearity, no requirement for derivatives	Computational intensity, dependence on initial population, limited scalability	[77]
	ANFIS	✓	Nonlinear approximation, adaptability to uncertainty, learning from data, rule-based interpretability	Complex parameter tuning, data requirements overfitting, interpretability trade-off, computational intensity	[88]
	ANN	✓✓	Nonlinear approximation, adaptability to system dynamics, learning from data, parallel processing, feature extraction	Data Requirements, overfitting, complex parameter tuning, lack of interpretability, computational intensity	[93]
	DL	✓✓	Hierarchical feature learning, adaptability to diverse data, end-to-end learning,	Data requirements, interpretability, overfitting, complexity, and parameter tuning	[103]
	FL	✓	Interpretability, rule-based system, adaptability, simplicity, and ease of Implementation	Limited learning capability, sensitivity to rule parameters, limited generalization	[106]
	SVM	✓	Effective in high-dimensional spaces, kernel trick for nonlinear relationships, global optimization, regularization for generalization	Memory intensive for large datasets, limited interpretability, difficulty in handling noisy data, limited adaptability to changing conditions	[109]
Advanced algorithms	TL	✓	Data efficiency, reduced training time, enhanced robustness, addressing limited data availability	Model overfitting, transferability issues, fine-tuning challenges	[114]
	Hybrid methods	✓✓	Enhanced robustness, improved accuracy, adaptability to dynamic conditions, flexibility in data fusion	Complex implementation, model fusion challenges, parameter tuning complexity, computational load	[119]

✓✓✓✓: Very High, ✓✓✓: High, ✓✓: Medium, ✓: Low, X: Not use in directly in EV BMSs.

5. Conclusions

The research in recent years has been focused on advanced SOC estimation methods for Li-Ion batteries, especially in the context of EVs. The increasing interest in EV has driven the need for accurate and reliable SOC estimation to optimize battery usage and enhance driving range. Various approaches have been explored to improve SOC estimation accuracy, including data-driven techniques, machine learning algorithms, and advanced filtering methods. Data-driven estimation methods, such as Coulomb counting, and model-based techniques like Kalman filters, have been widely used and have shown promising results. The integration of artificial intelligence, deep learning, and hybrid models has further improved SOC estimation performance. Algorithms like CNN, ANN, TL and LSTM networks have demonstrated their ability to capture complex relationships between SOC and measurable variables. However, challenges remain in SOC estimation, particularly in dealing with non-linear battery behavior, temperature variations, and diverse operating conditions. Researchers are persistently working to improve the robustness and adaptability of SOC estimation methods in response to these challenges. The main contribution of this study is to provide an overview of the most recent advancements in SOC estimation methods. It includes a comprehensive review of the latest research and literature on battery SOC estimation, highlighting the innovative approaches and developments in this area.

As the EV market continues to growth, the demand for accurate SOC estimation will remain crucial for optimal battery management and overall vehicle performance. Further research in this area will focus on refining existing algorithms, exploring new data-driven techniques, and integrating advanced sensor technologies to achieve real-time and reliable SOC estimation in electric vehicles. The subsequent phase of this study involves the creation of an inclusive review article, designated as Part 2, that will extensively explore the field of battery health estimation. This segment aims to provide an in-depth analysis of relevant literature sources, contributing significantly to the understanding of this subject matter. During this phase, a meticulous review of existing knowledge pertaining to battery health prediction will be conducted. By scrutinizing a range of scholarly materials, research papers, and related publications, this study endeavors to offer a comprehensive grasp of the predictive techniques utilized for assessing battery health.

CRediT authorship contribution statement

Osman Demirci: Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Sezai Taskin:** Supervision, Validation, Writing – review & editing. **Erik Schaltz:** Methodology, Supervision, Writing – review & editing. **Burcu Acar Demirci:** Investigation, Visualization, Writing – original draft.

Declaration of competing interest

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

Data availability

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

References

[1] V. Chobanov, K. Bojkov, Evaluation of economic and social effects of integrating a BMS system in residential and commercial housing, in: ISMSIT 2021 - 5th Int. Symp. Multidiscip. Stud. Innov. Technol. Proc, 2021, pp. 74–77, https://doi.org/10.1109/ISMSIT52890.2021.9604703.

[2] International Energy Agengy, Global EV Outlook 2015, Geo, 2015, pp. 9–10.

[3] C.C. Chan, An overview of electric vehicle technology, Proc. IEEE 81 (1993) 1202–1213, https://doi.org/10.1109/5.237530.

[4] J. Kim, V. Mathew, B. Sambanam, M.H. Alfaruqi, S. Kim, Recent developments of zinc-ion batteries, Energy-Sustainable Adv. Mater. 33 (2021) 27–57, https://doi.org/10.1007/978-3-030-57492-5_2.

[5] Electric vehicle battery market sales projected to grow at 26.52% CAGR by 2032 driven by decreasing costs of lithium-ion batteries. https://www.globenewswire.com/en/news-release/2023/04/06/2642915 (accessed June 5, 2023).

[6] H.A. Gabbar, A.M. Othman, M.R. Abdussami, Review of battery management systems (BMS) development and industrial standards, Technologies 9 (2021), https://doi.org/10.3390/technologies9020028.

[7] D. Marcos, M. Garmendia, J. Crego, J.A. Cortajarena, Functional safety bms design methodology for automotive lithium-based batteries, Energies 14 (2021) 1–19, https://doi.org/10.3390/en14216942.

[8] N.G. Panwar, S. Singh, A. Garg, A.K. Gupta, L. Gao, 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. 9 (2021) 1–17, https://doi.org/10.1002/ente.202000984.

