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Review Article

Analysis of State-of-Health Estimation Approaches and Constraints for Lithium-Ion Batteries in Electric Vehicles

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Energy storage systems (ESS) are seeing rapid market growth due to the changing worldwide landscape of electricity distribution and consumption. An ESS must possess the capability to oversee the functioning of the system's modules under abnormal circumstances, while also having the ability to supervise, manage, and optimize the performance of one or more battery modules. At present, the condition of batteries is assessed based on two factors: the level of charge (SOC) and the overall condition (SOH). By using these two characteristics, it becomes feasible to compute the anticipated battery lifespan and evaluate a battery's efficiency. The assessment of SOH is a crucial determinant in guaranteeing the effectiveness, dependability, and security of batteries in electric vehicles (EVs). Nevertheless, the safety issues resulting from the imprecise estimation and forecasting of battery health status have garnered significant attention in academic circles. This study presents a comprehensive evaluation of several SOH monitoring techniques. In order to achieve this objective, various scientific and technical literatures are examined and the corresponding methodologies are categorized into distinct groupings. The groupings are categorized based on the manner in which the procedure is executed: methods and techniques used in experiments and models. This paper provides a comprehensive overview of the benefits and drawbacks of several SOH assessment and prediction techniques, along with the associated obstacles in SOH estimation.

1. Introduction

LIBs have found extensive use as energy storage devices in many applications, including EVs and HEVs [1]. The deterioration of electrochemical components in LIBs leads to a decline in their performance with time and with use, resulting in a decrease in both capacity and power [2]. The demand for energy is on the rise due to the significant growth in productivity and power consumption in the contemporary day. The aforementioned factor has facilitated the continued development of the energy and power sector [3]. LIBs have emerged as a fundamental energy storage technology with extensive utilization across several industries, rendering them a significant component within the energy sector. Nevertheless, a significant obstacle faced by LIBs in many applications, including power grids, electric cars, and mobile phones, is deterioration. This degradation plays a pivotal role in determining the cycle life of LIBs. LIBs are widely used for their ability to effectively store and deliver energy [4, 5]. LIBs are extensively used as power sources in the EV power system owing to their notable benefits, including high energy density, extended operational lifespan, and little self-discharge rate. Nevertheless, it is important to note that lithium-ion batteries have a steady degradation over time as they are used. Battery degradation results in a rise in electrical resistance and a decline in energy storage capacity, thus resulting in a reduction in overall battery performance.

Once the battery's capacity declines to below 80% of its designated nominal capacity, it is regarded as reaching the termination of its lifespan. Consequently, this stage is associated with a significant likelihood of encountering safety concerns such as thermal runaway. A very effective and simple thermal management technique, utilizing a minichannel cooling plate, is introduced for the $LiFePO_4$ pouch cell in [6]. The proposed design significantly enhances the consistency of surface temperature differential by over 100% when compared to available data on similar designs. The authors in [7] conduct a computational analysis of passive heating systems that utilize Fins and PCM for thermal management of 18650 Li-ion batteries at low temperatures. The analysis specifically focuses on battery module analysis. An investigation is conducted using Ansys Fluent to analyze the effect of changing the thickness of PCM on heat transmission. The study is aimed at forecasting the distribution of temperature and examining its influence on the performance of the battery's output. In [8], the researchers conducted a computer study to examine the temperature distribution on the surface of a liquid-cooled battery pack during discharge at current rates ranging from 1C to 4C. They used an Al_2O_3/EG-water dispersion as the cooling medium. In [9], the authors investigating the performance of a phase change material-based thermal battery management system for controlling battery temperature and battery life. The applications of LIBs extend across several sectors, including consumer electronics, stationary storage systems, electric automobiles, and aerospace vehicles [10, 11]. In order to guarantee the safe and dependable functioning of a battery system over its entire lifespan, the implementation of a BMS is used. This system is responsible for the measurement and monitoring of battery parameters, as well as the regulation of battery operation. The BMS is a compact electronic device that facilitates the regulation and supervision of the battery system, therefore guaranteeing both the safety and efficiency of battery operations [12, 13]. Nevertheless, it is worth noting that the power and energy attributes of LIBs experience a decline over time due to ageing [14]. Additionally, their performance is also affected by cyclic ageing, which is influenced by factors such as environmental conditions and operational use [15, 16]. Battery deterioration results in an elevation of electrical resistance and a reduction in energy storage capacity, thus resulting in a decline in overall battery performance. Once the battery's capacity diminishes to below 80% of its designated rated capacity, it is said to have reached the termination stage of its lifespan. At this junction, there exists a significant likelihood of encountering safety concerns such as thermal runaway or other related hazards.

The demand for energy is on the rise due to the significant growth in productivity and power consumption in the contemporary day. The aforementioned phenomenon has facilitated the continued development of the energy and power sector. LIBs have emerged as a prominent energy storage technology with extensive utilization across several industries, making them a significant component in the field of energy storage. Nevertheless, a significant obstacle faced by LIBs in many applications, including power grids, electric cars, and mobile phones, is the issue of deterioration. This degradation significantly affects the cycle life of LIBs and is thus of utmost importance to address. Research indicates that the process of draining is often more detrimental than its corresponding charging cycle [17]. The quantification of battery deterioration is often done via the use of the SOH indicator. SOH is a metric used to assess the current state of a battery in relation to its nominal or design conditions. By assessing the SOH of a battery, it is possible to enhance the overall performance of the battery and perhaps extend its lifespan [18]. Hence, the assessment of SOH has significant importance in ensuring the optimum performance of batteries across diverse applications that need extended battery lifespans, such as electric cars [19].

