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Review Article

State of Health Estimation Methods for Lithium-Ion Batteries

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Contemporary lithium-ion batteries (LIBs) are one of the main components of energy storage systems that need effective management to extend service life and increase reliability and safety. Their characteristics depend highly on internal and external conditions (ageing, temperature, and chemistry). Currently, the state of batteries is determined using two parameters: the state of charge (SOC) and the state of health (SOH). Applying these two parameters makes it possible to calculate the expected battery life and a battery's performance. There are many methods for estimating the SOH of batteries, including experimental, model-based, and machine learning methods. By comparing model-based estimations with experimental techniques, it can be concluded that the use of experimental methods is not applicable for commercial cases. The electrochemical model-based SOH estimation method clearly explains processes in the battery with the help of multidifferential equations. The machine learning method is based on creating a program trained to predict the battery's state of health with the help of past ageing data. In this review paper, we analyze the research available in the literature in this direction. It is found that all methods used to assess the SOH of an LIB play an essential role, and each method has its pros and cons.

1. Introduction

Lithium-ion batteries (LIBs) are one of the primary components of an energy storage system that requires appropriate management to extend service life and improve reliability and safety. Lithium-ion batteries are nonlinear electrochemical devices with a complicated electrochemical structure. Their performance is heavily influenced by internal and external factors (ageing, temperature). An accurate evaluation of a battery's state of health (SOH) aids in predicting the operational range, preventing potential damage, and enhancing performance [1]. In scientific papers, the main description of a battery SOH is mainly focused on building a battery model and developing an algorithm. In recent years, the importance of lithium-ion batteries has grown, and, in this regard, much scientific research appears devoted to the battery's performance and reliability. Accordingly, intelligent battery management systems (BMS) perform actual SOH estimation or control of batteries that optimize battery efficiency [2]. It is widely accepted that when the capacity of batteries is decreased to 80% of its initial capacity, the battery is considered dead and no longer has any use. The battery capacity degradation occurs around 400 cycles and is hard to predict. The first phase relates to an initial capacity increase at the start of life (Figure 1). This behavior might be explained by the geometrical properties of the cells and is unrelated to any ageing process. As a result, the data from Phase 1 was disregarded for the construction of the ageing model. Each cell's most significant capacity point was identified as the beginning of the life point during the data preprocessing step and assigned to the "zero cycled Ah-throughputs" state. The second phase is characterized by a steady rate-constant fall in cell capacity. This phase is occasionally followed by a third phase characterized by an abrupt capacity loss, as seen in Figure 1. The presence of lithium plating in these examined cells triggered

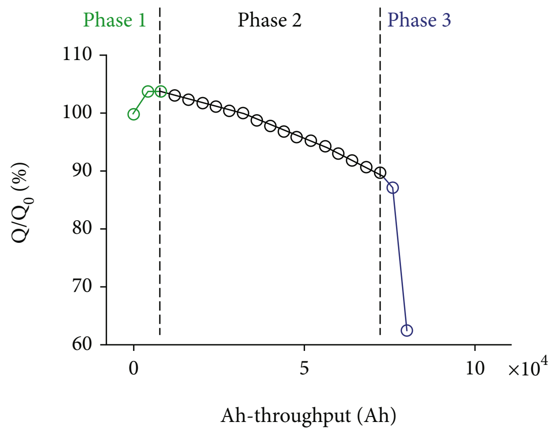

Figure 1: The degradation curve of capacity retention with cycle number. The first phase is capacity growth, the second is a steady deterioration, and the third is a dramatic decrease in capacity (Creative Commons (CC-BY) [3]).

the third phase. The modeling of Phase 3 is omitted from the scope of the research, and the accompanying data was deleted from the modeling dataset. As a result, the modeling effort in this study focused on capturing the relationships between cycling circumstances and cell capacity loss during the gradual deterioration corresponding to the second phase in Figure 1 [3]. Currently, the state of the batteries can be determined by two parameters: the state of charge (SOC) and the state of health (SOH). Applying these two parameters makes it possible to calculate the expected battery life and affect its performance. The level of the SOH of batteries might vary due to irreversible physical and chemical reactions during battery life. As a rule of thumb, the SOH is a quality indicator that indicates the level of degradation of a battery. The accuracy of assessing the health status is directly proportional to evaluating the nutritional status and the state of charge [4].

Typically, battery ageing is a complex process which includes many characteristics, such as battery internal resistance, conductivity, capacity, and others. To record these factors, batteries are equipped with a BMS. Internal resistance, impedance spectroscopy, capacity, entropymetry, accelerated cycling, and other methods are used to determine the SOH of lithium-ion batteries.

Lerner's invention of a nickel-cadmium battery in 1970 was one of the first attempts to explore the status of the charge. He discovered that the only dependable way to determine a battery's charge state at that time was to compare the output current value to a known battery current level. The output current of the battery (the charge level of which had to be calculated) was compared to the current of the battery, where the charge level was known, in this manner. This comparison allowed us to determine the precise level value of an unknown battery [5]. Furthermore, it is necessary to consider all methods to accurately identify the charge level using all the accumulated knowledge because they are all interrelated. There are many methods for estimating SOH batteries, including experimental, model-based, and machine learning methods (Figure 2).

2. Battery State of Health (SOH) Estimation: Experimental Methods

Experimental methods play an essential part in the SOH assessment of a battery and demand a considerable number of procedures to collect the necessary data. During the experiment, it is not always possible to obtain reliable information since there are systematic errors and many external factors. With the help of experimental methods, it is possible to measure internal resistance based on direct and indirect measurements. Direct measurements subdivide into battery capacity measurements, internal resistance, impedance measurements, and others. In the case of indirect methods, these include data optimization and processing to locate parameters of SOH, the charging curve method, the ICA and DVA method, and ultrasonic inspection [6]. Experimental methods are usually carried out in laboratories due to the requirement for specific equipment and are often time-consuming [7]. They are founded on a set of data and measures that may be utilized to comprehend and assess battery ageing behavior. This section discusses some major experimental approaches [8].

2.1. Internal Resistance Measurement. Internal resistance (R_i) plays a vital role in the SOH of a battery as this property provides information promptness about the end of the battery life. The general description of internal resistance is the resistance of a substance through which an electric current is passed. The battery materials and their structure, the state of charge (SOC), temperature, and discharge rate impact the internal resistance and specific characteristics ensue to help identify the battery's length of life. The internal resistance of the lithium-ion battery has two main contributions, namely polarization resistance (PR) and ohmic resistance (OR) [9]. The internal resistance is the prominent feature which defines the lithium-ion battery's voltage drop at a certain current. The ohmic resistance combines the contact resistance of diverse components: electrolyte, electrode materials, and separator. Researchers at Tongji University have studied certain aspects of the state of health of lithium-ion batteries by measuring the internal resistance [9]. The polarization resistance is the conversion state between the electrolyte and the electrodes during the electrochemical reaction. The increase of internal resistance is related to the battery's capacity and discharge time. Prior investigations considered that the ohmic resistance directly correlates with temperature and SOC. During the experiment, an effective equivalent circuit model for the lifetime estimation of the battery was established. According to this equivalent circuit, Xuezhe Wei and his coworkers could provide accurate and accelerated descriptions of the ohmic or internal resistance of the battery for use in fuel elements [10]. Much attention has been drawn to current pulse methodology, and research generally confirms that the SOC and temperature affect the battery's internal resistance [6, 8, 11]. Special additives are introduced into the electrolyte in lithium-ion batteries to reduce the problems of internal corrosion which correlate with internal resistance. The internal resistance of a battery might then become independent of

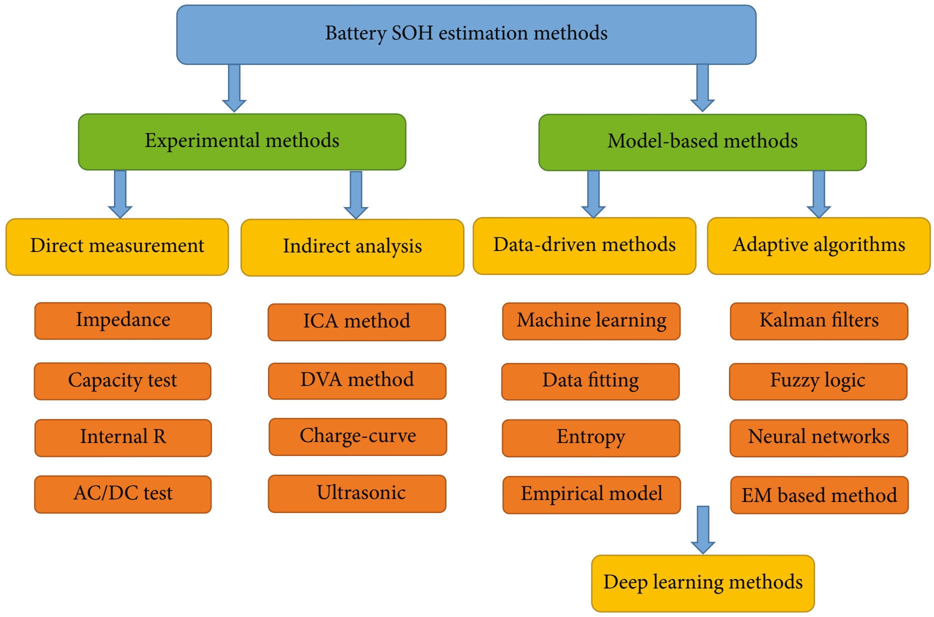

Figure 2: Classification of battery SOH assessment.