[9] J. Qi, D. Dah-Chuan Lu, Review of battery cell balancing techniques, in: 2014 Australas. Univ. Power Eng. Conf. AUPEC 2014 - Proc, 2014, pp. 1–6, https://doi.org/10.1109/AUPEC.2014.6966514.

[10] M. Zheng, B. Qi, H. Wu, A li-ion battery management system based on CAN-bus for electric vehicle, in: 2008 3rd IEEE Conf. Ind. Electron. Appl. ICIEA 2008, 2008, pp. 1180–1184, https://doi.org/10.1109/ICIEA.2008.4582704.

[11] Y. Wang, J. Tian, Z. Sun, L. Wang, R. Xu, M. Li, Z. Chen, A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems, Renew. Sustain. Energy Rev. 131 (2020) 110015, https://doi.org/10.1016/j.rser.2020.110015.

[12] M. Adaikkappan, N. Sathiyamoorthy, Modeling, state of charge estimation, and charging of lithium-ion battery in electric vehicle: a review, Int. J. Energy Res. 46 (2022) 2141–2165, https://doi.org/10.1002/er.7339.

[13] Z. He, Z. Yang, X. Cui, E. Li, A method of state-of-charge estimation for EV power lithium-ion battery using a novel adaptive extended Kalman filter, IEEE Trans Veh Technol 69 (2020) 14618–14630, https://doi.org/10.1109/TVT.2020.3032201.

[14] J. Yu, State-of-health monitoring and prediction of lithium-ion battery using probabilistic indication and state-space model, IEEE Trans. Instrum. Meas. 64 (2015) 2937–2949, https://doi.org/10.1109/TIM.2015.2444237.

[15] J. Kim, S. Lee, B.H. Cho, Complementary cooperation algorithm based on DEKF combined with pattern recognition for SOC/capacity estimation and SOH prediction, IEEE Trans. Power Electron. 27 (2012) 436–451, https://doi.org/10.1109/TPEL.2011.2158554.

[16] B. Saha, S. Poll, K. Goebel, J. Christophersen, An integrated approach to battery health monitoring using Bayesian regression and state estimation, in: AUTOTESTCON (Proceedings), 2007, pp. 646–653, https://doi.org/10.1109/AUTEST.2007.4374280.

[17] M. Ahwiadi, W. Wang, An enhanced particle filter technology for battery system state estimation and RUL prediction, Meas. J. Int. Meas. Confed. 191 (2022) 110817, https://doi.org/10.1016/j.measurement.2022.110817.

[18] Y. Song, D. Liu, H. Liao, Y. Peng, A hybrid statistical data-driven method for on-line joint state estimation of lithium-ion batteries, Appl. Energy 261 (2020) 114408, https://doi.org/10.1016/j.apenergy.2019.114408.

[19] A. Otto, S. Rzepka, T. Mager, B. Michel, C. Lanciotti, T. Günther, O. Kanoun, Battery management network for fully electrical vehicles featuring smart systems at cell and pack level, Adv. Microsystems Automot. Appl. 2012 Smart Syst. Safe, Sustain. Networked Veh. (2012) 3–14. doi:https://doi.org/10.1007/978-3-642-29673-4_1.

[20] B. Gou, Y. Xu, X. Feng, State-of-health estimation and remaining-useful-life prediction for lithium-ion battery using a hybrid data-driven method, IEEE Trans Veh Technol 69 (2020) 10854–10867, https://doi.org/10.1109/TVT.2020.3014932.

[21] I. Aydin, Ö. Üstün, A basic battery management system design with IoT feature for LiFePO4 batteries, in: 2017 10th Int. Conf. Electr. Electron. Eng. ELECO 2017. 2018-Janua, 2018, pp. 1309–1313.

[22] M.H. Hung, C.H. Lin, L.C. Lee, C.M. Wang, State-of-charge and state-of-health estimation for lithium-ion batteries based on dynamic impedance technique, J. Power Sources 268 (2014) 861–873, https://doi.org/10.1016/j.jpowsour.2014.06.083.

[23] Y. Xing, E.W.M. Ma, K.L. Tsui, M. Pecht, Battery management systems in electric and hybrid vehicles, Energies 4 (2011) 1840–1857, https://doi.org/10.3390/en4111840.

[24] M.S. Hossain Lipu, M.A. Hannan, T.F. Karim, A. Hussain, M.H.M. Saad, A. Ayob, M.S. Miah, T.M. Indra Mahlia, Intelligent algorithms and control strategies for battery management system in electric vehicles: progress, challenges and future outlook, J. Clean. Prod. 292 (2021), https://doi.org/10.1016/j.jclepro.2021.126044.

[25] M.K. Tran, S. Panchal, T.D. Khang, K. Panchal, R. Fraser, M. Fowler, Concept review of a cloud-based smart battery management system for lithium-ion batteries: feasibility, logistics, and functionality, Batteries 8 (2022), https://doi.org/10.3390/batteries8020019.

[26] B. Balasingam, M. Ahmed, K. Pattipati, Battery management systems-challenges and some solutions, Energies 13 (2020) 1–19, https://doi.org/10.3390/en13112825.

[27] C.F. Chiasserini, R.R. Rao, Energy efficient battery management, IEEE J Sel Areas Commun 19 (2001) 1235–1245, https://doi.org/10.1109/49.932692.