The utilization and acceptance of electric cars are seeing a notable increase in both public interest and practical use. The increasing popularity of EVs has led to a significant focus on research pertaining to BMSs as a fundamental component of their technology. SOH serves as a measure for assessing the battery's ageing process and plays a pivotal role in establishing the appropriate time for battery replacement or projecting the driving range. The measurement of SOH in several research has mostly relied on two approaches: (1) the EC model and (2) capacity fading. The EC model is used due to the fact that the parameters of the model tend to vary and the battery's capacity tends to decline as it ages and undergoes usage. Nevertheless, these metrics are defined within stringent parameters by all of them, rendering them unsuitable for evaluating the SOH of EV batteries. This is due to the fact that EV batteries need real-time calculations and are often subject to partial and dynamic charging and discharging. Hence, it is essential to conduct a precise assessment of the SOH of the battery in order to guarantee its optimal performance and safety. Numerous approaches for estimating the SOH have been developed over the years. A frequently used approach involves the utilization of cellular models to simulate cell behaviors, afterwards using diverse optimization algorithms and observers, such as the KF family [20] and particle filter [21], to ascertain the parameters and SOH. One often used methodology is the utilization of electrochemical models, which employ partial differential equations to replicate the dynamics of mass and charge transfer that are intricately linked to the process of ageing [22]. Electrical models that include electrical-circuit analogues, like as resistors and capacitors, are also prevalent. In [23], the authors investigated the battery resistance characteristics by performing EIS measurements. Then, the extracted outcomes were connected with the heat generation and used to explain the trends of the battery thermal characteristics at different temperatures and current rates. These models describe the dynamics of cells under various input currents [24]. This area has shown notable vibrancy, as seen by the existence of many review publications on this subject [25, 26]. Nevertheless, precisely determining the SOH of a battery may be challenging owing to the complex interplay of several components, including internal side reactions, diverse working environments, and varying operating circumstances of the battery. The existing approaches for estimating the SOH of batteries may be categorized into three main groups: direct measurement techniques, model-based methods, and data-driven methods. In contrast, empirical models exhibit superior online capacity, particularly when combined with techniques such as KFs [27, 28], enabling the attainment of very precise SOH estimations. Typically, experimental methodologies include offline and laboratory-based investigations aimed at precisely assessing battery deterioration via several metrics, including internal resistance [29, 30], impedance [31, 32], and capacity levels [33, 34]. The primary drawbacks associated with experimental methodologies are the considerable time required for conducting the requisite measurements, as well as their inherent limitation in terms of real-time estimation of SOH.

Model-based approaches use several variables to develop models that effectively capture the behavior of battery SOH. Frequently used methodologies include KF, observers, and comparable ECM. The authors in reference [35] provide evidence that the dual extended KF, which is often used SOC and SOH estimates, encounters limitations throughout the lifespan of the battery. The authors in reference [36] provide a multi-time-scale observer that is suggested for the assessment of both SOC and SOH. In the study conducted by the authors in [37], they have successfully included the impact of diminishing SOH into an ECM in order to precisely ascertain Thevenin parameters. The use of model-based SOH estimate has shown its capability to attain a notable level of accuracy and precision. In [38], the authors first extract novel indirect health indicators from the voltage and current curves while the battery is being charged. They then optimize these indications using the KF. The PCA approach demonstrates a strong link between the collected HIs and the capacity. The hyperparameters of the multikernel Gaussian process regression (GPR) model are optimized using PSO to minimize mistakes resulting from manual adjustments. However, it often necessitates substantial computing resources and may be reliant on an extensive array of characteristics and variables.

Data-driven SOH estimate approaches, particularly those based on ML techniques, are aimed at integrating the benefits of both the aforementioned conventional methods. The reliance on conventional approaches is inherent due to their need for data, which is acquired by measurements or models, in order to effectively train estimating models. Consequently, the quality of this data becomes a crucial factor in their dependency. Nevertheless, they have shown a remarkable ability to provide accurate estimations while also being very easy to execute. A diverse array of ML algorithms is now being used for SOH estimation. The authors emphasize the use of SVM [39, 40], fuzzy logic [41], and ANN. In [42], the authors developed CNN-based battery SOH estimation model trained to estimate SOH from constant current charge and discharge data. The implementation of other models, such as regression tree and random forest, has been explored in [43] with varied levels of accuracy. The paper [44] discusses a technique for estimating the SOH of LIBs using an upgraded wide learning system (BLS) network and ICA. Initially, the IC curves are generated using the voltage data from the constant current charging phase and then refined using the smoothing spline filter to remove noise. Subsequently, the Pearson correlation coefficient approach is used to identify the crucial health markers from the characteristics derived from the IC curves. The SOH is evaluated using an optimized BLS network with L2 regularization and PSO in the SOH estimate model.

2. Definition of SOH for LIBs

The rate at which a battery is depleted in relation to its maximum capacity is known as the battery C rating. Battery C rating regulates how quickly a battery charges and discharges. Stated differently, it is the controlling factor that determines the rate at which the intended batteries are charged or discharged. In this work, the loss of rated capacity, which can be provided as, is used to explain that the SOH of the LIBs is calculated using the following equation:

$$\mathrm{SOH} = \frac{\text{current actual capacity}}{\text{nominal capacity}}. \tag{1}$$

2.1. Capacity Definition. SOH is one of the essential parameters of LIBs, and it is calculated using the following equation:

$$\mathrm{SOH} = \frac{Q_m}{Q_r} * 100, \tag{2}$$

where Q_m is the current maximum available capacity and Q_r is the rated capacity of the battery [45, 46].

The values of SOH also exhibit substantial variation due to the impact of the current multiplier and temperature used in the measuring process [47, 48]. In order to guarantee the fulfilment of performance criteria for LIBs, it is explicitly outlined in IEEE standard 1188.1996 that if the SOH of the battery falls below, certain measures need to be taken. When the battery level reaches 80%, it signifies that the battery has reached the end of its lifespan and necessitates replacement [49, 50].

2.2. Internal Resistance (IR). SOH is defined according to the IR of the battery, which is calculated using the following equation:

$$\mathrm{SOH} = \frac{R_e - R}{R_e - R_n} * 100\%. \tag{3}$$

The variables R, R_e, and R_n represent the IR of the battery under different conditions. R represents the IR in the current state, R_e represents the IR of the battery when it approaches the end of its life, and R_n represents the IR of a fresh battery. SOH is often defined by academics by the measurement of IR. Additionally, scientists use the IR of the battery to estimate and anticipate its SOH [51, 52]. The escalation of IR is a significant metric in assessing battery degradation and contributes to the subsequent deterioration of battery SOH.

