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STATE OF CHARGE ESTIMATING METHODS FOR LITHIUM ION BATTERY: A REVIEW AND FUTURE CHALLENGES

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Abstract—**Energy storage systems (ESS) are essential for the development of electric vehicles in the future. Regardless of this, there is still need for improvement in the safety and administration of ESS. An essential part of any ESS that uses Lithium-ion batteries (LIB) is the battery management system (BMS). The battery's state of charge (SOC) is an important parameter of the battery management system. In recent years, SOC has recently emerged as a hotspot for BEV research. Energy storage has emerged as a top priority for contemporary communities, and lithium-ion chemistry battery technology has proven to be a highly effective solution for storage applications. State of charge (SOC) denotes the available battery capacity and is one of the most crucial states that must be monitored to optimize battery performance and prolong battery life. This article provides a summary of the methodologies for estimating the SOC of lithium-ion batteries (LIBs).The SOC estimation methods are presented with an emphasis on describing the techniques and elaborating their limitations for use in on-line battery management system (BMS) applications. SOC estimation is a difficult undertaking hampered by significant changes in battery characteristics over the battery's lifetime due to ageing and distinct nonlinear behavior. This has prompted researchers to propose a variety of methods that have made it difficult to establish a correlation between the accuracy and robustness of the methods and their ease of implementation. This paper is an exhaustive review of the works presented over the past decade, during which estimation techniques have tended towards a hybrid of probabilistic and artificial intelligence techniques. The review concludes with a concise discussion of difficulties associated with BEV LIB SOC prediction investigation**

Keywords **-- State of charge (SOC), Battery electric vehicle, Battery management system.**

I. INTRODUCTION

In recent years, the development of sophisticated and intelligent state-of-charge (SOC) estimators for LIBs has become an hotspot area of study. SOC's advancement is hampered by three primary technological obstacles. The first is that the structure of lithium ion battery is nonlinear, making accurate modeling challenging. This is due to the multiscale nature active materials, cells and battery packs all have distinct spatial scales and time scale aspects (such as ageing).In middle, the internal environment is highly challenging to determine and subject to external environment fluctuations. When transitioning from laboratory production of lithium ion batteries to industrial production, the correlation between calculated and real values declines. This makes it difficult to verify with certainty the states that are present inside the battery. Lastly, the disparities between LIBs have a direct impact on the efficacy of the LIB pack, increasing the LIB's instability. Estimation methods that were developed for smaller LIBs are unnecessary for large-scale LIBs and it is challenging to arrive at an accurate and reliable estimate of SOC. For this reason, cutting-edge SOC methodologies are necessary as soon as possible in order to conquer these challenges[1,2]. A variety of methods have been developed for SOC estimation. The online methods can be used to estimate the battery's state in real time. Due to stringent experimental schemes or high computational costs, however, offline methods are inapplicable during battery operation. Methods for estimating online SOC can be categorized into three groups: the ampere-hour counting (AHC) method, the model-based method, and the data-driven method. In practice, the AHC method is subject to initial SOC error and accumulative measurement system error [3]. As a result of the weak estimation accuracy, it is unsuitable for online EV applications.

On the basis of the functional OCV–SOC relationship, the open-circuit voltage (OCV) method is implemented. However, the OCV of the battery can only be measured after an extended period of repose, rendering it unsuitable for real-time SO estimation. In addition, the OCV exhibits differences between charge and discharging processes at the same SOC level due to hysteresis effects, which impacts the accuracy of SOC estimation [4].