[28] A. Nath, B. Rajpathak, Analysis of cell balancing techniques in BMS for electric vehicle, in: 2022 Int. Conf. Intell. Controll. Comput. Smart Power, ICICCSP 2022, 2022, pp. 1–6, https://doi.org/10.1109/ICICCSP53532.2022.9862513.

[29] M. Uzair, G. Abbas, S. Hosain, Characteristics of battery management systems of electric vehicles with consideration of the active and passive cell balancing process, World Electr. Veh. J. 12 (2021), https://doi.org/10.3390/wevj12030120.

[30] H. Wang, S. Zhang, T. Qiu, H. Liu, L. He, Z. Wang, Battery management system design for industrial manufacture, in: 2022 IEEE 25th Int. Conf. Comput. Support. Coop. Work Des. CSCWD 2022, 2022, pp. 1065–1070, https://doi.org/10.1109/CSCWD54268.2022.9776233.

[31] J. Kim, J. Oh, H. Lee, Review on battery thermal management system for electric vehicles, Appl. Therm. Eng. 149 (2019) 192–212, https://doi.org/10.1016/j.applthermaleng.2018.12.020.

[32] F. Basic, C. Steger, C. Seifert, R. Kofler, Trust your BMS: designing a lightweight authentication architecture for industrial networks, in: Proc. IEEE Int. Conf. Ind. Technol. 2022-Augus, 2022, pp. 1–6, https://doi.org/10.1109/ICIT48603.2022.10002825.

[33] A. Samanta, S.S. Williamson, A survey of wireless battery management system: topology, emerging trends, and challenges, Electron 10 (2021) 1–12, https://doi.org/10.3390/electronics10182193.

[34] W. Menghua, X. Bing, A real-time android-based monitoring system for the power lithium-ion battery used on EVs, in: Proc. - 10th Int. Conf. Intell. Comput. Technol. Autom. ICICTA 2017. 2017-Octob, 2017, pp. 245–249, https://doi.org/10.1109/ICICTA.2017.62.

[35] K. Liu, Q. Peng, Y. Che, Y. Zheng, K. Li, R. Teodorescu, D. Widanage, A. Barai, Transfer learning for battery smarter state estimation and ageing prognostics: recent progress, challenges, and prospects, Adv. Appl. Energy 9 (2023) 100117, https://doi.org/10.1016/j.adapen.2022.100117.

[36] T.A. Abdul-Jabbar, A. Kersten, A. Mashayekh, A.A. Obed, A.J. Abid, M. Kuder, Efficient battery cell balancing methods for low-voltage applications: a review, in: 2022 IEEE Int. Conf. Power Eng. Appl. ICPEA 2022 - Proc, 2022, pp. 1–7, https://doi.org/10.1109/ICPEA53519.2022.9744677.

[37] M. Waseem, M. Ahmad, A. Parveen, M. Suhaib, Battery technologies and functionality of battery management system for EVs: current status, key challenges, and future prospectives, J. Power Sources 580 (2023) 233349, https://doi.org/10.1016/j.jpowsour.2023.233349.

[38] X.G. Yang, G. Zhang, S. Ge, C.Y. Wang, Fast charging of lithium-ion batteries at all temperatures, Proc. Natl. Acad. Sci. U. S. A. 115 (2018) 7266–7271, https://doi.org/10.1073/pnas.1807115115.

[39] T. Kim, J. Ochoa, T. Faika, H.A. Mantooth, J. Di, Q. Li, Y. Lee, An overview of cyber-physical security of battery management systems and adoption of blockchain technology, IEEE J. Emerg. Sel. Top. Power Electron. 10 (2022) 1270–1281, https://doi.org/10.1109/JESTPE.2020.2968490.

[40] M.A. Hoque, M.K. Hassan, A. Hajjo, M.O. Tokhi, Neural network-based Li-ion battery aging model at accelerated C-rate, Batteries 9 (2023), https://doi.org/10.3390/batteries9020093.

[41] C.F. Oeste, Battery state of charge calculation with EPC converters, in: Appl. Note - AN026. 5, 2020. www.epicpower.es.

[42] Y. Miao, Z. Gao, Estimation for state of charge of lithium-ion batteries by adaptive fractional-order unscented Kalman filters, J. Energy Storage 51 (2022) 104396, https://doi.org/10.1016/j.est.2022.104396.

[43] S. Piller, M. Perrin, A. Jossen, Methods for state-of-charge determination and their applications, J. Power Sources 96 (2001) 113–120, https://doi.org/10.1016/S0378-7753(01)00560-2.

[44] W.-Y. Chang, The state of charge estimating methods for battery: a review, ISRN Appl. Math. 2013 (2013) 1–7, https://doi.org/10.1155/2013/953792.

[45] M.A. Hannan, M.S.H. Lipu, A. Hussain, A. Mohamed, A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: challenges and recommendations, Renew. Sustain. Energy Rev. 78 (2017) 834–854, https://doi.org/10.1016/j.rser.2017.05.001.

[46] X. Wu, M. Li, J. Du, F. Hu, SOC prediction method based on battery pack aging and consistency deviation of thermoelectric characteristics, Energy Rep. 8 (2022) 2262–2272, https://doi.org/10.1016/j.egyr.2022.01.056.

[47] I.U. Khalil, SOC prediction of lithium-ion battery using extended Kalman filter, in: Encycl. Ocean Eng, 2022, pp. 517–521, https://doi.org/10.1007/978-981-10-6946-8_300259.

[48] C. Lv, X. Zhou, L. Zhong, C. Yan, M. Srinivasan, Z.W. Seh, C. Liu, H. Pan, S. Li, Y. Wen, Q. Yan, Machine learning: an advanced platform for materials development and state prediction in lithium-ion batteries, Adv. Mater. 34 (2022) 1–17, https://doi.org/10.1002/adma.202101474.