2.3. The Capacity Contained in the Electrode. The movement of the LIB occurs concomitantly with the transfer of charge when using LIBs. The assessment of the SOH of LIBs may be determined by examining the aggregation of lithium ions inside the electrode, as indicated by the electrochemical reaction mechanism [53]. In the hypothetical state, the principle of SOH can be mathematically represented as

$$\mathrm{SOH} = \frac{Q}{Q_o} * 100\%, \tag{4}$$

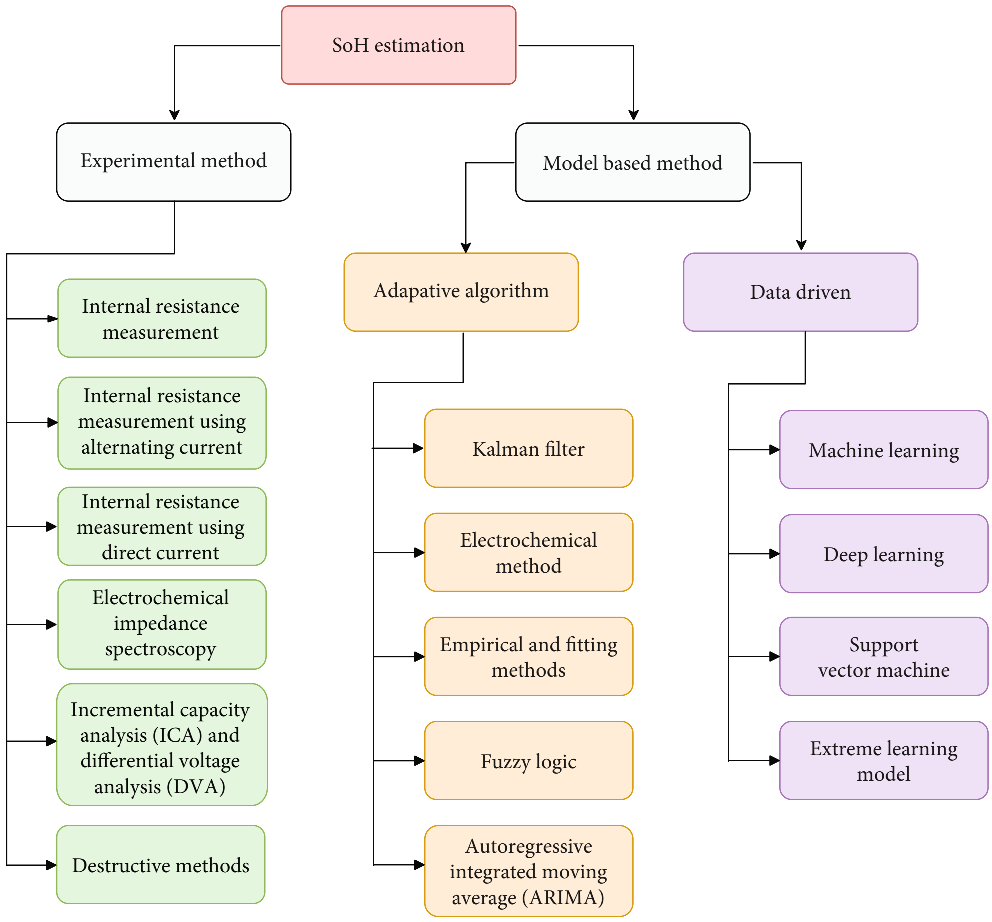

Figure 1: Classification of SOH estimation method.

where Q is rated capacity and Q_o is the lithium concentration after multiple cycles.

3. SOH Estimation Methods

There are various techniques for determining the battery's health. In the given work, they are mainly classified into experimental and model based which is further divided into data driven and adaptive algorithms as shown in Figure 1.

3.1. Experimental Methods. The SOH evaluation of a battery employs experimental techniques, which are crucial and require numerous actions to gather the essential data. Every time, it is unfeasible to collect useful data throughout the experiment due to a variety of systematic errors and external effects. Capacity analysis, internal resistance, impedance spectroscopy, and voltage analysis are some of the experimental methods that can be used to measure internal resistance. Model-based approaches, employing data-driven techniques such as ML and DL, are used to assess SOH. Adaptive algorithms, on the other hand, include techniques like the Kalman filter, electrochemical method, and empirical fitting approaches.

3.1.1. IR Measurement. The battery's SOH is greatly influenced by internal resistance (R_i), which signals when a battery's life is ready to expire. Internal resistance is frequently described as the material's resistance to electrical current flow. Discharge rate, temperature, SOC, and composition and structure of the battery all have an impact on internal resistance. Consequently, some traits become apparent that may be utilized to estimate the battery's lifespan. IR in batteries is primarily brought on by two elements, namely, ohmic resistance (OR) and polarization resistance (PR) [54]. In an electrochemical reaction, the polarization resistance represents the state of conversion between the electrolyte and electrodes. Internal resistance rises as the battery's capacity and rate of discharge increase. Using the voltage drop of the battery at a specific current value and the equation below, this method calculates R_b (SOC, T) [55, 56] using the following equation:

$$R_b(\mathrm{SOC}, T) = \frac{\mathrm{OCV}(\mathrm{SOC}, T) - V_{\mathrm{bat}}(\mathrm{SOC}, T)}{I_{\mathrm{pulse}}}, \quad (5)$$

where R_b is the IR of the battery, V_{bat} is the voltage of the battery, and I_{pulse} is the current. Delivering extremely precise outcomes in a range of circumstances is one of this equation's key benefits.

3.1.2. IR Measurement Using A.C. Method. Power, energy efficiency, and heat loss are all greatly affected by the battery's internal resistance. Alternating current methods, thermal loss methods, and electrochemical impedance spectroscopy are all methods use for determining the internal resistance of the cell. By applying small current ripples with an average frequency of 1 kHz, the A.C. technique is used to measure the IR of LIBs. The ability to calculate through the phase angle and suitability for complex measurements are the key advantages of the AC approach [57, 58]. The fact that the A.C. method is a nondestructive approach for measuring IR is a considerable benefit. Due to the narrow voltage range, this approach is not commercially viable for multicell batteries [59].