The offline methods comprise of capacity and internal resistance measurements, since capacity and internal resistance are the two most important battery degradation parameters. The SOH of a battery can be determined by measuring these two degradation characteristics using specialized experiments. For instance, the measurement of capacity must be exhausted at a slow rate until the battery's cutoff voltage is reached. Current methods for estimating SOC can be categorized as model-based, data-driven, and advanced sensing-based. With the rapid development of LIBs and EVs, more research papers on advanced condition monitoring technologies have appeared in the past three years. This progressively renders obsolete the review work discussed previously. In order to close the lacuna in research, this paper examines in detail the most recent developments in SOC estimation of LIBs. Science Direct and IEEE are the primary resources for finding relevant articles using keywords such as electric vehicles, lithium ion battery, and state of charge. The contributions of this review are as follows, in comparison to previous research: (1) The SOC/SOH estimation methods are divided into two categories, i.e. online and offline ones. The promising online estimation methods are specially discussed. For online SOC estimation, primarily model-based and data-driven methods are introduced. In addition, the online SOH estimation is comprised of (DA) methods, model-based methods, and data-driven methods. (2) Existing online co-estimation strategies for both SOC and SOH are first discussed in this paper in order to fill in research voids in the field of joint estimation. Then, it is examined from the perspectives of model-based methods, data-driven methods, and sophisticated sensing-based methods. (3) On the basis of the classification of state estimation, the most recent research methods are selected and evaluated with respect to their advantages and disadvantages in terms of their practical applications. For the advancement of online SOC estimations of LIBs, (4) a list of critical issues and future work is proposed. Battery state estimation is a crucial sophisticated BMS function in BEVs. Accurate modeling and state estimation will enable stable operation, facilitate optimal battery operation, and lay the groundwork for security supervision [5]. This article discusses BEV lithium ion battery SOC modeling, estimation, and methodologies. The review concludes with a concise discussion of difficulties in lithium ion battery SOC investigation prediction along with its challenges.

II. DEFINITION OF SOC

SOC is defined as the percentage of the remaining capacity to the maximum available capacity of the battery and it can be given by

$$SOC\ (t) = \frac{C_r}{C_m} \times 100\% \quad (1)$$

Where C_r stands for the remaining capacity that can be powered to electric devices. C_m specifically presents the maximum available capacity that the cell can store, which is determined

by the electrochemical characteristics of the battery.SOC ranges from 0% to 100% in value. A SOC of 0% indicates the battery is completely drained. While a SOC of 100% means the battery is fully charged. In practice, the battery operates between 20% and 80% SOC to prevent over-discharging. Due to the relationship between charging/discharging current and battery capacity, SOC can also be expressed using the equation (2).

$$SOC\ (t) = SOC\ (t_0) - \int_{t_0}^{t} \frac{I(t)\eta}{C_m} dt \quad (2)$$

where SOC (t0) and SOC (t) represent the SOC at the initial timet0 and time t, respectively. η signifies the coulombic efficiency, which is the ratio of the discharge capacity to the charge capacity within the same cycle. The current I(t) varies with respect to time in which it is negative in charging state and positive in discharging state. And a discrete form of Eq. (2) can be described as

$$SOC_k = SOC_{k-1} - \frac{\eta \Delta T}{C_m} I_k \quad (3)$$

where ΔT is the sampling time, and I_k is the loading current. SOC_k and SOC_{k-1} represent the battery SOC at time step k and k-1, respectively.

In fact, the SOC values can be directly calculated when determining the initial SOC value according to previous equations. In practical applications, however, the inaccurate initial SOC value and the cumulative errors caused by the measurement system can result in significant estimation error. As a result, there is a growing interest in investigating advanced methods for more accurate real-time SOC estimation.