[49] F. Codecà, S.M. Savaresi, G. Rizzoni, On battery state of charge estimation: a new mixed algorithm, in: Proc. IEEE Int. Conf. Control Appl, 2008, pp. 102–107, https://doi.org/10.1109/CCA.2008.4629635.
[50] J.P. Rivera-Barrera, N. Muñoz-Galeano, H.O. Sarmiento-Maldonado, Soc Estimation for Lithium-Ion Batteries: Review and Future Challenges, 2017, https://doi.org/10.3390/electronics6040102.
[51] K. Movassagh, A. Raihan, B. Balasingam, K. Pattipati, A critical look at coulomb counting approach for state of charge estimation in batteries, Energies 14 (2021) 1–33, https://doi.org/10.3390/en14144074.
[52] K. Movassagh, S.A. Raihan, B. Balasingam, Performance analysis of coulomb counting approach for state of charge estimation, in: 2019 IEEE Electr. Power Energy Conf. EPEC 2019 vol. 3, 2019, pp. 1–6, https://doi.org/10.1109/EPEC47565.2019.9074781.
[53] K.S. Ng, C.S. Moo, Y.P. Chen, Y.C. Hsieh, Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries, Appl. Energy 86 (2009) 1506–1511, https://doi.org/10.1016/j.apenergy.2008.11.021.
[54] Y.M. Jeong, Y.K. Cho, J.H. Ahn, S.H. Ryu, B.K. Lee, Enhanced coulomb counting method with adaptive SOC reset time for estimating OCV, in: 2014 IEEE Energy Convers. Congr. Expo. ECCE 2014, 2014, pp. 4313–4318, https://doi.org/10.1109/ECCE.2014.6953989.
[55] K.S. Ng, Y.F. Huang, C.S. Moo, Y.C. Hsieh, An enhanced coulomb counting method for estimating state-of-charge and state-of-health of lead-acid batteries, in: INTELEC, Int. Telecommun. Energy Conf, 2009, pp. 1–5, https://doi.org/10.1109/INTLEC.2009.5351796.
[56] J. Xie, J. Ma, K. Bai, Enhanced coulomb counting method for state-of-charge estimation of lithium-ion batteries based on Peukert's law and Coulombic efficiency, J. Power Electron. 18 (2018) 910–922, https://doi.org/10.6113/JPE.2018.18.3.910.
[57] Y. Xing, W. He, M. Pecht, K.L. Tsui, State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures, Appl. Energy 113 (2014) 106–115, https://doi.org/10.1016/j.apenergy.2013.07.008.
[58] X. Chen, H. Lei, R. Xiong, W. Shen, R. Yang, A novel approach to reconstruct open circuit voltage for state of charge estimation of lithium ion batteries in electric vehicles, Appl. Energy 255 (2019) 113758, https://doi.org/10.1016/j.apenergy.2019.113758.
[59] O.S. Mendoza-Hernandez, H. Ishikawa, Y. Nishikawa, Y. Maruyama, Y. Sone, M. Umeda, State of charge dependency of graphitized-carbon-based reactions in a lithium-ion secondary cell studied by electrochemical impedance spectroscopy, Electrochim. Acta 131 (2014) 168–173, https://doi.org/10.1016/j.electacta.2014.01.057.
[60] U. Westerhoff, T. Kroker, K. Kurbach, M. Kurrat, Electrochemical impedance spectroscopy based estimation of the state of charge of lithium-ion batteries, J. Energy Storage 8 (2016) 244–256, https://doi.org/10.1016/j.est.2016.09.001.
[61] Q.K. Wang, Y.J. He, J.N. Shen, X.S. Hu, Z.F. Ma, State of charge-dependent polynomial equivalent circuit modeling for electrochemical impedance spectroscopy of lithium-ion batteries, IEEE Trans. Power Electron. 33 (2018) 8449–8460, https://doi.org/10.1109/TPEL.2017.2780184.
[62] M. Charkhgard, M. Farrokhi, State-of-charge estimation for lithium-ion batteries using neural networks and EKF, IEEE Trans Ind Electron 57 (2010) 4178–4187, https://doi.org/10.1109/TIE.2010.2043035.
[63] Q. Wang, J. Wang, P. Zhao, J. Kang, F. Yan, C. Du, Correlation between the model accuracy and model-based SOC estimation, Electrochim. Acta 228 (2017) 146–159, https://doi.org/10.1016/j.electacta.2017.01.057.
[64] T.R. Ashwin, A. McGordon, P.A. Jennings, Electrochemical modelling of Li-ion battery pack with constant voltage cycling, J. Power Sources 341 (2017) 327–339, https://doi.org/10.1016/j.jpowsour.2016.11.092.
[65] L.D. Couto, M. Kinnaert, Partition-based unscented Kalman filter for reconfigurable battery pack state estimation using an electrochemical model, in: Proc. Am. Control Conf. 2018-June, 2018, pp. 3122–3128, https://doi.org/10.23919/ACC.2018.8431508.
[66] P. Spagnol, S. Rossi, S.M. Savaresi, Kalman filter SoC estimation for Li-ion batteries, in: Proc. IEEE Int. Conf. Control Appl, 2011, pp. 587–592, https://doi.org/10.1109/CCA.2011.6044480.
[67] M. Mer, M.O. Gülbahçe, Batarya Şarj Durumu Kestirim Yöntemleri Üzerine İnceleme Review on the SOC Estimation Methods, 2022.
[68] P. Shrivastava, T.K. Soon, M.Y.I. Bin Idris, S. Mekhilef, Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries, Renew. Sustain. Energy Rev. 113 (2019) 109233, https://doi.org/10.1016/j.rser.2019.06.040.
[69] J. Lee, O. Nam, B.H. Cho, Li-ion battery SOC estimation method based on the reduced order extended Kalman filtering, J. Power Sources 174 (2007) 9–15, https://doi.org/10.1016/j.jpowsour.2007.03.072.
[70] R. Xiong, H. He, F. Sun, K. Zhao, Evaluation on state of charge estimation of batteries with adaptive extended kalman filter by experiment approach, IEEE Trans Veh Technol 62 (2013) 108–117, https://doi.org/10.1109/TVT.2012.2222684.
[71] Y. Tian, Z. Huang, J. Tian, X. Li, State of charge estimation of lithium-ion batteries based on cubature Kalman filters with different matrix decomposition strategies, Energy 238 (2022) 121917, https://doi.org/10.1016/j.energy.2021.121917.
[72] A. Wadi, M. Abdel-Hafez, H.A. Hashim, A.A. Hussein, An invariant method for electric vehicle battery state-of-charge estimation under dynamic drive cycles, IEEE Access 11 (2023) 8663–8673, https://doi.org/10.1109/ACCESS.2023.3237972.
[73] X. Zhang, H. Zhou, M. Lan, State of charge estimation algorithm for unmanned aerial vehicle power-type lithium battery packs based on the extended Kalman filter, in: Proc. - 2019 Chinese Autom. Congr. CAC 2019, 2019, pp. 518–523, https://doi.org/10.1109/CAC48633.2019.8996745.