3.1.3. IR Measurement Using D.C. Method. D.C. method is the tried-and-true technique for calculating batteries' IR [60]. The D.C. method uses a set load with a known resistance to deplete batteries quickly. The capacity of the batteries affects the load current. The following algorithm illustrates how to test the battery's IR using direct current:

(i) In the absence of a load, the open-circuit voltage is measured via use of voltmeter

(ii) After attaching the load, the voltage is measured across it

(iii) Calculate the circuit's internal resistance using Kirchhoff's law

Direct current measurement is effective for determining internal resistance of batteries with large capacity. Their ohmic values can be precisely and regularly monitored. A D.C. method is used to quantify the voltage drop that takes place as a cell receives current. The D.C. approach is among the most often used method to figure out a battery's SOH as it cycles. One of the most popular techniques for determining a battery's SOH throughout the cycling process is the D.C. method. The main benefit of using the D.C. method to measure internal resistance compared to the A.C. method lies in the fact that it is more accurate because of diffusion polarization. The A.C. technique is limited to measuring low impedance values of LIBs during diffusion polarization tests [61, 62].

3.1.4. Electrochemical Impedance Spectroscopy (EIS). EIS is another well-liked nondestructive method for measuring internal impedance. When measuring the electrical system resistance, the experiments are always carried out using sinusoidal alternating current [63–65]. The frequency band range should be as wide as possible. Numerous applications exist for impedance measurements. At frequencies below 107-108 Hz, various bridges are widely utilized. Hand-balanced bridges include the Wheatstone and Schering bridges [66].

3.1.5. Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA). As the name suggests, the cycle counting method counts the number of revolutions a battery has gone through and compares it to the manufacturer's recommended value to assess the battery state of health. This counting strategy takes the DOD into consideration [67, 68]. The differential voltage range has an impact on the IC curves, which should be taken into account as inaccurate analysis may ensue. The MA and Gaussian filters must be used in conjunction with one another to solve this issue [69]. The power amplified as the voltage varies is shown by the IC curve. Capacity and voltage of the battery are typically utilized to find IC curves when utilizing the charging method which are calculated using equations (6) and (7). The battery's capacity and voltage therefore must be determined first [70] which is calculated using the following equations:

$$Q = I \times t, \tag{6}$$

$$V = f(Q), \tag{7}$$

$$Q = f^{-1}(V). \tag{8}$$

Hence, the following features of the IC curve can be identified by

$$\left(f^{-1}\right)' = \frac{dQ}{dV} = I \times \frac{dT}{dV}. \tag{9}$$

For the purpose of raising the accuracy of the battery's SOH evaluation, Gaussian process regression is used, which assesses the resemblance of the input variables and builds a covariance function, and is essential to SOH estimation.

3.1.6. Destructive Methods. Generally, in this method, the precise value of the SOH is estimated because of the exact deterioration information that was offered. However, the battery must be disassembled on the back face in order to examine the ageing process, as specified in the procedures like scanning electron microscopy. Moreover, these methods can damage the battery for lifelong, and hence, these methods are not applicable in industrial applications. applications. Figure 2 illustrates a range of destructive methods, encompassing Raman spectroscopy [71–80], X-ray diffraction [81, 82], scanning electron microscope [83, 84], X-ray photoelectron spectroscopy [85–89], scanning transmission electron microscope [90, 91], cyclic voltammetry [92, 93], Auger electron spectroscopy [94, 95], and atomic force microscopy [96–98]. Various destructive methods are listed in Figure 2. Table 1 shows the advantages and drawbacks of the various experimental-based methods.

3.2. Model-Based Methods. Model-based estimate is another technique for assessing a battery's SOH. With this method, the goal is to ascertain how the battery's crucial characteristics, including current, voltage, and capacity, vary over time. Therefore, battery management systems can use the technique. The fact that this method can be used in scientific pursuits sets it apart from the experimental estimating method. Among the main categories of model-based estimates are KF, electrochemical model-based techniques, empirical fitting techniques, ML techniques, and DL strategies.

3.2.1. Adaptive Algorithm. The adaptive methods are self-designing and may automatically normalize the SOH for different discharge situations.

(1) KF Method. The common KF is a filtering method that bases its error on the least RMS variance and evaluates the

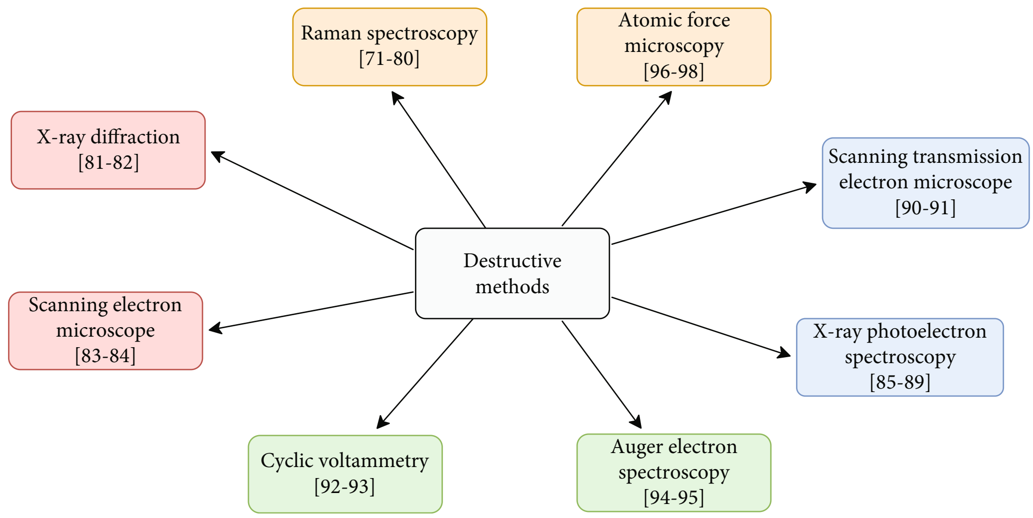

Figure 2: Different destructive methods.