the ageing and degradation of the battery. So, the capacity does not decrease concerning the internal resistance during cycling [10]. Battery internal resistance does not always remain consistent throughout a cycle. It is determined by various factors, including a battery's state of charge, the temperature of the electrolyte inside the battery, the load current, and the battery's capacity. According to the literature, the more excellent the load current, the lower the battery's internal resistance because charge transfer activities inside the electrolyte are more intensive and active from the electrode to the electrode [12]. Several types of research have been conducted to evaluate internal resistance utilizing the current pulse approach based on Ohm's law. This method determines the battery's voltage decline at a given current and calculates $R_b(\mathrm{SOC}, T)$ using the following equation. [13, 14]

$$\mathrm{R_b}(\mathrm{SOC}, T) = \frac{\mathrm{OCV}\,(\mathrm{SOC}, T) - V_{\mathrm{bat}}\,(\mathrm{SOC}, T)}{I_{\mathrm{pulse}}}, \quad (1)$$

where R_b is the internal resistance of the battery, OCV is the open-circuit voltage, V_{bat} is the voltage of the battery, and I_{pulse} is the current. One of the key benefits of this equation is that, under various circumstances, it can provide answers with high accuracy. During the experiment, the temperature was constant and was approximately 21°C. After measuring the internal resistance, the lithium-ion battery is discharged with a continuous current and with a current pulse equal to 10 A. This measurement method works well for large stationary batteries. High-quality instrumentation allows taking resistance readings in the 10 μOhm range [14]. Other research has emphasized that using Joule's law is more effective for calculating energy loss of the internal resistance of the battery and is characterized by the following equation: [15]

$$\frac{dQ_{\mathrm{joule}}}{dt} = I_{\mathrm{bat}}^2 \times R_{\mathrm{bat}}, \quad (2)$$

where Q_{joule} is the heat generation of the battery. This method uses a calorimeter to detect heat loss for the duration of the charge/discharge. In addition, this type of assessment uses high-cost laboratory equipment. If, during the cycling process, the LIBs have an equal amount of specific capacity (discharge/recharge) at a given SOC, then the reversible thermal effect is neutralized. In this case, the researchers applied Joule's law to control the heat input. To identify the internal resistance, the change in temperature in the cycle must be controlled using an electrochemical calorimeter [15]. For this purpose, the limited energy during the procedure should be calculated using the following equation:

$$Q = I^2 \times R \times t = (C_{\mathrm{cal}} + C_{\mathrm{cell}}) \times \Delta T. \quad (3)$$

Then, the internal resistance may be described by

$$R_i = \frac{(C_{\mathrm{cal}} + C_{\mathrm{cell}}) \times (T_2 - T_1)}{\int_{t1}^{t2} (I(t))^2\, dt}, \quad (4)$$

where I is the current strength, R is the resistance; C_{cal} is the heat capacity of the calorimeter, C_{cell} is the heat capacity of the battery, and ΔT is the temperature difference. It is well known that heat is generated when a certain current is set for LIBs. For all types of LIBs, the amount of heat is characterized by the matching formula I_2R_i during the discharging/recharging process. The process in which heat is released with the help of internal resistance is called Joule heating. According to Joule's law, internal resistance can be measured, and for this purpose, a calorimeter is used to measure the heat generated [16–18]. Experiments on direct electrochemical calorimetric analysis of zinc-bromine and zinc-air batteries were carried out in 1984 by a group of researchers from the University of Ottawa [19]. The experiments were conducted in aqueous solutions and under galvanostatic conditions, and the method's efficiency was about 82%. In this study, it was possible to determine the Peltier electrolytic heats using the total anode and cathode currents. Pesaran et al. developed a special calorimeter and tested it for large battery modules with dimensions of $21 \times 39 \times 20\ \mathrm{cm}^3$ [20]. This paper outlines the heat dissipation measurement of full-size batteries to determine internal resistance accurately. Studies based on LIB capacitance reduction used an isothermal calorimeter to determine the Joule heating [18, 20]. The identification of the internal resistance of lithium-ion batteries can also be carried out by the alternating current (AC) or direct current (DC) method. The AC method should be used initially to measure the internal resistance of the same lithium-ion batteries utilizing both methods. There is no need to discharge/charge the battery between the AC and DC testing in this situation. However, batteries charged at an ambient temperature of 20 + 5 ∘ C should be kept at this temperature for 1 to 4 hours [21].

The lithium-ion battery's state of charge (SOC) and state of health (SOH) are two crucial state parameters (LIBs). The battery's capacity is essential in obtaining these states, but it is difficult to detect directly online. On the other hand, this parameter strongly correlates with battery internal resistance [22]. Under isothermal and iso-SOC conditions, the linear fitting relation of internal resistance and capacity can be established using correlation analysis of internal resistance and capacity. The battery capacity obtained by linear fitting the internal resistance can be used directly as an EKF algorithm for estimating SOC. The experimental results show that this capacity fitting method is not only simple to implement, but it also improves the accuracy of the SOC algorithm evaluation.

2.2. Internal Resistance Measurement Using the Alternating Current (AC) Method. The internal resistance of a lithium-ion battery is a critical quantity for determining power, energy efficiency, and lost heat. This value must be precisely understood when constructing battery systems for automotive applications. Current step methods, alternating current methods, electrochemical impedance spectroscopy, and thermal loss methods have been used to assess a cell's internal resistance. The results of these measures were compared to one another. Current step approaches produce the same results as energy loss methods when the cell's charge or discharge is restricted [22]. In addition, it is necessary to measure the active, inductive, and capacitive components of the internal resistance. The active and capacitive components of the internal resistance were calculated using a bridge circuit, as shown in Figure 3 [23]. However, the inductive component is often not taken into account due to its small value.

Figure 3 illustrates the bridge circuit for calculating the alternating current of lithium-ion batteries. The two left sides of the bridge consist of active and capacitive resistance (R_1, C_1, and R_2, C_2), while the right sides contain only active

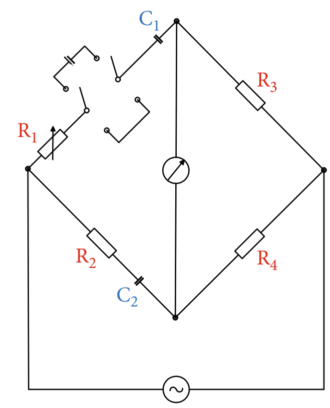

Figure 3: Bridge circuit to measure the internal resistance of the LIB.

resistance (R_3 and R_4). The capacitance of C2 is a reference used as a precision capacitor. In the case of capacitor C_1, it is a variable that should compensate for the capacity of the lithium-ion battery. It is essential to note that the resistances R_3 and R_4 are approximately equal, and R_2 has a slight resistance value. Moreover, the value of R_1 depends on the lithium-ion battery's resistance and other circuit resistances. The equilibrium of the bridge circuit to calculate the internal resistance is achieved using two conditions:

First condition:

$$\frac{R_2}{R_1} = \frac{R_4}{R_3} \tag{5}$$

Second condition:

$$\frac{C_2}{C_1} = \frac{R_3}{R_4} \tag{6}$$

Hence, an unknown value could be found:

$$R_1 = \frac{R_2 C_2}{C_2}. \tag{7}$$

The resistance value of the battery is defined as the difference between the two measurements: the first measurement is calculated by connecting the battery; the second one is without the battery. However, calculating the internal resistance of complex loads is significantly more challenging since the measurement outcome is determined not only by the device's ohmic behavior but also by its capacitive and inductive behavior. Things become much more problematic if the measuring technique causes extra nonlinearity, such as temperature dependency and other time-variant behavior of the equipment under test. As a result, sophisticated measurement methodologies must be utilized to quantify the resistive component of a complex system. These approaches are dependent on the gadget under the test's frequency dependence [15]. This type of bridge has been developed and used for exothermic and endothermic energy changes in battery cells [19]. The measurement of the internal resistance of LIBs by the AC method is carried out using small current ripples, which stimulate the voltage with a regular frequency of 1 kHz. The main features of the AC method are the possibility to measure through the phase angle, and it is suitable for complex measurements [23, 24]. A significant advantage of the AC method is that it is a nondestructive method for internal resistance measurement. However, this method is not commercial for multicell batteries due to the limited voltage range [25].