[74] Z. Lao, B. Xia, W. Wang, W. Sun, Y. Lai, M. Wang, A novel method for lithium-ion battery online parameter identification based on variable forgetting factor recursive least squares, Energies 11 (2018), https://doi.org/10.3390/en11061358.
[75] K.C. Lim, H.A. Bastawrous, V.H. Duong, K.W. See, P. Zhang, S.X. Dou, Fading Kalman filter-based real-time state of charge estimation in LiFePO4 battery-powered electric vehicles, Appl. Energy 169 (2016) 40–48, https://doi.org/10.1016/j.apenergy.2016.01.096.
[76] N.E. Helwig, S. Hong, E.T. Hsiao-Wecksler, No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する共分散構造分析Title, (n.d.).
[77] L. Rozaqi, E. Rijanto, SOC estimation for Li-ion battery using optimum RLS method based on genetic algorithm, in: Proc. 2016 8th Int. Conf. Inf. Technol. Electr. Eng. Empower. Technol. Better Futur. ICITEE 2016, 2017, pp. 1–4, https://doi.org/10.1109/ICITEED.2016.7863224.
[78] C. Lin, H. Mu, R. Xiong, W. Shen, A novel multi-model probability battery state of charge estimation approach for electric vehicles using H-infinity algorithm, Appl. Energy 166 (2016) 76–83, https://doi.org/10.1016/j.apenergy.2016.01.010.
[79] J. Yao, J. Ding, Y. Cheng, L. Feng, Sliding mode-based H-infinity filter for SOC estimation of lithium-ion batteries, Ionics (Kiel) 27 (2021) 5147–5157, https://doi.org/10.1007/s11581-021-04234-3.
[80] E. Ipek, M. Yilmaz, A novel method for SOC estimation of Li-ion batteries using a hybrid machine learning technique, Turkish J. Electr. Eng. Comput. Sci. 29 (2021) 18–31, https://doi.org/10.3906/ELK-1912-42.
[81] P. Tejaswini, P. Sivraj, Artificial intelligence based state of charge estimation of Li-ion battery for EV applications, in: Proc. 5th Int. Conf. Commun. Electron. Syst. ICCES 2020, 2020, pp. 1356–1361, https://doi.org/10.1109/ICCES48766.2020.09137999.
[82] T. Kim, W. Qiao, L. Qu, Online SOC and SOH estimation for multicell lithium-ion batteries based on an adaptive hybrid battery model and sliding-mode observer, in: 2013 IEEE Energy Convers. Congr. Expo. ECCE 2013, 2013, pp. 292–298, https://doi.org/10.1109/ECCE.2013.6646714.
[83] T.P. Bagchi, What are genetic algorithms?, in: Multiobjective Sched. by Genet. Algorithms, 1999, pp. 19–54, https://doi.org/10.1007/978-1-4615-5237-6_2.
[84] Y. Shen, Improved chaos genetic algorithm based state of charge determination for lithium batteries in electric vehicles, Energy 152 (2018) 576–585, https://doi.org/10.1016/j.energy.2018.03.174.
[85] L. Chen, Z. Wang, Z. Lu, J. Li, B. Ji, H. Wei, H. Pan, A novel state-of-charge estimation method of lithium-ion batteries combining the grey model and genetic algorithms, IEEE Trans. Power Electron. 33 (2018) 8797–8807, https://doi.org/10.1109/TPEL.2017.2782721.
[86] C. Sun, H. Lin, H. Cai, M. Gao, C. Zhu, Z. He, Improved parameter identification and state-of-charge estimation for lithium-ion battery with fixed memory recursive least squares and sigma-point Kalman filter, Electrochim. Acta 387 (2021) 138501, https://doi.org/10.1016/j.electacta.2021.138501.
[87] P.R. Shabarish, D.V.S. Sai Aditya, V.V.S.S. Phani Pavan, P.V. Manitha, SOC estimation of battery in hybrid vehicle using adaptive neuro-fuzzy technique, in: Proc. - Int. Conf. Smart Electron. Commun. ICOSEC 2020, 2020, pp. 445–450, https://doi.org/10.1109/ICOSEC49089.2020.9215263.
[88] H. Dai, P. Guo, X. Wei, Z. Sun, J. Wang, ANFIS (adaptive neuro-fuzzy inference system) based online SOC (State of Charge) correction considering cell divergence for the EV (electric vehicle) traction batteries, Energy 80 (2015) 350–360, https://doi.org/10.1016/j.energy.2014.11.077.
[89] C.H. Cai, D. Du, Z.Y. Liu, Battery state-of-charge (SOC) estimation using adaptive neuro-fuzzy inference system (ANFIS), IEEE Int. Conf. Fuzzy Syst. 2 (2003) 1068–1073, https://doi.org/10.1109/fuzz.2003.1206580.
[90] B.X. Sun, L. Wang, C. Liao, SOC estimation of NiMH battery for HEV based on adaptive neuro-fuzzy inference system, in: 2008 IEEE Veh. Power Propuls. Conf. VPPC 2008, 2008, pp. 5–8, https://doi.org/10.1109/VPPC.2008.4677676.
[91] M. Ismail, R. Dlyma, A. Elrakaybi, R. Ahmed, S. Habibi, Battery state of charge estimation using an Artificial Neural Network, in: 2017 IEEE Transp. Electrif. Conf. Expo, ITEC 2017, 2017, pp. 342–349, https://doi.org/10.1109/ITEC.2017.7993295.
[92] A. Bonfitto, S. Feraco, A. Tonoli, N. Amati, F. Monti, Estimation accuracy and computational cost analysis of artificial neural networks for state of charge estimation in lithium batteries, Batteries 5 (2019), https://doi.org/10.3390/batteries5020047.
[93] G.C.S. Almeida, A.C.Z. de Souza, P.F. Ribeiro, A Neural Network Application for a Lithium-Ion Battery Pack State-of-Charge Estimator With Enhanced Accuracy, 2020, p. 33, https://doi.org/10.3390/wef-06915.
[94] Z. Cui, L. Wang, Q. Li, K. Wang, A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network, Int. J. Energy Res. 46 (2022) 5423–5440, https://doi.org/10.1002/er.7545.
[95] E. Chemali, P.J. Kollmeyer, M. Preindl, R. Ahmed, A. Emadi, Long short-term memory networks for accurate state-of-charge estimation of Li-ion batteries, IEEE Trans Ind Electron 65 (2018) 6730–6739, https://doi.org/10.1109/TIE.2017.2787586.
[96] F. Yang, X. Song, F. Xu, K.L. Tsui, State-of-charge estimation of lithium-ion batteries via long short-term memory network, IEEE Access 7 (2019) 53792–53799, https://doi.org/10.1109/ACCESS.2019.2912803.
[97] M.A. Hannan, D.N.T. How, M.S.H. Lipu, M. Mansor, P.J. Ker, Z.Y. Dong, K.S. M. Sahari, S.K. Tiong, K.M. Muttaqi, T.M.I. Mahlia, F. Blaabjerg, Deep learning approach towards accurate state of charge estimation for lithium-ion batteries using self-supervised transformer model, Sci. Rep. 11 (2021) 1–13, https://doi.org/10.1038/s41598-021-98915-8.