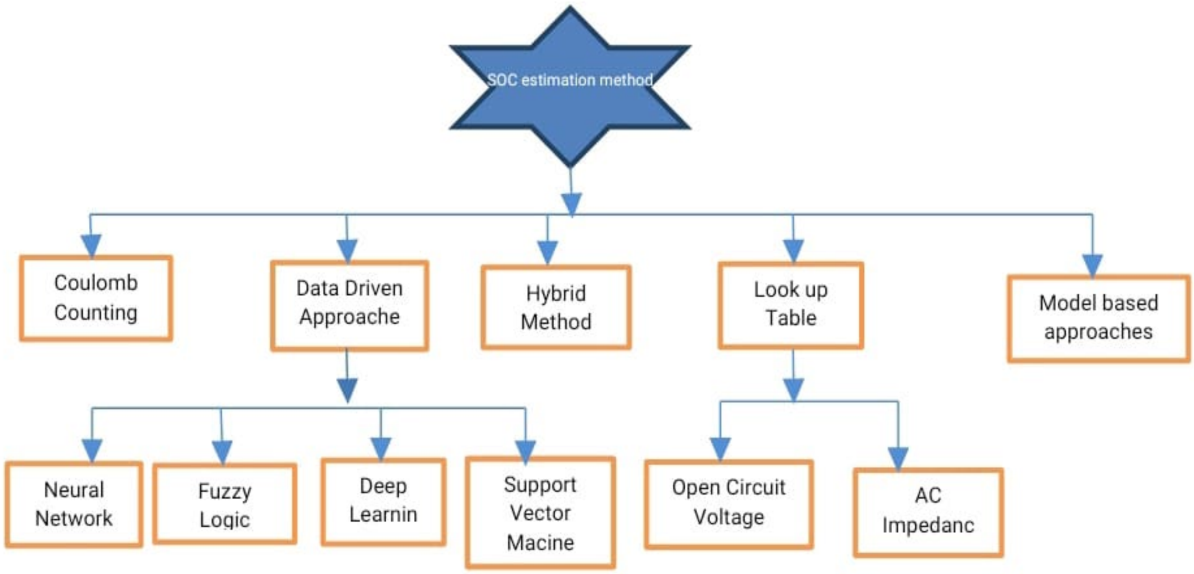

Fig .2 SOC Estimation method

III. BATTERY MANAGEMENT SYSTEMS (BMS)

A BMS is a device that is built with hardware and software that control the operational conditions of the battery to prolong its life, guaranteeing its safety and providing energy management with an accurate estimation of the battery's various states. To accomplish this, a BMS is equipped with a variety of features to control and monitor the battery's state at the battery cell, battery module, and battery pack levels [6]. The ability of a battery to store energy diminishes as it ages. Condition of health (COH) is an indicator of this decline. The battery's remaining useful life (RUL) is the amount of time or load cycles left until it hits the end of its life (EOL). A BMS must be more than just a protective circuit; it must also be a thorough and accurate device that can anticipate the SOC, SOH, RUL, capacity, and available power in order to maximize the battery's efficiency and safety. The aforementioned parameters can be determined by continuously measuring current, voltage, and temperature in battery. The literature describes numerous approaches to designing a BMS based on the functionalities desired for a particular application, but the majority of them concentrate on a specific BMS function, such as SOC estimation [8-20] or the balancing process. [21-25]. Few studies present BMS research from a global perspective like [26], which demonstrates a BMS design employing a distributed structure for improved scalability and portability. As previously stated, the current trend for EVs and HEVs is the design of intelligent BMS, which requires research in artificial intelligence applied to battery state estimation [27]. Large battery cells for applications such as EVs and grid integration require a predictive and adaptive BMS based on models [28-30]. In the study described in [31], a The BMS estimates the state of charge (SOC) based on a seventh-order, single-particle battery model with electrolyte diffusion and temperature-dependent components that exploit the Li ion cell's reaction changes as temperature changes.

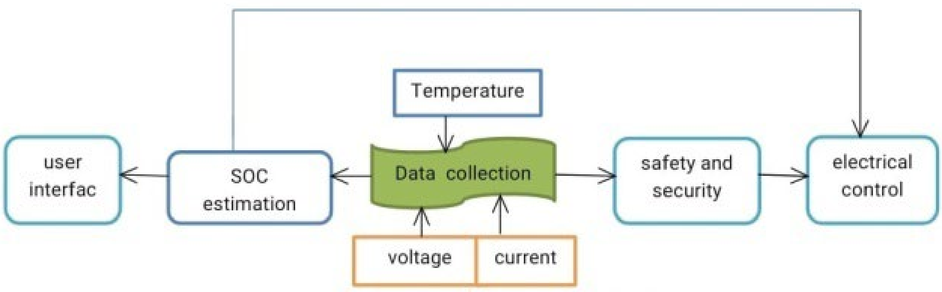

Fig.3Battery Management Systems

IV. OVERVIEW OF SOC MODELING APPROACHES

For model-based SOC estimation the battery models are very helpful and it can be classified into physical electrochemical models [32], electrical equivalent circuit models [33-35], and data-driven models [36,37], with the latter two models being routinely employed in SOC estimation. These models with emphasis on data-driven models and electrical equivalent circuit models has been introduced in this section.