2.3. Internal Resistance Measurement through the Direct Current (DC) Method. The direct current internal resistance analysis of lithium-ion batteries is the oldest and most reliable method [21]. The direct current method consists of a short-term battery discharge through a certain load with a known resistance. The battery capacity selects the load current. The algorithm for the measurement of the internal resistance of the battery via the direct current method is as follows:

(i) A voltmeter is used to measure the open-circuit voltage without a load

(ii) Connect the load and measure the voltage across it

(iii) From Kirchhoff's law for the circuit, calculate the value of the internal resistance

The direct current method for measuring internal resistance is suitable for lithium-ion batteries, which have a high capacity. Their ohmic values are accurate and repeatable with constant measurements. State-of-the-art high-quality instruments for internal resistance measurement allow internal resistance readings in the range of 10 μOhm. The DC method measures the voltage drop during the current supply to a cell. The DC method is among the most widely used for assessing the SOH of a battery during the cycling procedure. The primary advantage of measuring internal resistance with the DC approach over the AC method is that it is more precise owing to diffusion polarization. If diffusion polarization occurs during the experiments, then the AC method can only measure low impedance values of LIBs [26, 27].

2.4. Electrochemical Impedance Spectroscopy. Another commonly used nondestructive method for measuring internal impedance is electrochemical impedance spectroscopy (EIS). The experiments are always based on determining the electrical system resistance and using a sinusoidal alternating current [28–30]. The main fundamental characteristics of impedance spectroscopy are the identification of the ageing state of a battery. Scientists in previous research distinguished two things about the battery SOH during the experiment [31]. The first phenomenon is a charge transfer on the positive electrode, and the next is the displacement of lithium ions through the solid electrolyte interphase (SEI) layer [32, which provides a battery model to assess SOH through impedance spectroscopy. This study has established the ability to measure the ageing of batteries and their neural network. Previous studies have explored EIS measurements during charge and discharge. Thus, the impedance measurement in the potentiostatic approach at a specific open-circuit voltage (OCV) was taken. For this purpose, the required current was dropped and left to restore equilibrium capacitance. However, some researchers substantiate the belief that the impedance measurement at the equilibrium condition will differ from the measurement during the charge and discharge of the battery [8, 33, 34]. Throughout this paper, scientists used the galvanotactic voltage-transient technique to obtain the desired impedance parameters [34]. EIS analysis is widely accepted to predict detailed information about the tested coin cell, namely, reaction kinetics, local corrosion, corrosion rate, electrochemical mechanisms, and the remaining useful life (RUL) of the LIB [35]. A galvanostatic voltage-transient technique has been generating considerable interest in the possibility of obtaining electrochemical impedance and RUL estimation results in a nondestructive method. In some cases, there is a possibility of getting erroneous results of LIBs causing drift voltage at the output. Those errors could be terminated via the filtering of high-frequency current and voltage signals [33, 34]. Generally, impedance is defined as the total resistance of a device or circuit to the flow of alternating current at a given frequency and is expressed as a complex number. The leading role of these complex numbers is determined by phasors or complex amplitudes that characterize the amplitude and phase of a monochromatic or quasimonochromatic wave perturbation. Phasors or complex amplitudes describe the relationship between circuit voltage (E) and current (I) by determining the amplitudes of the rotating voltage and current vectors in the complex planes [36]. Impedance spectroscopy plays an increasingly essential role in fundamental and applied research. This spectroscopy can investigate solid and liquid materials: ionic, mixed, semiconductor, and even insulators [37]. The method is essential for studying charge transfer in heterogeneous systems, including phase boundaries, electrode boundaries, and microstructural elements. With the help of EIS, it is possible to study the behavior of chemical sensors, fuel cells, and corrosion processes. It is necessary to measure at least two quantities to determine the impedance since it is a complex quantity. Many modern impedance-measuring devices measure the real and imaginary parts of the impedance vector and then convert them to the desired parameters [38, 39]. The operator only needs to connect the test object, circuit, or material to the measuring device. However, sometimes, the result obtained is unexpected by being too large or too small. One probable explanation is an incorrectly set method (technique) of measurements or the natural behavior of an unknown device. The frequency spectrum should be as broad as feasible. There are many ways to implement impedance measurements: each of which has several advantages and disadvantages. The choice depends on the specific conditions and measurement requirements, particularly the frequency domain, measurement range, measurement accuracy, and ease of experimentation. Ideally, impedance measurements require 6 to 7 orders of magnitude in frequency, for example, 10^{-2}-10^{5} Hz. At frequencies below 10^{7}-10^{8} Hz, various bridges are widely used. In the past, manually balanced bridges (Wheatstone bridge, Schering bridge) were used, but modern devices are computer-controlled and autobalance (Figure 4) [40].

Figure 4 illustrates four arms of the Wheatstone bridge AB, BC, AD, and DC with the resistances R_X, R_0, R_1, and R_2, respectively. According to the described procedure, the values of R and C are determined that are connected in various combinations and operate as an electrochemical cell in frequency measurements. The galvanometer (G) is connected to the BD diagonal, while the power source is connected to the AC diagonal. Generally, the source ε will flow through all circuit parts, including the galvanometer (G). Discussions regarding impedance have dominated research in recent years and are taken as a function of AC frequency. The parameters R and C must balance simultaneously, for a bridge of the simplest form is a slow process. Therefore, the method applies only to static or very slowly changing systems [40]. The main goal of studying the electrochemical impedance and solid-state systems is to obtain information about electrode processes, which means processes occurring at the electrode or electrolyte interface. Previous studies have promoted measuring impedance mainly using closed-loop amplifiers or frequency response analyzers. The main feature of using closed-loop amplifiers is that they are faster and more convenient than AC bridges [41, 42].

Measuring EIS spectra does not necessitate disassembling the battery cell, preventing sensitive samples from impregnating with moisture and oxygen. EIS measurements can also be performed under operating parameters, which helps obtain spectra without disrupting the cell. Finally, EIS analyses require little time and money [6]. The RSEI represents resistance from an interfacial layer formed by electrolyte decomposition. Initially, research on this SEI layer was aimed at a deeper understanding of the deterioration of graphite electrodes by establishing a link between the resistance features of the SEI layer and the cycling conditions. However, in recent studies on nanosized electrode materials for high-performance lithium-ion batteries, the SEI layer has been taken into account as another factor resulting in additional capacity via reversible reactions. The reversible SEI establishment with additional capacity is still being worked out in detail. As a result, analyzing the SEI layer with EIS is very effective for monitoring the anode material's resistance and additional capacity from reversible SEI layer formation.

2.5. Battery Capacity Measurement. Recent theoretical developments have revealed that battery capacity tends to degrade over time and reflects the total amount of energy in the batteries [43]. This method has useful applications due to accurately determining the amount of energy in lithium-ion batteries for health assessment. For example, with the predicted findings, research was done on detecting charge capacity regulated by the voltage across the charge/discharge of the batteries. The battery's capacity is widely characterized as power and energy capacity [44]. Pecht's use of various temperature conditions from 25°C to 40°C over 800 cycles of battery to measure its capacity is fully justified [45]. Further analysis showed that this kind of method could only be carried out in laboratory conditions in an offline mode [46]. The power rating is the power that can deliver the underrated charge and discharge time interval. In the case of energy capacity, it deals with the energy that may be eliminated or preserved in the LIB. Specific energy density and power rating highlights the cost price of the battery. The rapid development of technologies for the production of lithium-ion batteries has significantly expanded, including batteries with a capacity of tens and hundreds of ampere-hours [47]. Using new electrode materials in LIBs instead of traditional anode materials based on carbon, cathode materials, and lithiated Co, Mn, and Ni oxides made it possible to ensure a high safety level even when operating in abnormal modes of operation. The application of electrodes using modified nanosized materials made it possible to increase the service life of LIBs at deep (70–80%) discharges up to 3000–5000 cycles and the discharge currents, up to 10–20°C and above. The capacity of a battery reflects the amount of energy it can store.

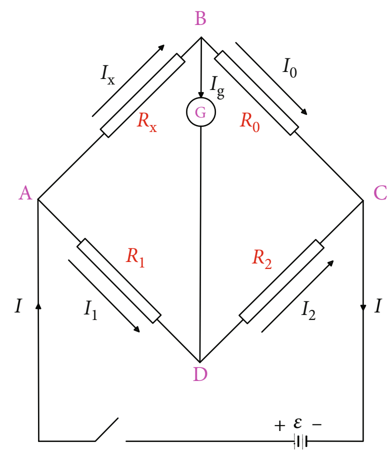

Figure 4: The straightforward Wheatstone bridge for R and C measurements.

Meanwhile, internal resistance and impedance are indicators of its power. Different indicators show the health status depending on battery mode. The hybrid battery may lose up to 20% of its capacity at the end of its life while the internal resistance grows to 160% of its starting value ε.