[98] L. You, K. Yan, N. Liu, Assessing artificial neural network performance for predicting interlayer conditions and layer modulus of multi-layered flexible pavement, Front. Struct. Civ. Eng. 14 (2020) 487–500, https://doi.org/10.1007/s11709-020-0609-4.

[99] E. Chemali, P.J. Kollmeyer, M. Preindl, A. Emadi, State-of-charge estimation of Li-ion batteries using deep neural networks: a machine learning approach, J. Power Sources 400 (2018) 242–255, https://doi.org/10.1016/j.jpowsour.2018.06.104.

[100] M.T. Vellingiri, I.M. Mehedi, T. Palaniswamy, A novel deep learning-based state-of-charge estimation for renewable energy management system in hybrid electric vehicles, Mathematics 10 (2022), https://doi.org/10.3390/math10020260.

[101] L. Ma, T. Zhang, Deep learning-based battery state of charge estimation: enhancing estimation performance with unlabelled training samples, J. Energy Chem. 80 (2023) 48–57, https://doi.org/10.1016/j.jechem.2023.01.036.

[102] J. Tian, R. Xiong, J. Lu, C. Chen, W. Shen, Battery state-of-charge estimation amid dynamic usage with physics-informed deep learning, Energy Storage Mater. 50 (2022) 718–729, https://doi.org/10.1016/j.ensm.2022.06.007.

[103] J. Tian, R. Xiong, W. Shen, J. Lu, State-of-charge estimation of LiFePO4 batteries in electric vehicles: a deep-learning enabled approach, Appl. Energy 291 (2021) 116812, https://doi.org/10.1016/j.apenergy.2021.116812.

[104] D.N.T. How, M.A. Hannan, M.S.H. Lipu, K.S.M. Sahari, P.J. Ker, K.M. Muttaqi, State-of-charge estimation of Li-ion battery in electric vehicles: a deep neural network approach, IEEE Trans. Ind. Appl. 56 (2020) 5565–5574, https://doi.org/10.1109/TIA.2020.3004294.