4.1 Physical Electrochemical Models:

The simple model for physics-based electrochemical analysis [38] is the single-particle model. The concentration of Li-ions in the electrode is represented by a single particle. Primary output and the solid-phase diffusion impact of electrodes can both be analyzed with this model.but its precision is inadequate. To increase precision, a model has been created that takes into account the effect of the electrolyte on the output potential and proposes liquid electrolyte material conservation using a partial differential equation [39]. The anode and cathode of a cell have been modeled as porous, ball-like particles with electrolyte occupying the spaces in between. Due to the presence of multiple coupled partial differential equations in the pseudo-two-dimensional model, it must be simplified from an engineering standpoint [40-43]. A significant reason why physics-based models are difficult to implement is that a large number of indeterminate variables must be defined by means such as global optimization. Obviously, they may experience over fitting or local optimization problems. Without accurate and exhaustive parameters, the open loop simulations of physics-based electrochemical models are not optimal for SOC calculations. Despite their high accuracy, high-resolution detailed models typically contain a large number of nonlinear partial differential equations that make model solving computationally intensive and prohibit online estimation. Online estimation applications benefit greatly from reduced-order models because of their simplicity and reduced computing requirements in comparison to full-order models. [44]. These advantages, however, are paid for with higher estimating mistakes.

4.2 Electrical Equivalent Circuit Models-

The popularity of electrical equivalent circuit models has increased in recent years due to their more straightforward construction, which enables their incorporation into real-time applications. Models of electronic Energies 2021, 14, 3284 3 of 24 counterparts use electrical components to imitate LIB behavior. Models like these can be broken down into two categories: integral-order and fractional-order.

4.2.1 Integral-Order Models-

The majority of equivalent circuit models that are commonly employed are integral-order models. The Rint model is the most widely utilized integral-order model [45]. The Rint model has a simple structure, However, it does not take into account the dynamics of polarization or diffusion. The resistor–capacitor model, a first-order model capable of simulating LIB charging and discharging behavior with a single resistor–capacitor network[46]. In addition, the behavior of the open-circuit voltage hysteresis can be taken into consideration to improve the precision of the model[47]. It is straightforward to infer the input/output relationship of the LIB from integral-order analog circuit models. In light of this, the least-squares recursive algorithm is the most prevalent technique for online parameter detection. In addition, a co-estimator has been suggested for predicting model parameters and battery status [48]. This can take the form of parameter identification based on electrochemical properties [49] or a genetic algorithm with multiple objectives [50].

4.2.2 Fractional-Order Models-

Due to their fractional nature, models based on fractional-order calculus are also often used in modeling. Modeling the electrochemical processes of lithium ions can be done in an accurate way using a technique called electrochemical impedance spectroscopy (EIS). However, it is quite challenging to estimate SOC using only EIS; consequently, many fractional-order models are employed in conjunction with EIS to improve estimation [51]. Some studies use Bode plots [52] to assist circuit models with estimation improvement. However, in order to use electrical equivalent circuit models for efficient online SOC estimate, an appropriate parameter identification approach (either online or offline) must be used. Some examples of such methods include curve fitting, recursive least square, particle swarm, and genetic algorithm. In addition to capacitors, resistor–capacitor networks can also incorporate constant phase elements [53]. A genetic algorithm can classify model constraints with an error of 0.5% using a simplified fractional-order impedance[54].Model constraints can also be classified with high precision and robustness using Model derivatives with non-integer values and a particle swarm optimization algorithm. [55]. Commonly employed to estimate SOC in LIBs [56, 57] are fractional-order equivalent circuit models with Kalman filter alternatives.