2.6. Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA). Lithium-ion batteries can be examined by analyzing the change in their incremental capacity analysis (ICA) and differential voltage analysis (DVA) [48]. These parameters change during the operation of the battery, and it is possible to track the ageing through experimental testing. One downside of the ICA and DVA approaches is that they require more time throughout the experiment since their curves are obtained at a low current, about equivalent to $C/20$. Prior studies collected data for 11 months to assess battery ageing, while this study only covers a subset of operating situations [49]. Based on the study of the SOH estimation for the LIB, the article considered a method for predicting the capacity and RUL of batteries based on the ICA method. In addition, the ICA method is considered one of the valuable tools for obtaining accurate battery characteristics by integrating changes in capacitance and battery voltage. As its name indicates, the cycle counting method consists of counting the number of cycles a battery has experienced and comparing it to the number given by the manufacturer to evaluate the battery's condition. This counting method considers a vital parameter—the depth of discharge (DOD) [50, 51]. The core problem of the ICA method is that IC curves are very sensitive to noise, which is why some data results may contain undesirable peaks. Researchers apply to filter algorithms to obtain clean peaks, such as wavelet transform (WT) and moving averages (MA). It should be noted that the IC curves depend on the differential voltage range, which can lead to inaccurate analyses. Two types of filtering algorithms (MA and Gaussian filter) must be used to avoid this difficulty [49]. The IC curve represents the degree of power amplification as the voltage changes. The battery voltage and capacity were commonly employed to detect IC curves during the charging method. As a result, the battery capacity and voltage initially should be determined [52].

$$\begin{aligned} Q &= It, \\ V &= f(Q), \\ Q &= f^{-1}(V). \end{aligned} \tag{8}$$

Thus, the IC curve can be distinguished as follows:

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

The ICA method requires a tremendous amount of high-quality research data, and it takes much time to preprocess the input data [53]. Gaussian process regression plays a vital role in SOH estimation since it measures the similarity of input variables and constructs a covariance function to improve the accuracy of the SOH assessment of the battery. Yang and his coworkers provided an effective procedure, a novel Gaussian process regression model through the ICA curves [52]. In the works of Barker et al., the ICA and DVA methods were used for the first time to evaluate the remaining useful life of LIBs [54, 55]. During this research, the ICA and DVA methods have gained much importance in recent years and confirmed the electrochemical features of the spinel phase LIBs based on carbon anode material. Dubarry et al. have utilized these methods in the research regarding the lifetime estimation of the battery cell [56–58]. The DVA method is valuable because it reflects the lithium distribution's homogeneity and does not depend on the sensor voltage. Generally, the DVA method is described as the gradient of the battery voltage to its capacity, and during the discharge state, it is calculated as follows.

$$\frac{dV}{dQ} = \frac{dV}{\int I dt} = \frac{dV}{I dt}, \tag{10}$$

where V is voltage and Q is capacity.

Alternatively, DV can be defined in a specific form, as follows:

$$\frac{dV}{dQ}|t = k+1| \approx \frac{V_{|t=k+1|} - V_{|t=k|}}{I_{(t_{k+1}-t_k)}}, \tag{11}$$

where $dV/dQ|t = k+1|$ is the DV meaning at the $k+1$ time and $V_{|t=k+1|} - V_{|t=k|}$ is the values of the voltage. Overall, experimental methods can significantly impact predicting the SOH of a battery [52, 59]. However, precision and accuracy may vary from method to method. The sum of experimental methods considered in this section is listed in Table 1, along with their main benefits and drawbacks.

3. Battery State of Health (SOH) Estimation: Model-Based Methods

Another method to estimate a battery's state of health is a model-based estimation. However, the model can only be used with enough experimental preresults [61]. This method is based on determining the dependence of essential characteristics of the battery, such as current, voltage, and capacity, on the battery's ageing. After verification of the model by a set of experimental results, the state of health of the battery can be estimated without battery destruction. Therefore, the method is suitable for battery management systems. The destruction of the battery during estimation is not economically effective when applied in a battery management system. The main difference between this method and the experimental estimation method is that the experimental estimation method can also be used for scientific purposes. A survey of scientific papers revealed that there are several main types of model-based estimation: such as Kalman-based filters, equivalent circuit model-based methods, electrochemical model-based methods, empirical fitting methods, machine learning methods, and deep learning methods.

3.1. Kalman-Based Filters. The standard Kalman filter is a filtering algorithm based on the minimum root-mean-square variance that applies to the measurement of the state of linear systems, and the error follows a Gaussian distribution [60, 62]. In practice, many systems have some nonlinearity that manifests itself in the nonlinearity of the equation of state or measurement equation. Therefore, the standard Kalman filter algorithm does not give satisfactory results [62]. In this case, the solution consists of a linear approximation of the nonlinear relation: converting a nonlinear problem into a linear one. Based on the extended Karman filter algorithm, the battery health assessment process determines the model's parameters following the initial health value [63]. The first step in estimating health status is creating a model. The model parameters, operating current, and voltage are inserted into the extended Karman filter's recursive equation, and the model parameters are then updated in real time based on the value of the improved battery SOH [64]. The next step is to analyze the findings and use a prediction approach. A filtering method is required to detect the

Table 1: Experimental methods.

Method	Benefits	Drawbacks
Internal resistance measurement	Reliable Widely used as an indicator for evaluating the charge Direct and common Noninvasive	Time-consuming Not suitable for online assessment [60]
Electrochemical impedance spectroscopy	Nondestructive Accurate estimation of RUL Prediction of the degradation of the battery	Requires a long time Used only for a particularly stable environment
Battery capacity measurement	Fastest	Not suitable for online assessment Not possible when the battery running (requires the battery to be fully charged)
ICA/DVA	Effective tool to analyze the capacity loss of battery Robust and reliable High accuracy	Not suitable for other types of batteries (only for LIB) due to the difference in charging IC curves

dependency and eliminate the noises based on the results. The most often used approach in battery characterization is adaptive Kalman filtering. There are numerous Kalman filtering variations. Some articles, for example, have provided the following types of filtering: dual unscented Kalman filtering, linear regression filtering support, and double-scale particle filtering.[64] [65], Kalman filtering can also be used to simultaneously assess the state of charge and the state of health of the battery.

3.2. Equivalent Circuit Model-Based Methods. In this estimation method, the battery system is considered an electric circuit. An electrical circuit contains elements such as resistance, inductor, and capacitor, which can be connected in series or parallel. The model is varied depending on the number of elements and types of connections [66]. As is known, the ageing of a battery depends on several conditions of exploitation, such as temperature, storage time, C-rate, overcharging, or overdischarging [67]. Yang et al. analyzed the ageing of a battery at constant voltage and constant current charging [68]. To estimate the SOH of the battery, the battery was treated as an electrical circuit that consists of a parallel-connected inductor and resistance as characterized in Figure 5. The model is described as a resistor-capacitor circuit with self-healing resistance. This model has been examined for experimental results of lithium iron phosphate batteries and found that if the circuit has three resistances and three inductors, the model has high accuracy. Prior studies discovered that the battery's self-healing mechanism accurately predicts SOH [69]. One study proposed representing the self-healing mechanism with an analogous circuit model. Pei et al. used two different circuit models for the ageing and self-healing process [70]. The model has a self-healing process in a standing state, and the ageing process is carried out in a discharging state. The equivalent circuit model of the discharging state and standing state is illustrated in Figure 6. According to another article, the presence of a parallel connection between a constant phase element and ohmic resistor elements in the circuit model was used to consider overcharging of the battery [70] [71]. Most researchers have applied accelerated ageing experiments to collect the data at a minimum time. According to Xia and Abu Qahouq, the data on electrochemical impedance was collected during the accelerated ageing of the battery [72]. Based on the collected data, an equivalent circuit model was created, which consisted of a series of resistors and capacitors. It was verified that the acceleration of the ageing process leads to an increase in resistance value and a decrease in capacity value in the circuit model. To decrease the time of the data collection, some people have suggested that the circuit model consists of a double resistance and capacitor with one-state hysteresis. The work introduced the Sobol method to investigate the ageing characteristics of the battery [73]. According to the ageing experiments, it was concluded that this method needs only half of the data of ageing results. Consequently, it means that the time of data collection decreases. Some researchers established that the equivalent circuit model could be used for lead-acid batteries in low-voltage applications. Topan et al. used the recursive least square (RLS) and Kalman filtering based on the Thevenin circuit model to estimate the SOH of the battery [65]. They concluded that Kalman filtering results are better than RLS [74].

3.3. Electrochemical Model-Based Methods. Understanding the processes that occur during battery operation is required to evaluate the state of health of a battery using the electrochemical model. An article study found that battery ageing reduces battery capacity and increases internal resistance. Doyle et al. developed the first lithium-ion battery electrochemical model. This approach is abbreviated as the DFN model (Doyle-Fuller-Newman) [75, 76]. It analyzes battery parameters with high accuracy, yet it is too sophisticated for use in a BMS. The model was developed based on the partial differential form of the mass and charge conservation equations in the solid and electrolyte interphases. It also

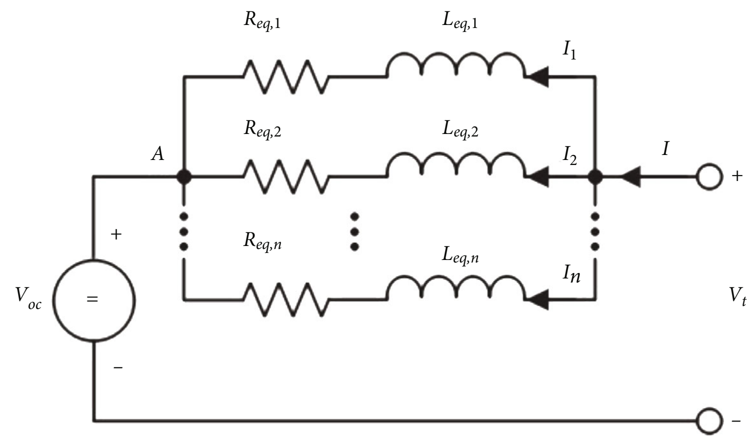

Figure 5: The equivalent circuit model consists of parallel-connected resistance and inductor. Reproduced with permission from Elsevier [68].