[105] S. Malkhandi, Fuzzy logic-based learning system and estimation of state-of-charge of lead-acid battery, Eng. Appl. Artif. Intel. 19 (2006) 479–485, https://doi.org/10.1016/j.engappai.2005.12.005.

[106] M.J. Esfandyari, M.R. Hairi Yazdi, V. Esfahanian, M. Masih-Tehrani, H. Nehzati, O. Shekoofa, A hybrid model predictive and fuzzy logic based control method for state of power estimation of series-connected Lithium-ion batteries in HEVs, J. Energy Storage 24 (2019) 100758, https://doi.org/10.1016/j.est.2019.100758.

[107] J.C. Alvarez Anton, P.J. Garcia Nieto, C. Blanco Viejo, J.A. Vilan Vilan, Support vector machines used to estimate the battery state of charge, IEEE Trans. Power Electron. 28 (2013) 5919–5926, https://doi.org/10.1109/TPEL.2013.2243918.

[108] J.N. Hu, J.J. Hu, H.B. Lin, X.P. Li, C.L. Jiang, X.H. Qiu, W.S. Li, State-of-charge estimation for battery management system using optimized support vector machine for regression, J. Power Sources 269 (2014) 682–693, https://doi.org/10.1016/j.jpowsour.2014.07.016.

[109] B. Liu, H. Wang, M.L. Tseng, Z. Li, State of charge estimation for lithium-ion batteries based on improved barnacle mating optimizer and support vector machine, J. Energy Storage 55 (2022) 105830, https://doi.org/10.1016/j.est.2022.105830.

[110] T. Zahid, K. Xu, W. Li, C. Li, H. Li, State of charge estimation for electric vehicle power battery using advanced machine learning algorithm under diversified drive cycles, Energy 162 (2018) 871–882, https://doi.org/10.1016/j.energy.2018.08.071.

[111] L. Yao, S. Xu, A. Tang, F. Zhou, J. Hou, Y. Xiao, Z. Fu, A review of lithium-ion battery state of health estimation and prediction methods, World Electr. Veh. J. 12 (2021), https://doi.org/10.3390/wevj12030113.

[112] I. Oyewole, A. Chehade, Y. Kim, A controllable deep transfer learning network with multiple domain adaptation for battery state-of-charge estimation, Appl. Energy 312 (2022) 118726, https://doi.org/10.1016/j.apenergy.2022.118726.

[113] Z. Ni, B. Li, Y. Yang, Deep domain adaptation network for transfer learning of state of charge estimation among batteries, J. Energy Storage 61 (2023) 106812, https://doi.org/10.1016/j.est.2023.106812.

[114] Y. Liu, J. Li, G. Zhang, B. Hua, N. Xiong, State of charge estimation of lithium-ion batteries based on temporal convolutional network and transfer learning, IEEE Access 9 (2021) 34177–34187, https://doi.org/10.1109/ACCESS.2021.3057371.

[115] E. Pineau, N. De Lara, T. Paristech, Li-Ion Battery State of Charge Estimation Using Long Short-Term Memory Recurrent Neural Network With Transfer Learning, 2019, pp. 1–8.

[116] Y. Qin, S. Adams, C. Yuen, Transfer learning-based state of charge estimation for lithium-ion battery at varying ambient temperatures, IEEE Trans. Ind. Informatics 17 (2021) 7304–7315, https://doi.org/10.1109/TII.2021.3051048.

[117] D. Liu, L. Li, Y. Song, L. Wu, Y. Peng, Hybrid state of charge estimation for lithium-ion battery under dynamic operating conditions, Int. J. Electr. Power Energy Syst. 110 (2019) 48–61, https://doi.org/10.1016/j.ijepes.2019.02.046.

[118] Z. Cui, J. Dai, J. Sun, D. Li, L. Wang, K. Wang, Hybrid methods using neural network and Kalman filter for the state of charge estimation of lithium-ion battery, Math. Probl. Eng. 2022 (2022), https://doi.org/10.1155/2022/9616124.

[119] Z. Cui, L. Kang, L. Li, L. Wang, K. Wang, A hybrid neural network model with improved input for state of charge estimation of lithium-ion battery at low temperatures, Renew. Energy 198 (2022) 1328–1340, https://doi.org/10.1016/j.renene.2022.08.123.

[120] J.C. Álvarez Antón, P.J. García Nieto, E. García Gonzalo, J.C. Viera Pérez, M. González Vega, C. Blanco Viejo, A new predictive model for the state-of-charge of a high-power lithium-ion cell based on a PSO-optimized multivariate adaptive regression spline approach, IEEE Trans Veh Technol 65 (2016) 4197–4208, https://doi.org/10.1109/TVT.2015.2504933.

[121] G.O. Sahinoglu, M. Pajovic, Z. Sahinoglu, Y. Wang, P.V. Orlik, T. Wada, Battery state-of-charge estimation based on regular/recurrent Gaussian process regression, IEEE Trans Ind Electron 65 (2018) 4311–4321, https://doi.org/10.1109/TIE.2017.2764869.

[122] M.S. Hossain Lipu, M.A. Hannan, A. Hussain, S. Ansari, S.A. Rahman, M.H. M. Saad, K.M. Muttaqi, Real-time state of charge estimation of lithium-ion batteries using optimized random forest regression algorithm, IEEE Trans. Intell. Veh. 8 (2023) 639–648, https://doi.org/10.1109/TIV.2022.3161301.

[123] H.H. Afshari, M. Attari, R. Ahmed, A. Delbari, S. Habibi, T. Shoa, Reliable state of charge and state of health estimation using the smooth variable structure filter, Control. Eng. Pract. 77 (2018) 1–14, https://doi.org/10.1016/j.conengprac.2018.04.015.