Table 1: Advantages and drawbacks of the various experimental methods [63–70].

Model name	Advantages	Drawbacks and limitation
IRM	Reliable	Time consuming
EIS	Nondestructive battery degradation prediction	Requires long time Used for only specific environment
ICA and DVA	Loss of battery, high accuracy robust, and reliable	Suitable only for Li-ion battery
Destructive	Precise estimation of value	Can permanently damage cell

present state of linear systems [99, 100]. The expanded Kalman filter technique is used by the battery health estimation procedure to determine the model's parameter after the previous health value [101]. To estimate health status, a model needs to first be developed. The operational current, voltage, and model parameters are contained in the recursive equation of the extended Kalman filter. Then, the model variables are modified in real time in accordance with the value of the enhanced battery SOH [102]. Utilizing a prediction approach after looking at the outcomes is the next step. Finding the reliance and eliminating the noises based on the findings requires a filtering technique. The battery's charge and health can both be assessed simultaneously using the Kalman filtering. A RC equivalent circuit model has been built in [103], in which the recursive least squares approach has been used to recognize the model's parameters. Additionally, the AUKF technique simultaneously estimates the SOH and SOC of the battery. In [104], the charging data are used to produce the temperature difference curves, which are then rounded using the Kalman filter. The connection between temperature and ageing is then described by extracting the capacity degradation-related health features using differential temperature curves. The battery's health is then predicted using a deep learning model and hybrid attention that combines the benefits of convolutional recurrent neural networks, neural networks, gated recurrent unit, and attention mechanisms. A novel and efficient model-based approach, called the state of X (SOX) estimation technique, is introduced in [105] to simultaneously estimate several battery states, including SOC, state of energy (SOE), state of power (SOP), and SOH. The estimate of SOC and SOE is carried out using a novel approach that combines both parameters. This method uses a multi-time-scale dual EKF for accurate estimation. Next, the estimate of SOP is conducted using the T-method and a 2RC battery model in order to assess the noninstantaneous peak power during charge and discharge. The battery's current capacity is estimated using a simple approach called coulomb counting. This method uses a sliding window and has been shown to have an experimental error of less than 1%. In [106], the authors present a complete coestimation approach for accurately determining the battery states, maximum accessible capacity, and maximum available energy. The SOC and SOE are estimated using the dual forgetting factor AEKF method, which combines SOC and SOE estimation and utilizes experimental quantitative linkages between SOC and SOE. The Rint model is used for the estimate of SOP employing a multiple constraint approach, mostly because to its cheap computing cost and simplicity. The assessment of the maximum available capacity and maximum available energy is carried out using a novel approach called SW-AWTLS.

(2) Fuzzy Logic. Fuzzy logic processes data obtained from intricate, nonlinear systems using a collection of fuzzy rules. Afterwards, the data is separated into fuzzy subgroups. The subgroup is then divided into groups based on the corresponding uncertainties. The membership function to which the members of the fuzzy sets belong determines the SOH

precisely. It is not necessary to comprehend the equations and system process in order to implement fuzzy logic. However, it enables the use of an advance level of abstraction that results from experimental research and practical applications to represent complicated systems. This approach has a higher accuracy but takes more processing because it is entirely data driven. Shahriari and Farrokhi's [107] investigation into the SOH and SOC of valve-controlled lead acid (VRLA) batteries is based on the electrochemical characteristics of VRLA cells and the fluctuations in voltage and current during discharge and charge. Based on observations of numerous experiments conducted on VRLA cells of various ages, the SOH is calculated from the relationship between the stored charge and the curve representing the OCV of the battery. The slope of the curve serves as the input value to the planned fuzzy system, and the predicted SOH is the system's output. This method's independence from the battery type is a key benefit. However, this approach necessitates a prediction of the real battery power in prior. In [108], a new neural network with conjectural jump places and an interval fuzzy set is given. A graded membership function is used by the quantum fuzzy set to improve class overlap recognition. While employing the decoupled EKF for parameter estimation in the quantum fuzzy set, the quantity of rules is automatically modified and advanced. The suggested approach estimates the capacity of NMC batteries over 600 charging-discharging cycles using data on voltage, current, and sampling time.

(3) ARIMA. All ARIMA needed is data from a previous time series. In order to predict next points in the series, time series data are fitted to this model. As a result, single-step estimate is where ARIMA shines rather than multiple step prediction. In an ARIMA model, the parameter selection is generally unique. In this context, Long et al. replaced the ARIMA model with a high-order autoregressive (AR) model and changed the challenge of searching nonlinear ARIMA model parameters into searching linear AR model parameters [109]. In addition, they suggested using the PSO method for the reduction of risk associated with determining order subjectively by humans. The data metabolic method is used to enable adaptive modification of the AR model. In an effort to build-on the accuracy in the long-term prediction process, Liu et al. present a determining element to distinguish "accelerated" decay and merged this element with the AR model [110]. To further increase the forecast accuracy, they added a regularized particle filter in his subsequent work [111].

(4) Electrochemical Model-Based Methods. When assessing a battery's health using the electrochemical model, it is important to take into consideration the procedure that take place while the battery is in use. As batteries age, IR increases and battery capacity declines. Doyle et al. developed the initial electrochemical representation of LIBs. This method is known by the acronym Doyle-Fuller-Newman (DFN) model [112, 113]. The battery parameter analysis is accurate. The model's construction was supported by the mass-charge conservation equations in electrolyte and solid interphases. The chemical process that results in the production of the SEI, that decreases LIB capacity, is also described as an outcome of the synthesis of nonconsumable lithium ions. The formulae associated with the DFN model are listed as follows:

$$\frac{\partial C_s}{\partial t} = \frac{D_s}{r^2}\frac{\partial}{\partial x}\left(r^2\frac{\partial C_s}{\partial r}\right), \tag{10}$$

where δ and $\delta +$ are the negative and positive electrode thickness, respectively, and δC_s is the mass in solid phase.