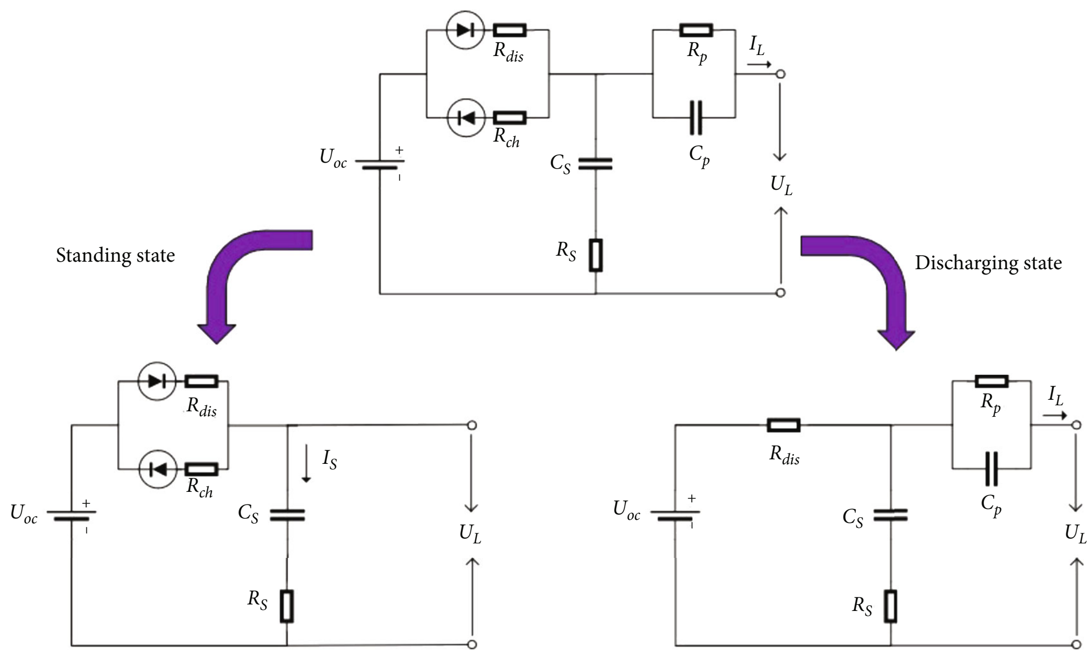

Figure 6: The equivalent circuit model scheme of the battery's self-healing process (Creative Commons (CC-BY) [70].

describes the chemical process that occurs before the creation of the solid electrolyte interphase layer (SEI), which reduces the capacity of lithium-ion batteries due to the production of nonconsumable lithium ions. The DFN model equations are provided below:

δ^- is the thickness of the negative electrode; δ^+ is the thickness of the positive electrode, and δ_{sep} is the thickness of the separator.

$$\frac{\partial C_s}{\partial t} = \frac{D_s}{r^2}\frac{\partial}{\partial r}\left(r^2\frac{\partial C_s}{\partial r}\right), \tag{12}$$

where C_s is the concentration of lithium in solid phase.

The boundary conditions are as follows:

$$\frac{\partial Cs}{\partial r}(r=0)=0, \tag{13}$$

$$D_s\frac{\partial Cs}{\partial r}(r=Rs)=\frac{j_{Li}}{a_s \times F}, \tag{14}$$

where j_{Li} is the volume specific rate of the chemical reaction, $a_s = 3\varepsilon_s/R_s$ is the specific surface area of spherical particle, R_s is the radius of spherical particle, and ε_s is the active material volume fraction. In Equation (14), the mass conservation of lithium ions in the cathode and anode material is defined. According to the charge conservation in the electrode material, the following equations are produced:

$$\frac{\partial}{\partial x}\left(\sigma_{eff}\frac{\partial \varphi_s}{\partial x}\right) = j_{Li}. \tag{15}$$

The boundary conditions are

$$\begin{aligned}
\sigma_{eff}\frac{\partial \varphi_s}{\partial x}(x=0) &= \frac{i_{app}}{A},\\
\frac{\partial \varphi_s}{\partial x}(x=\delta_-) &= 0,\\
\frac{\partial \varphi_s}{\partial x}(x=L-\delta_+) &= 0,\\
-\sigma_{eff}\frac{\partial \varphi_s}{\partial x}(x=L) &= \frac{i_{app}}{A}.
\end{aligned} \tag{16}$$

A is the surface area of the electrode, i_{app} is the applied current, φ_s is the potential of solid phase, and L is the thickness of electrolyte.

$$\frac{\partial}{\partial x}\left(k_{eff}\frac{\partial \varphi_e}{\partial x} + k_D^{eff}\frac{\partial lnce}{\partial x}\right) = -j_{Li}. \tag{17}$$

The boundary conditions are

$$\frac{\partial \varphi_s}{\partial x}(x=0) = \frac{\partial \varphi_s}{\partial x}(x=L) = 0. \tag{18}$$

The open-circuit voltage is defined as follows:

$$V(t) = \varphi_s(L,t) - \varphi_s(0,t) - \frac{R}{A}i_{\mathrm{app}}(t). \tag{19}$$

Overall, there are several considerations about the electrochemical model: (1) the electrochemical reaction is proceeding in the interphase of the solid and liquid phase, and the Butler-Volmer equation describes it; (2) in the electrode, the mass transfer of lithium-ion is only defined by diffusion. According to a review of articles, the model is simplified to a single-particle model (SP) [77]. The single-particle model considers the electrode material as one with a spherical shape. It means that the charge is uniformly distributed over the solid phase. This model has high precision at low C-rates because it does not consider particles' cracking and volume expansion during the intercalation of lithium ions. The assumption of fracture propagation in electrode material is made to improve the accuracy of the SP model. The article hypothesized that the SEI layer was created by a four-step method. In the first stage, an SEI layer is applied to the whole surface of the single particle until 10% of the lithium ions are intercalated. Then, the new SEI layer on the surface of the initially produced SEI starts growing. In the third step, the SEI layer reaches enough thickness, leading to cracks forming. The final step is forming the SEI layer on the surface of the cracks. The voltage profile results of a $LiFePO_4$ cathode material were observed at different temperatures, C-rates, and cycle numbers to test the model's precision. The creation of the SEI layer on the surface of the generated fractures has a more significant impact on the battery's state of health than the production of the SEI layer on the original SEI layer. Following the creation of the model, it is critical to extract the battery's physical characteristics from the SP model's equations, which can be easily tested in real time. According to another study, the single-particle model should be enhanced by specifying the SP model's final equation with the following physical parameters: I: applied current, t: time, y_{average}: the ratio of the average concentration of lithium to a maximum concentration of lithium in the positive electrode, and x_{average}: the ratio of the average concentration of lithium to a maximum concentration of lithium in the negative electrode [78]. Transformation of the SP model with the above physical parameters leads to simplifying Equations (7)– from 26 distribution parameters to 11. All parameters can be estimated in real-time except the lithium concentration in an electrolyte which must be obtained from the battery manufacturer. Finally, due to their sensitivity to ageing, the magnitude of lithium-ion loss and diffusion into the liquid was chosen as the state of health indicators from the physical parameters [79]. Selecting the magnitude of lithium diffusion as the assessing parameter of the battery's state of health shows good applicability. As previously stated, the electrochemical model consists of many partial differential equations that cannot be solved analytically; instead, numerical solution methods are needed, such as Euler's, Heun's, and nth-order Runge-Kutta's methods [80]. The distinction between this article and others is that the diffusion parameter is evaluated at different levels of charge to improve the prediction of the state of health empirically, demonstrating the method's high precision with a relative error of 2% [81]. Besides measuring the battery's health, the electrochemical model may also be used to determine the battery's charge level. Some papers discuss the simultaneous measurement of SOH and SOC of a battery. The topic of the equivalent circuit model for evaluating the SOH has previously explained the adaptive filtering approach [82, 83]. It is used to process the dynamic behavior of the battery's physical properties. In the subsequent papers, which demonstrate the simultaneous evaluation of the SOC and SOH, the sigma-point Kalman filter adaptive filtering approach paired with an electrochemical model is utilized for this purpose [64].

In summary, the electrochemical model for battery state of health (SOH) estimation and degradation trajectory prediction plays a crucial role in the understanding and predicting the performance of a battery. The Butler-Volmer equation describes the electrochemical reaction at the interphase of the solid and liquid phases. The single-particle (SP) model considers the electrode material as one with a spherical shape. The SP model is a simplified version of the electrochemical model. It has high precision at low C-rates, but its accuracy can be improved by considering the formation of cracks in the electrode material. To extract the battery's physical characteristics, the SP model's equation can be enhanced by including physical parameters such as the applied current, time, and the ratio of the average concentration of lithium in the positive and negative electrodes. Lithium-ion loss and diffusion into the liquid are chosen as the state of health indicators. The electrochemical model requires numerical solution methods, such as Euler's, Heun's, and *n*th-order Runge-Kutta's methods, to solve its partial differential equations. The adaptive filtering approach, such as the sigma-point Kalman filter, can process the dynamic behavior of the battery's physical properties. The electrochemical model can also be used to simultaneously determine the battery's charge level (SOC) and SOH.