[124] X. Sun, Q. Chen, L. Zheng, J. Yang, Joint estimation of state-of-health and state-of-charge for lithium-ion battery based on electrochemical model optimized by neural network, IEEE J. Emerg. Sel. Top. Ind. Electron. 4 (2022) 168–177, https://doi.org/10.1109/jestie.2022.3148031.

[125] F. Marini, B. Walczak, Particle swarm optimization (PSO). A tutorial, Chemom. Intel. Lab. Syst. 149 (2015) 153–165, https://doi.org/10.1016/j.chemolab.2015.08.020.

[126] D. Castanho, M. Guerreiro, L. Silva, J. Eckert, T. Antonini Alves, Y. de S. Tadano, S.L. Stevan, H.V. Siqueira, F.C. Corrêa, Method for SoC estimation in lithium-ion batteries based on multiple linear regression and particle swarm optimization, Energies 15 (2022) 1–21, https://doi.org/10.3390/en15196881.

[127] G. Zhang, B. Xia, J. Wang, B. Ye, Y. Chen, Z. Yu, Y. Li, Intelligent state of charge estimation of battery pack based on particle swarm optimization algorithm improved radical basis function neural network, J. Energy Storage 50 (2022), https://doi.org/10.1016/j.est.2022.104211.

[128] F. Zhong, H. Li, S. Zhong, Q. Zhong, C. Yin, An SOC estimation approach based on adaptive sliding mode observer and fractional order equivalent circuit model for lithium-ion batteries, Commun. Nonlinear Sci. Numer. Simul. 24 (2015) 127–144, https://doi.org/10.1016/j.cnsns.2014.12.015.

[129] L. Zhao, P. Qin, Accurate SOC prediction and monitoring of each cell in a battery pack considering various influencing factors, IEEE Trans Ind Electron 70 (2023) 1025–1035, https://doi.org/10.1109/TIE.2022.3146505.

[130] Y. Xie, W. Li, X. Hu, M.K. Tran, S. Panchal, M. Fowler, Y. Zhang, K. Liu, Coestimation of SOC and three-dimensional SOT for lithium-ion batteries based on distributed spatial-temporal online correction, IEEE Trans Ind Electron 70 (2023) 5937–5948, https://doi.org/10.1109/TIE.2022.3199905.

[131] X. Shu, Z. Chen, J. Shen, F. Guo, Y. Zhang, Y. Liu, State of charge estimation for lithium-ion battery based on hybrid compensation modeling and adaptive H-infinity filter, IEEE Trans. Transp. Electrif. 9 (2023) 945–957, https://doi.org/10.1109/TTE.2022.3180077.

[132] A. Mondal, A. Routray, S. Puravankara, Parameter identification and co-estimation of state-of-charge of Li-ion battery in real-time on Internet-of-Things platform, J. Energy Storage. 51 (2022), https://doi.org/10.1016/j.est.2022.104370.

[133] H. Tang, Y. Wu, Y. Cai, F. Wang, Z. Lin, Y. Pei, Design of power lithium battery management system based on digital twin, J. Energy Storage 47 (2022) 103679, https://doi.org/10.1016/j.est.2021.103679.

[134] G.R. Sylvestrin, H.F. Scherer, O. Hideo Ando Junior, Hardware and software development of an open source battery management system, IEEE Lat. Am. Trans. 19 (2021) 1153–1163, https://doi.org/10.1109/TLA.2021.9461844.

[135] S. Li, P. Zhao, Big data driven vehicle battery management method: a novel cyber-physical system perspective, J. Energy Storage 33 (2021) 102064, https://doi.org/10.1016/j.est.2020.102064.

[136] X. Song, F. Yang, D. Wang, K.L. Tsui, Combined CNN-LSTM network for state-of-charge estimation of lithium-ion batteries, IEEE Access 7 (2019) 88894–88902, https://doi.org/10.1109/ACCESS.2019.2926517.

[137] J. Lee, J. Won, Enhanced coulomb counting method for SoC and SoH estimation based on Coulombic efficiency, IEEE Access 11 (2023) 15449–15459, https://doi.org/10.1109/ACCESS.2023.3244801.

[138] Z. Wang, G. Feng, D. Zhen, F. Gu, A. Ball, A review on online state of charge and state of health estimation for lithium-ion batteries in electric vehicles, Energy Rep. 7 (2021) 5141–5161, https://doi.org/10.1016/j.egyr.2021.08.113.

[139] W. Liu, T. Placke, K.T. Chau, Overview of batteries and battery management for electric vehicles, Energy Rep. 8 (2022) 4058–4084, https://doi.org/10.1016/j.egyr.2022.03.016.

[140] Y. Wang, R. Xu, C. Zhou, X. Kang, Z. Chen, Digital twin and cloud-side-end collaboration for intelligent battery management system, J. Manuf. Syst. 62 (2022) 124–134, https://doi.org/10.1016/j.jmsy.2021.11.006.

[141] X. Hu, Z. Deng, X. Lin, Y. Xie, R. Teodorescu, Research directions for next-generation battery management solutions in automotive applications, Renew. Sustain. Energy Rev. 152 (2021) 111695, https://doi.org/10.1016/j.rser.2021.111695.

[142] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, D.U. Sauer, Digital twin for battery systems: cloud battery management system with online state-of-charge and state-of-health estimation, J. Energy Storage. 30 (2020) 101557, https://doi.org/10.1016/j.est.2020.101557.