(5) Empirical and Fitting Methods. This method relies on mathematical equations like polynomial and exponential functions that can be fitted to the health battery's status. This method's drawback is that the mathematical model does not adequately capture the physical and chemical reactions that take place inside the battery. Deshpande and Bernardi assert that by using Equation (11), it is possible to develop a mathematical model that has a capacity based on the DOD, the number of phases (n), and the duration of storage time (t) [114]. Calendars and cycle ageing are both considered in this calculation:

$$Q_t = Q_0\left(1 - B \times \mathrm{DOD}^2 \times n - K_t\right), \tag{11}$$

where Q_0 represents the battery's initial capacity, Q_t represents the calendar time, B represents the cycling ageing coefficient, and K_t represents the calendar ageing coefficient. Table 2 shows the advantages and drawbacks of the various model-based adaptive algorithm methods.

3.2.2. Data-Driven Methods. It is a technique that involves developing a preliminary model and then improving it with lots of data to make it compatible with the data. Model-based methods are those where the starting model is an existing battery model; model-less methods are those where it is not.

(1) ML Method. The ML strategy focuses on making a computer that has been taught to predict the battery's health using information previously obtained on battery ageing. The benefit of this strategy is that machine learning may be applied without taking into consideration the battery's electrochemical model. Based on the review of the literature, the following categories can be applied to machine learning techniques:

(i) The estimation of SOH is rooted on accurate measurements of the battery temperature, voltage, and current

(ii) Based on the battery charge-discharge curve, the SOH estimate is constructed. The training data in the 20–60% capacity range is used to acquire and choose data features on the battery's charge-discharge behavior. The battery's health is finally predicted using LSTM and CNN [115]

(iii) Charge-discharge characteristic analysis data which has undergone processing, like IC analysis and DV analysis, are used to estimate SOH

When building a model, parameter selection in it refers to the process of selecting a subset of the features that are

Table 2: Advantages and drawbacks of model-based adaptive algorithm methods [75–85].

Model name	Advantages	Drawbacks and limitation
Equivalent circuit model	Nondestructive	Requirement of higher controller for identification of ageing parameter of the battery
Electrochemical model	Nondestructive Besides, it also gives measurement of current, voltage, and temperature	Need for high computational efficiency
Empirical and fitting method	Nondestructive and require low computational efficiency	Less reliable
Kalman filter	Accurate estimation No initial data required Easy data filter	Complex method Requires large amount of computation
Fuzzy logic	Applicable for nonlinear and complex system	High computation is required
ARIMA	For short-term forecasting Only needs historical data	Poor at predicting turning point Not for long-term forecasting High computational required

accessible or variables. The evaluation of the model is to be revised by choosing factors that are most crucial to the battery's health. Numerous techniques exist for selecting traits, such as progressive calculation, which is just a derivation of a function of parameters. The employment of a distinct noise processing technique is required for the incremental study of any parameter with diverse disturbances, which is one disadvantage of this feature selection. In addition to other algorithms, linear regression is one. This simple and well-known method considers a linear correlation between the desired variable and the attributes. The algorithm only functions, though, if it has a sufficient number of features as the battery is mostly determined by difficult equations. Despite being used for binary classification issues; this is analogous to linear regression. This tree-based technique continuously separates the data into progressively combat subgroups in accordance with the features via recursive partitioning. A random forest, a collection of decision trees, produces a single forecast. SVMs are an effective technique that may be used to solve classification and regression problems.

(2) DL Method. The ANN is among the most popular algorithms used for a number of applications, including pattern recognition, optimization, and prediction. It was created to mathematically duplicate the neural processes of the human brain. Three layers make up a standard ANN: input, hidden, and output layer. It is made up of "neurons" or points which are interconnected in order to collaborate and process the data arriving from the input layer. Lines connecting the dots reflect the weights of the layers, which are essentially functions. Before using the ANN for estimations, it must be trained to determine optimal values for these weights. The major drawback of an ANN is its training phase because it requires a huge amount of various data to produce a network that operates correctly. The IR is currently thought to be the most accurate indicator of the battery's SOH. The connection between a battery SOH and its complex impedance zero-phase crossover frequency was demonstrated by Xia and Qahouq using FFNN [116]. An online solution for SOH and RUL tracking basis on the merging of partial incremental capacity and FFNN was proposed by Zhang et al. [117]. After buffing the first partial progressive curve for the Spearman correlation analysis, two strongly related features were extracted as input from the partial progressive curve, and two FFNN models were built for the simultaneous estimation of SOH and RUL. This led to a straightforward model structure that performed well in terms of accuracy and generality. FFNNs are the source of the architecture of RNNs. The RNN, in contrast to the FFNN, has an extra context unit for storing the past data. As a result, certain hidden layer outputs are returned back into the input layer before them. With this innovation, RNNs become strong models with a special ability to handle sequential input. An estimated approach for accurately determining the SOH of a battery is presented in [118]. This method utilizes progressive decreasing current, double correlation analysis, and GRU to get precise estimates. The raw data consists of the measurement of the steady decrease in current during the constant voltage charging phase. Next, we suggest the use of the double correlation analysis approach to pick a combination of characteristics that accurately describe the SOH of the battery. These features are chosen from several categories of features. The GRU algorithm is used to establish a model for estimating the SOH. The learning rate of this model is enhanced by using a sparrow search algorithm (SSA), which aims to uncover the concealed correlation between variables and SOH. Chen et al. used the EMD approach to handle the unprocessed ageing data while designing an Elman NN for estimating the SOH in [119]. As a result, two different kinds of sequences are produced, one of which is the intrinsic mode function, which exhibits significant disturbance and can be calculated using the autoregressive moving average model. This eliminates the problem of capacity regeneration. The further one is the final remains, which may be calculated using an Elman NN that has already been trained. It is a flat monotonous curve. The fusion method is capable of precisely estimating the SOH as well as reflecting local variations in capacity fading. Elman NN is used in [120] for SOH estimation, which is