3.4. Empirical and Fitting Methods. The method is based on fitting the state of the health battery with mathematical functions such as polynomial and exponential. The drawback of such a method is that the mathematical model does not describe the chemical and physical processes happening in the battery. According to the literature, the mathematical model describing the battery's capacity could have the following variables: C-rate, the depth of discharge, temperature, storage time, number of cycles, and state of charge [84]. Calendar ageing and battery cycling ageing are two mathematical models for ageing. In the case of calendar ageing, it reduces battery capacity without using an electrical current. Cycling ageing reduces the capacity of a battery by delivering a steady charge-discharge current at a specific voltage range. Deshpande and Bernardi claim that Equation (20) may be used to develop a mathematical model in which the capacity of the model is specified by the depth of charge (DOD), the number of cycles (n), and storage duration (t) [83]. This calculation takes into account both calendar and cycle ageing.

$$Q_{(t)} = Q_0 \left(1 - B \times DOD_2 \times n - K_t\right), \tag{20}$$

where B is the coefficient that characterizes the cycling ageing, K_t is the coefficient that characterizes the calendar ageing, $Q_{(t)}$ is the real-time capacity of the battery, Q_0 is the initial capacity of the battery, and t is the calendar time.

The phase transition region during the charge-discharge can be determined by incremental capacity (IC) analysis [85]. IC analysis is the differential form of dependence of capacity to the voltage. Differentiation can give several peaks which correspond to specific phase transitions [86]. These peaks are sensitive to the battery's state of health; therefore, they can be used as the state of health assessment parameters, which has been verified in some articles. It was found that the INR-18650-25R cylindrical battery shows four peaks in the incremental capacity analysis [87]. Among the four peaks, the second and fourth peaks were selected as the state of health assessing parameter and created the mathematical model defined as in Equation (21), because the first and third peaks do not have a high linear correlation as in the following equation.

$$h_2 \text{ or } h_4 = a \times \ln\ (SOH - b) + c, \tag{21}$$

where h_2 or h_4 is the height of peaks in the incremental capacity analysis. a, b, and c are the parameters of a mathematical model.

The experiment must be performed at a C-rate equal to or less than 0.05 C to improve the visibility of IC analysis peaks. As a result, the experiment takes a long time in this scenario and is not appropriate inside a BMS. According to Li, the IC analysis of "NMC" batteries at various C-rates revealed four peaks at 0.05 C and two at peaks of 13 C [88]. The article discovered that the two peaks acquired at the 13 C-rate are more sensitive than the peaks obtained at the 0.05 C-rate by examining the four peaks at varied SOH of battery and depth of discharge. A low C-rate is no longer required to estimate the battery's health condition. The paper employed the linear regression model to build the mathematical model for SOH based on peak intensity.

$$\mathrm{SOH} = a - b \times h, \tag{22}$$

where a and b are the parameters of the model and h is the height of the peak.

Previously, it has been discussed about the creation of mathematical models based on the height of the IC analysis [89, 90]. Instead of the height of peaks, several studies suggested using the area of peaks to create the mathematical model [91]. For instance, several articles use the linear regression model with the area of the peak. The model was tested on the 60 Ah and 74 Ah $LiFePO_4$/C cells and resulted in an error of 4%. Zhou et al. indicated that data of the constant current charging of the profile of the battery in the range of terminal voltage to upper cut-off voltage is sensitive to the SOH of the battery [92]. To determine empirical dependence, they calculated the area of the charge-discharge profile by the following formula:

$$IV = \int_{t0}^{t1} v dt, \tag{23}$$

where IV is an area of the charge-discharge profile, v is voltage at time t, t is time, t_1 is the time when the battery reaches the upper cut-off voltage, and t_0 is the time when the battery reaches the terminal voltage. Finally, they found a linear relationship between the area of the charge-discharge profile and the SOH of the battery. The high precision of this linear dependence was verified by testing four $LiCoO_2$ cathode-based batteries [91]. In sum, the reviewed model-based methods are listed in Table 2 with their benefits and drawbacks.

3.5. Battery State of Health (SOH) Estimation: Data-Driven Method

3.5.1. Machine Learning Method. The machine learning method is based on creating a program trained to predict the battery's state of health with the help of past ageing data. In recent years, it has been used in different areas, such as genetics and genomics [93], cancer prediction of patients [94], mineral processing [95], economics analysis [96], and image recognition [97]. The advantage of this method is that the machine learning method can be used without introducing information about the electrochemical model of the battery. As previously discussed in Sections 2.2 and 2.3, we know that the prediction of the state of health of a battery without an electrochemical model is time-consuming if

Table 2: Model-based estimation methods.

Method	Benefits	Drawbacks
Equivalent circuit model	Nondestructive The estimation requires only analysis of direct measurements such as current, voltage, and temperature The kinetic of process in battery system can be investigated	In this model, the chemical and physical processes are not defined. Instead, the entire system of the battery is considered an electric circuit. It will be a drawback for cases in which necessary to understand the mechanism of degradation. Needs high controllers of characteristics of the battery for identification of ageing parameter
Electrochemical model	Nondestructive Besides the state of health of the battery, the model gives the exact description of chemical processes proceeding in the battery at appropriate circumstances (depth of discharge, temperature, and C-rate)	This model contains a lot of differential equations which needs high computational efficiency
Mathematical fitting	Nondestructive There is no need to use high computational efficiency due to the simplicity of mathematical equations	In this method, the mechanism of the degradation is not defined. Instead, the SOH is defined empirically by mathematical expression

there is not enough data. However, this disadvantage can be overcome using newly emerging big data technologies. For example, big data was collected by testing the batteries of 700 vehicles in different variables such as the depth of discharge, temperature, and cycling number [98]. For training, data was selected in the state of charge regions 20-80% due to its sensitivity to ageing. After using big data, the articles show the SOH estimation with a relative error of 4.5%. According to the literature analysis, machine learning methods can be divided into the following classifications:

(1) SOH estimation is based on direct temperature, voltage, and current measurements. For instance, Roman et al. used the gradient boosting regression tree model by direct measurements of the battery, and it showed results with a relative error of 7% [99]

(2) SOH estimation is based on the charge-discharge profile of a battery. According to the article, data on the battery's charge-discharge profile was collected and selected from training data in the 20-60% charge region. Finally, long short-term memory and convolutional neural networks were used to forecast the battery's health [99]

(3) SOH estimation is based on processed results of charge-discharge profiles such as IC analysis and DV analysis. Previously in Section 2.5, it was discussed about the sensitivity of peaks of IC and DV analysis to the ageing of batteries

Therefore, IC peak identification can be mixed with machine learning methods [100, 101]. These articles used the support vector machine tool. Prediction of the state of health of the battery based on the machine learning method can be estimated through various algorithms. Bandara et al. used a feedforward neural network (FNN) and long short-term memory (LSTM). The data for learning was taken from publicly available NASA data on lithium-ion 18650 cylindrical batteries [102]. The assessment of the SOH was done only by data on the current discharge profile. They concluded that this algorithm shows valid results for estimating the SOH of the battery. Nevertheless, it can be improved by inserting additional data for learning, such as impedance and temperature. According to Khan et al., bidirectional LSTM, support vector machine (SVM), adaptive boosting (AB), multilayer perceptron (MLP), and convolutional neural network (CNN) can be applied for the assessment of the SOH of the battery [103]. As the training data progressed, additional temperature data was obtained during charge-discharge of the "NCA" based 18650 cylindrical batteries besides the current and voltage data. Bai and Wang integrated the dual extended Kalman filtering with an artificial neural network and used the battery's terminal voltage for the program's training [104]. By comparing the mean squared error (MSE) and root-mean square deviation (RMSE) of each algorithm, they concluded that the method with high precision is a bidirectional LSTM. Furthermore, the tested batteries' results showed that the maximum and minimum mean absolute percentage errors are 0.38% and 2.72%, respectively. Most researchers collect data on battery cycling for the program's training in constant current mode. However, Ruan et al. built the artificial neural network based on data on the constant voltage cycling of the battery [105]. The proposed high-precision model was verified by testing the three "NCA" half-coin cells. The model's training on the input dataset is one of the differences between machine learning and other model-based methods. In some cases, the model demonstrates high accuracy only for the appropriate dataset [106]. To test the model's accuracy, the dataset is divided into two parts: training data and test data. This is referred to as model overfitting. As a result, tenfold cross-validation must be used to validate the model's accuracy.

In general, it will be helpful for readers if feature selection and algorithm selection are discussed in the machine learning method. Feature selection in machine learning refers to choosing a subset of the available features or variables to use in model training. The goal is to select features most relevant to the battery's state of health and improve the model's performance. Several feature selection techniques can be used, including incremental calculation: this is just a derivative of the function of parameters. For example, the value obtained from the incremental capacity analysis can be used as a feature in the machine learning method.

Nevertheless, this feature selection has disadvantages, such as the value of incremental analysis of any parameter with many noises, which needs an additional noise processing algorithm. Therefore, the most impactful features are selected for inclusion in the final model. Time-related features can be advantageous in time-series analysis or forecasting problems.

Features such as time of day, day of the week, or trend over time can provide vital information for the model. The envelope area of a feature is the area enclosed between the minimum and maximum values of that feature. Features with a large envelope area are often more relevant and impactful for the model. Using energy can be considered a feature with a large envelope. Because energy can be obtained by computation of the area of current–voltage function; however, this feature has an advantage related to high sampling frequencies. To obtain more valuable information about the state of health, it needs more data on the charge-discharge profile of the battery. The model's parameters can also provide information about the importance of features. For example, linear models such as linear regression assign coefficients to each feature, which can be used to determine the relative importance of each feature. Once the relevant features have been selected, the next step is to choose the appropriate algorithm for training the model.

Several algorithms can be used, including linear regression: This simple and widely used algorithm assumes a linear relationship between the features and target variable. However, the algorithm only applies if it has enough features because complex equations mainly define the battery. This is similar to linear regression but is used for binary classification problems. This tree-based algorithm uses recursive partitioning to divide the data into smaller and smaller subgroups based on the features. Random forest is an ensemble of decision trees combined to produce a single prediction. Support vector machines (SVMs) is a robust algorithm that can be used for classification and regression problems.

3.6. Deep Learning Method. In the field of artificial intelligence, besides the machine learning method, there is also the deep learning method. The use of artificial neural networks distinguishes the deep learning method [107]. However, the deep learning method requires more datasets for training than the machine learning method. As a result, some scientists use publicly available and reliable datasets on battery ageing. As discussed in previous sections, the variation of capacity accumulation at the corresponding voltage range varies for the different ageing states of the battery. Section 3.4 describes the estimation methods based on the differential capacity analysis's peaks. The previous section stated that machine learning was an assessment method based on charge-discharge profiles at 20-60% SOC. [108] However, the disadvantage of the described methods is the long estimation time of the SOH because the peaks in the differential capacity analysis and the charge-discharge profile with 20-60% SOC are less available in real-world BMS applications. Tian et al. used the deep neural network to train the model at different voltage windows of the charge-discharge profile to avoid the previously mentioned drawback. Finally, they confirmed that assessing the battery's status based on the 300 mV voltage window had a 2.28% inaccuracy [109]. As a result, the SOH estimate time is reduced to 10 minutes by using this low-voltage window. Section 3.3 examined the mechanisms of battery deterioration, such as fracture propagation in the electrode, side reaction, and collector corrosion. However, these pathways are primarily explored in half-cells. Furthermore, it is difficult to determine if the entire cell battery is deteriorating owing to cathode or anode deterioration. Tian et al. used a convolutional neural network model to estimate the battery's SOH [110]. In addition to the battery's high-precision SOH calculation, they got an extra model that can detect the ageing status of each electrode. The deep learning method is the encoder-decoder model, which uses recurrent neural networks for sequence-to-sequence forecasting problems. Gong et al. applied the encode–decoder model for the publicly available dataset of NASA and Oxford [111]. They obtained three encoders–decoders for regions of the charge-discharge profile. In addition, they obtained that by decreasing the sampling interval, the accuracy of the SOH estimation can be increased. According to the review analysis, the prospect of deep learning is up-and-coming. That is why it offers two significant advantages:

(1) It does not require any particular data, such as impedance or differential capacity analysis. This model can calculate the SOH based only on the charge-discharge profile recorded by the battery's BMS chip

(2) It requires the shortest period to compute since input data may be collected in the appropriate high C-rate mode

The downside is that it needs a large amount of accurate data for training. As a result, many scientists begin by attempting to build models using publicly verifiable and available datasets. The model is then applied to their sample dataset, which was gathered using their proprietary battery tester.

4. The SOH Estimation for Various Types of the Battery Chemistry

In this section, the SOH methods used for the different chemistry of LIB are listed in Table 3. Most of this table's articles are devoted to deep learning methods, ICA, and DVA approaches. Because according to the review analysis, these methods have good potential to use in practical applications. The reviewed estimation methods for various types of chemistries for LIBs are listed in Table 3. The majority of the articles in the review are on deep learning methods,

Table 3: The SOH estimation for various types of battery chemistry.

Battery chemistry	SOH estimation method	Advantage	Drawbacks
$LiFePO_4/C$ [112]	Based on ICA, the ridge and OLS regression were fitted to the height of the peaks	(1) The ICA approach may be used to detect the cause of capacity declines, such as LLI, LAM, or conductivity loss (2) The mean absolute error of the regression is limited to 2% (3) One peak was considered more related to the ageing condition based on the best feature selection	(1) The peaks of the ICA analysis depend on the mode of ageing of the battery; the method would be more usable if ICA peaks only depend on SOH
$LiFePO_4/C$ [112]	The new method of DVA plotting was proposed. The new method can assess the SOH of the battery more accurately	(1) The linear regression was fitted to the position interval between two SOH battery inflection points. It also revealed a 2.5% inaccuracy for three batteries	(1) The model needs additional testing to verify that this model is reliable (2) The model does not have a relationship with the mode of ageing
$LiFePO_4/C$ [113]	Deep neural network battery charging curve prediction using 30 points collected in 10 min	(1) The SOH is precisely estimated based on just any small portion of the charge-discharge profile (2) The method is very fast	(1) The method requires more data than other known methods
(1) $LiCoO_2/C$ (2) $LiFePO_4/C$ (3) $LiNiCoAlO_2/C$ (4) $LiNiMnO_2/C$ [113]	State of health estimation for lithium-ion battery based on energy features	(1) The SOH was calculated using the energy characteristics of the batteries at various ageing stages. The benefit of utilizing this feature is that the model derived from various sorts of materials may be used for other materials. As a result, there is a strong generalization capacity (2) For 95% of the datasets analyzed, the *R*2 is more than 98%	(1) The model is only verified for batteries used in Artemis urban drive cycle
(1) NCA/C (2) LiFePO4/C [114]	State of health estimation of lithium-ion batteries based on the regional frequency	(1) The calculation of this method is simple	(1) This is a very new method; that is why the method is not verified yet for other datasets
(1) $LiNiMnO_2/C$ (2) $LiCoO_2/C$ (3) $LiFePO_4/C$ [114]	Battery health evaluation using a short random segment of constant current charging	(1) The SOH is precisely estimated based on just any small portion of the charge-discharge profile (2) The method is very fast (3) The accuracy and estimation time can be regulated. By increasing the estimation time, the accuracy is increased	(1) The method requires more data than other known methods

ICA, and DVA approaches. The key advantages of deep learning methods are their short estimating time and excellent precision. However, training the deep learning model requires a large and accurate dataset for diverse battery and ageing conditions. Deep learning algorithms are faster than ICA and DVA. ICA and DVA are slower than deep learning algorithms. However, the precision of this assessment is excellent, and meaningful information about the reason for the battery degradation can also be obtained.

Nevertheless, the precision of this assessment is excellent, and meaningful information about the reason for the battery degradation can also be obtained. Among various chemistry of batteries, it is essential to note that LiFePO4 battery has only one peak at ICA and DVA analysis which means that it has only one Plato in the charge-discharge profile. These unique characteristics of the battery lead to a detailed assessment of the state of the battery. According to the review analysis, it is adequate to use deep neural network battery charging curve prediction to assess this type of battery. The advantages and disadvantages are written in Table 3 [112]. It is hard to say that one battery chemistry can only use one assessment method. According to Table 3, a universal model can be obtained if the feature of SOH selects the energy profile of the battery. Huang et al. estimated the battery's state of health based on the battery's energy value using the deep learning method. Furthermore, they achieved a universal model [112].

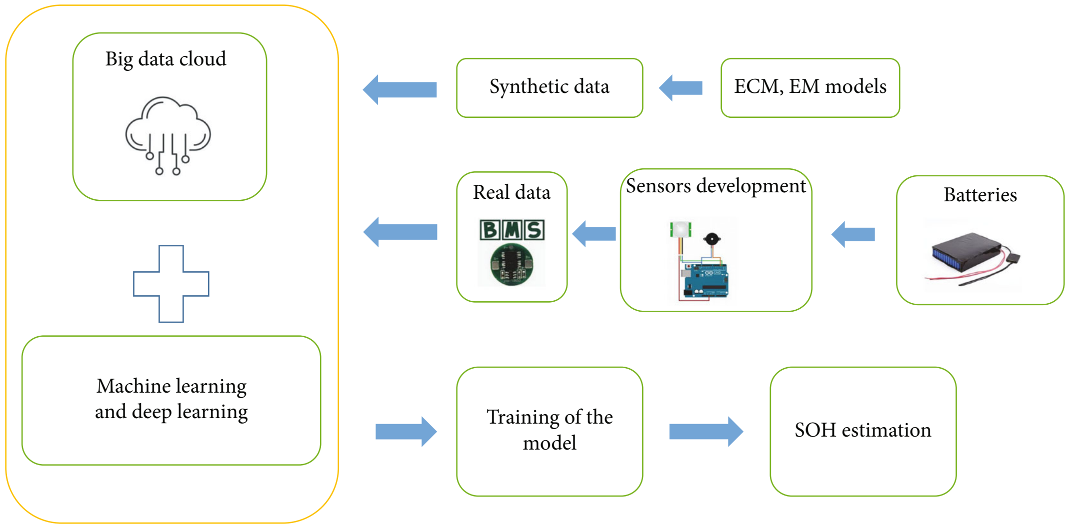

Figure 7: The future practical application prospects.