further applied to real-time battery SOC correction. In the preliminary stages of qualification tests, this study suggests using a CNN to predict the succeeding SOH value of LIBs. To highlight the time series characteristics of the data, capacity degradation data are first converted into two-dimensional pictures using Gramian angular and recurrence plot fields. In order to figure out Li-ion battery SOH values for a specific cycle, five different types of convolutional neural network models are created. To illustrate how the models arrive at their results, class activation maps are created in this instance [121]. In [122], the optimal mix of features, hyperparameters, and attention layer of the network are simultaneously found using an evolutionary multiobjective (EMO) technique, allowing for flexible SOH estimate under a variety of operational scenarios. The partial voltage curve is intended to be compressed while retaining its tendency properties using a piecewise aggregate approximation. To create the data-driven model, a LSTM is used, and to complete the feature selection process, an attention layer is added. In order to address the issue of battery capacity regeneration in the assessment of SOH, Li et al. [123] provide a technique that utilizes IEA and bidirectional long short-term memory (BiLSTM) to estimate battery SOH. Initially, the IE curve, which accurately characterizes the intricate chemical properties of the battery, is derived based on the energy data computed during the CC charging phase. Subsequently, an examination is conducted on the correlation between the IE curve and the deterioration attributes of battery SOH. The peak magnitude of the IE curve is then isolated as the indicative feature of battery ageing. Additionally, PCA is used to ascertain the linear link between the suggested ageing features and the SOH of the battery. The findings show that the suggested approach successfully calculates the SOH of the battery under two distinct charging scenarios, achieving a root mean square error of less than 0.5% and a coefficient of determination above 98%.

(3) SVM Method. The SVM examines the given data and assists to figure out the pattern for nonlinear systems. SVM is also use for various classification problem in pattern analysis and more. SVM is broadly used because of its potential of managing small datasets. Although when the data size increases the number of support vector rises, hence the computation cost also rises. For SOH estimation, an SVM with a kernel function based on a RBF is used. An improved SVM based on PCA was suggested [124] to optimize the extracted dataset, remove noise, and apply a PSO method to fulfil the vector machine's global optimization, which further reduces prediction accuracy and calculation speed. A better learning machine built on sparse Bayesian theory is the relevance vector machine (RVM). It has less reliance on the kernel function and choice of penalty factor than the support vector machine. Adjusting parameters allows for flexible management of underfitting and overfitting problem, and the computation is made simpler. The SOH estimation for LIB using the RVM method is covered in the following pertinent literature [125–129]. Widodo et al. applied the sample entropy to check the SVM and RVM execution. The results unveil that the RVM surpass SVM-based health prognostics in the view of precision [130]. The benefits of low high sparsity, parameter identification, and variable kernel function allow RVM to precisely calculate the probability of findings' uncertainty. However, if the data are too sparsely collected, it can easily result in small stability and poor swift repeatability of the RVM algorithm's outputs. While this is going on, more research needs to be done on how accurate forecast and estimation of long-term trends are [131].

(4) Extreme Learning Model. However, ANNs frequently experience issues with sluggish training speed and large computing demands. As a result, an ELM-style quick learning model has been suggested for on-board estimate. In contrast to previous ANNs, the threshold of the hidden layer and the connection weight between the hidden layer and the input layer can both be set arbitrarily with no subsequent adjustment needed. Additionally, the generalized inverse matrix must be solved in order to establish the connection weights between the output and the hidden layer. Thus, the learning model gives more accuracy the traditional neural network. With easily observed terminal ambient temperature, load current, and voltage, Pan et al. employed the Thevenin equivalent model to determine the ohmic IR and polarization IR of the battery [132]. Online battery life estimates were made using the ELM approach by taking the addition of two resistance values as health factor. In comparison to the traditional FFNN, the results show that the estimation error is decreased with training speed. Table 3 shows the merits and drawbacks of the data-driven methods.

Table 4 provides a comprehensive collection of relevant academic publications focusing on the evaluation of the various SOH methodologies, accompanied with the average error value. The papers have been categorized based on the classification provided in this review from differen SOH methods [133–148].

3.3. SOH Estimation Challenges. In the context of automotive applications, the dynamic nature of operating circumstances, such as temperature fluctuations, poses significant challenges to the real-time viability of identification operations. Presently, significant progress has been made in the assessment and prognostication of the SOH pertaining to LIBs. However, in practical vehicle operation conditions or other real-world environments, the promptness and precision of the algorithm's prediction outcome remain the primary challenges in research based on the conventional forecasting model. The SOH estimation and the prediction of the future trajectory of LIB primarily depend on the following three aspects:

(i) Extraction of feature parameters related to the coupling process at the micro- and macrolevels: parameters such as current, voltage, resistance, and temperature are often used to evaluate the degree of battery degradation throughout different stages of battery health. In essence, the battery is often seen as an enigmatic entity, as the emphasis is only on the relationship between the inputs and outputs.

Table 3: Merits and drawbacks of the data-driven methods [86–103].

Model name	Merits	Drawbacks and limitation
Neural network (NN)	Ideal for parameter estimation, requires less data, accurate	Needs a large set of training data as it depends on historic data
Recurrent neural network (RNN)	Efficient for sequential data	Gradient explosion or disappearance
Support vector machine (SVM)	Suitable for both high and nonlinear dimensional model, fast, and accurate	Sophisticated computational technique
ELM	Requires less computation Learning model is fast	Delicate to the number of hidden neurons
RVM	Better sparsity Avoids overfitting and underfitting of data	Lack of stability Not feasible for long-term prediction
Elman NN	Adaptive to time fluctuating features, quick approaching speed	Easy to fall in local optimality

Table 4: Average error of different SOH methods.

Model	Error rate (in %)	Error type	Reference
Elman NN	1.29	MAE	[133]
Semisupervised transfer component analysis	1.29	MAE	[134]
ICA	2.99	RMSE	[135]
RF	3.58	RMSE	[136]
SVM	3.62	RMSE	[137]
SVM	0.13 and 024	MAE and RMSE	[138]
CNN	1 and 2	MAE and RMSE	[139]
RNN	0.72-1.37	RMSE	[140]
ELM	2	RMSE	[141]
ELM	1.93	MAE	[142]
ELM	0.4	MAE	[143]
ELM	1	MAE	[144]
LSTM	0.23	RMSE	[145]
LSTM	4.26	MAE	[146]
LSTM	2.16	Average RMSE	[147]
LSTM	2	MAE	[148]

Nevertheless, as the theoretical study progresses, the macrocharacterization of response intensity in batteries is emerging as a vital area of investigation. This is due to its ability to more accurately and effectively ascertain the overall health condition of the battery

(ii) The use of multialgorithm cross fusion technology: batteries in real-world applications are continually affected by factors like as temperature, loading mode, and other external impacts, including coupling interference. The internal structure of batteries is complex due to variations in their charged state and ageing features. As a result, the characterization of parameters exhibits variability, hence posing a challenge for a singular algorithm to effectively predict the specific state or attributes of the battery at any given moment. The use of cross fusion technology in various algorithms has the potential to provide advantages for each respective approach, hence resulting in improved precision in estimation and prediction

(iii) The implementation of innovative 5G and cloud platform technologies: the utilization of 5G communication technology and advancements in cloud platform technology has facilitated the overcoming of computational processing limitations. This has enabled various applications, such as mobile communication interface-based downloads and the transmission of online processing outcomes to the BMS. Consequently, these developments have enhanced the system's capacity for state parameter identification and strength calculation, as well as the implementation

Table 5 presents the recent research trends in SOH estimate during the last three years. The trends can be summarized as consisting of five topics: correlation analysis between

Table 5: Trends in research for SOH methods.

Trends	References
Correlation analysis	[149–152]
Considering various conditions	[153]
Data-driven methods	[154, 155]
Parameter identification	[156, 157]
Real-time estimation	[158]

capacity and other variables [149–152], different conditions [124], highly precise data-driven methods [154, 155], parameter identification through new correlations for SOH [156, 157], and real-time implementation [158]. The research trends in SOH estimate align with the following development needs.

(1) Newly introduced feature variables have strong associations with battery capacity

(2) Accurate determination of capacity using battery models and simultaneous estimate with SOC

(3) Methods that use data to make accurate predictions and can handle nonlinear relationships

(4) Estimation of the SOH under different environmental and operational situations

(5) Estimation of the SOH in real time for the purpose of updating other indications of battery status

4. Conclusions

This paper reviewed various methods available for SOH estimation. The prospective SOH estimate systems for EV batteries are examined in this study with an emphasis on the last few years' worth of advancements. Real-time SOH estimate techniques using the experimental method and model-based methods are examined. Several methods are used to get information about the lifetime of lithium-ion batteries. In this paper, the rapid SOH estimation methods for EV batteries are reviewed and discussed. Although the model-based methods can better reflect the variation law of internal battery decay, most models are complex, with many parameters, weak online estimation, and prediction ability. Their advantages and disadvantages are discussed in consideration for the practical application. This review offers the following advice on how to get through the difficulties:

(i) A more realistic model that can adapt to the real-world environment's complexity may be created using the genetic multiphysical modelling approach in conjunction with comparable circuit modelling, temperature, and electrochemical analysis

(ii) There is a need to enhance the computational efficiency, estimation accuracy, and practical applications of parameter determination techniques

(iii) To increase estimation accuracy, coupled SOH estimation algorithms can be created. To accomplish quick state estimate, it is specifically recommended that the EIS model-based and data-driven-based approaches be supplementary investigated

(iv) In order to enable the batteries in various applications, such as the battery pack in electric vehicles and charging systems, estimate techniques should be created

(v) To enhance estimation of accuracy and efficiency using data-driven approaches, it is important to investigate efficient estimation techniques and feature selection based on sample data. And it is hoped that the big data platform-based data-driven methodologies would be created to enable real-world applications

(vi) In conclusion, developing the SOH estimation taking into account the real-world applications of LIBs is still a popular study area. For diverse application contexts, specific estimating approaches might be chosen

Nomenclature

ESS:	Energy storage systems
BMS:	Battery management system
EVs:	Electric vehicles
LIBs:	Lithium-ion batteries
HEVs:	Hybrid electric vehicles
SOC:	State of charge
SOH:	State of health
EC:	Equivalent circuit
KF:	Kalman filter
AUKF:	Adaptive unscented Kalman kilter
EKF:	Extended Kalman filter
ECM:	Enhanced cyclic mat
ML:	Machine learning
SVM:	Support vector machine
ANN:	Artificial neural networks
IR:	Internal resistance
DL:	Deep learning
ICA:	Incremental capacity analysis
DVA:	Differential voltage analysis
ARIMA:	Autoregressive integrated moving average
A.C.:	Alternating current
D.C.:	Direct current
EIS:	Electrochemical impedance spectroscopy
DVA:	Differential voltage analysis
DOD:	Depth of discharge
SOX:	State of X estimation technique
SOE:	State of energy
SOP:	State of power
SW-AWTLS:	Sliding window-approximate weighted total least square
VRLA:	Valve-controlled lead acid batteries
AR:	Autoregressive
DFN:	Doyle-Fuller-Newman
LSTM:	Long short-term memory
CNN:	Convolutional neural network

FFNN: Feed forward neural networks
RUL: Remaining useful life
RNN: Recurrent neural network
EDM: Electric discharge machining
Elman NN: Elman neural network
EMO: Evolutionary multiobjective
PCA: Principal component analysis
PSO: Particle swarm optimization
RVM: Relevance vector machine
RF: Random forest
MAE: Mean absolute error
RMSE: Root mean squared error
PCM: Phase change materials
GPR: Gaussian process regression
BLS: Broad learning system
SSA: Sparrow search algorithm
GRU: Gated recurrent unit
ELM: Extreme learning machine
Q_m: Current maximum available capacity
Q_r: Rated capacity of the battery
R: IR in the current state
R_e: IR of the battery when it approaches the end of its life
R_n: IR of a fresh battery
Q: Rated capacity
Q_0: Lithium concentration after multiple cycles
R_i: Internal resistance
OR: Ohmic resistance
PR: Polarization resistance
R_b: IR of the battery
V_{bat}: Voltage of the battery
I_{pulse}: Current
δC_s: Mass in solid phase
Q_0: Initial capacity
Q_t: Calendar time
B: Cycling ageing coefficient
K_t: Calendar ageing coefficient.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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