5. The Future Practical Application Prospects of SOH Estimation

The future application of SOH estimation definitely will be related to a model-based estimation and the data-driven method due to its online and nondestructive evaluation ability. After analyzing each estimation method, we think there are two ways to develop the application of the SOH estimation algorithm in the battery management system. The first is to increase the precision of the voltage, temperature, and current sensors. The precision of the SOH estimation is dependent not only on the precision of the estimation algorithm but also on the precision of the collected data. There are many discussed articles about each method's precision, but there are a few discussions about the precision of the sensor itself. For example, the applicability of the equivalent circuit model directly depends on the sensor's characteristics because susceptible instruments can collect the input data. The second way of developing the SOH application is to create a big reliable data cloud of ageing batteries. It can help apply emerging new technologies such as deep learning and machine learning more efficiently. The efficiency of the deep learning method is directly related to the amount and reliability of data for the algorithm's training. However, extensive data collections require a lot of funding and time. Therefore, we propose to use the developed model-based SOH estimation method (EC, ECM) in creating synthetic datasets, which can further be used for the training of the data-driven model. All the above-discussed future practical prospects are illustrated in Figure 7.

In addition to the use of big data, other trends in battery management include the integration of artificial intelligence (AI) and machine learning algorithms for model construction and improvement. AI algorithms can be used to analyze large amounts of data and identify patterns that can be used to predict battery health and degradation. Another trend is the integration of sensors and real-time monitoring systems to collect data on battery performance and health in real time, which can help improve the accuracy and robustness of battery health prognostic models. Moreover, developing low-cost and highly accurate sensors is also an important trend in battery management. These sensors can monitor various aspects of battery performance, including voltage, temperature, and current, providing valuable information for battery health prognostic models. In conclusion, digitizing batteries and integrating big data, AI, and real-time monitoring systems are important trends in future battery management. These trends will help improve the accuracy, robustness, and reliability of battery health prognostic models, which is crucial for ensuring the safe and reliable operation of battery-powered devices and systems.

In conclusion, there is a growing trend toward implementing SOH estimation methods in battery health management. However, several challenges still need to be addressed, including finding a trade-off between model complexity and computational efficiency, extracting and estimating SOH features under dynamic discharging and controllable charging processes, modeling the inconsistency in cell performance, and fusing multiple signals for comprehensive monitoring. In addition, there is a need for more research on the application of SOH monitoring results in battery health management, including performance optimization and safety management strategies. Developing SOH indicators or parameters that can be used to formulate these strategies is a promising area for future research. With the continuous advancements in technology and the increasing demand for reliable and efficient energy storage systems, it is expected that the field of SOH characterization, estimation, and application will continue to grow in the coming years.

Cloud computing and the digital twin are good instruments to improve battery diagnostics. In addition, advanced sensing technology helps detect the internal variation of batteries and extract the key parameters directly while helping reduce the complex parameter identification significantly. Another aspect that needs further research is the development of more robust and accurate feature extraction and estimation methods for SOH. The extraction and estimation of SOH feature under dynamic discharging and controllable charging processes are crucial for accurate SOH prediction. The quality and quantity of data also play a significant role in SOH estimation, and further research is needed in this area. Another challenge is estimating SOH in a large-scale lithium-ion battery pack composed of multiple individual cells. Cell performance needs more consistency due to temperature gradient, nonuniformity, and manufacturing variances. This calls for further research in imbalance modeling and the description of consistency dependence among battery parameters. Finally, integrating multiple sensors for comprehensive monitoring is another area that needs further research. Using fiber optic sensors or built-in piezoelectric sensors can provide comprehensive information about battery health, and fusing multiple signals is likely to become a research hotspot in the future. In terms of SOH application, there is still a wide gap between SOH diagnostics and SOH application. The goal of SOH monitoring is not only to determine the retirement point of a battery but also to provide guidance for battery ageing process optimization and safety management. Further research is needed on developing detailed health management strategies from the developer's side, including adaptive charging cut-off conditions and charging C-rate and safety operation boundaries for early warning. The use of SOH indicators and parameters for formulating battery health management strategies is still in its infancy, and this is a promising area for future research.

Another aspect of SOH estimation is the data-driven methods, which rely on large amounts of data to make predictions. Machine learning algorithms such as artificial neural networks (ANNs) and support vector machines (SVMs) have been applied to battery SOH estimation and degradation prediction. The benefits of data-driven methods are their fast prediction speed, ease of implementation, and adaptability to various batteries. However, the accuracy of these models depends on the quality and quantity of the data used for training, which can sometimes be limited in real-world applications. Moreover, the combination of model-based and data-driven methods, referred to as hybrid methods, is another research direction in battery SOH estimation. By combining the strengths of both methods, hybrid methods can improve the accuracy of SOH estimation while reducing computational costs.

In conclusion, there is still much room for improvement in the battery SOH estimation and degradation prediction field. The challenge of balancing model accuracy, computational efficiency, and practical applicability will continue to drive research in this field. Integrating multiphysics modeling, advanced sensing technology, and machine learning algorithms holds excellent potential for the future of battery SOH estimation and degradation prediction.

6. Conclusion

Several methods are used to get information about the lifetime of lithium-ion batteries. A prominent characteristic of these methods is the possibility of repetition, not only in laboratory conditions but also in actual life conditions. Included here is the measurement of internal resistance, the measurement of internal impedance, and the energy level. The following benefits of measuring internal resistance may be identified: accuracy and ease of the research; downsides of this approach include the inability to monitor parameters in real-time and the length of the investigation. The strong point of measuring the internal impedance is the accuracy of the data obtained, and when using this method, it is possible to identify the cause of battery degradation; the disadvantages of this method include the need to determine the chemical composition of the battery under study. The final method of measuring a battery's capacity is one of the quickest and most accurate methods for examining a battery's SOH; however, the disadvantages of this method include the need to have a fully charged battery before testing.

Since energy storage systems have been highlighted in personal electronics and electric vehicle hybrid implementations, SOC estimates' correctness has become increasingly relevant. Several scholars have conducted extensive research on SOC estimation in recent years. Estimation accuracy has steadily improved, and focused efforts in research and development are already underway. Several of these methods accomplish well under fixed discharging current conditions, while others perform much better under variable discharging current conditions. It is challenging to compare the effectiveness of the various methods because the applications and services use various discharging conditions and battery sizes. Numerous SOC analysis methods are predicted to benefit electrochemical devices, including BMS, in hybrid electric vehicles.

The practical technique may not be acceptable in the real-time estimation of the battery's state. That type of conclusion is necessary because it necessitates a large amount of input data on the battery's ageing experience and, at times, necessitates breaking the battery to investigate the inner structure. Conversely, the experimental technique remains critical because it is the foundation for modeling the SOH estimation method. The experimental technique is mainly used for understanding the battery's degradation mechanism rather than for estimation. For example, a machine learning approach requires a large amount of data that can only be obtained through experimental research to progress in the future. Even if the model SOH estimation methods overcome the drawbacks of the experimental method, it cannot be commercially applicable if the process has the following disadvantages: high computational efficiency, long assessment time, extensive sampling data, and high sensitivity of parameter measuring. The lengthy period is due to two significant factors. The first is the model's increased complexity, which results in the lengthy processing of findings. The second reason is that obtaining preliminary input findings takes a long time. A typical shortcoming of SOH estimates based on the equivalent circuit model (ECM) and mathematical model is the lack of an explanation of processes in the battery. The extended duration of the model-based assessment technique can be attributed to two factors. The first is the model's tremendous complexity, which results in the lengthy processing of findings. The second reason is that obtaining preliminary input findings takes a long time.

A typical shortcoming of SOH estimates based on the equivalent circuit model (ECM) and mathematical model is the lack of an explanation of processes in the battery. The electrochemical model-based SOH estimation technique clearly explains activities using multidifferential equations. The electrochemical model may necessitate a large number of computer resources due to the high complexity of numerical solutions of differential equations. Deep learning can approximate the complicated data-to-health link of battery cells. However, the proposed deep learning strategy has several drawbacks. The fixed-size input matrix and a lack of understanding of the inner working mechanism limit the recommended method's applicability in estimating battery capacity and necessitate further investigation. We hope that by reading this article, readers will understand each approach thoroughly and the best state of health for various types of batteries. Furthermore, we expect that readers who want to use the machine learning or deep learning approach will be able to modify the model by adding new characteristics that are more sensitive to the SOH of the battery. Combining an equivalent circuit model, electrochemical model, and incremental capacity analysis with machine learning or deep learning models could yield these additional characteristics.

Data Availability

Dataset(s) were derived from public resources and made available with the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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