4.3 Data-Driven Models-

Commonly, data-driven methods are used to design LIB models. The majority of data-driven online SOC estimation techniques are founded on machine learning techniques (such as neural networks, support vector machines, and fuzzy logics). Experiments on LIB have confirmed the effectiveness of the proposed neural-based thermal-electric coupled model [58]. It is also possible to estimate data by combining neural networks with particle filtering [59]. A 3D Monte Carlo model has recently demonstrated the structural evolution of solid sulfur and lithium sulfide

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dissolution and precipitation during lithium-sulfur battery discharge. [60]. A recent Monte Carlo 3D model illustrates the structural evolution of solid sulfur and lithium sulfide dissolution/precipitation during lithium-sulfur battery discharge using dynamic simulation technology. The kinetic model can predict battery changes over extended time periods. Even though data-driven techniques are effective in nonlinear scenarios, they can be impacted by the datasets and training method logic employed. In addition, a large data set is required to account for all potential working conditions. This indicates that the overall cost of computing is substantial.

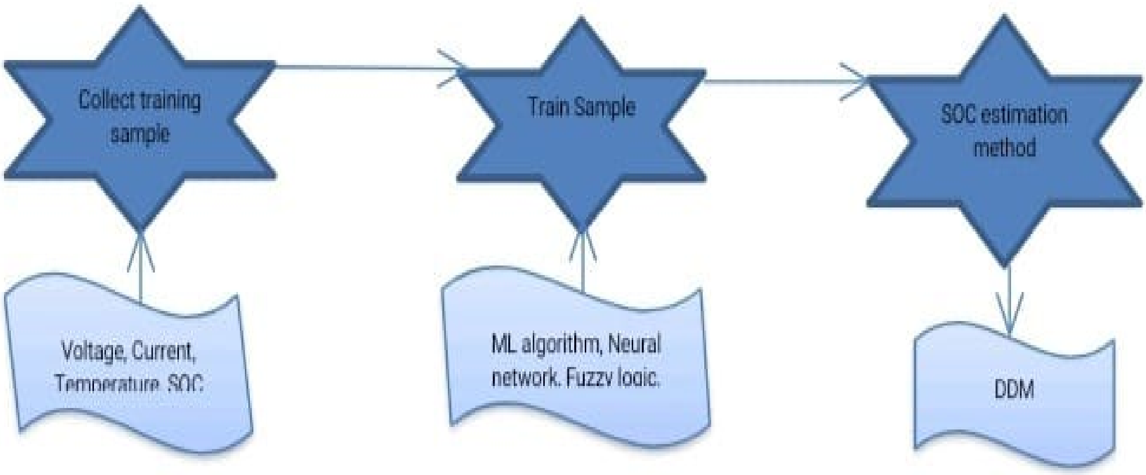

Fig.4.3 Establishing DDM

V. SOC ESTIMATION METHOD

Lithium-ion capacitor according to Table 5, SOC estimation methods can be broadly divided into four categories. Here, conventional methodologies are not required to construct a battery model or identify its parameters. The ampere hour integration (AHI) method is often used to estimate the SOC of lithium- ion batteries together with the OCV method. The AHI method requires knowledge of the initial SOC value and the charging and discharging currents of lithium ion batteries. If the initial value is ambiguous, the estimated charging state of the battery deviates significantly from the actual value. Both the OCV method and the internal resistor (IR) method establish the relationship between voltage, IR, and SOC, and then estimate the SOC based on this relationship. However, the OCV technique requires a lengthy holding period, whereas the IR method is excellent. The AHI method requires knowledge of the initial SOC value and the charging and discharging currents of lithiumion batteries. If the initial value is ambiguous, the estimated charging state of the battery deviates significantly from the actual value. Both the OCV method and the internal resistor (IR) method establish the relationship between voltage, IR, and SOC, and then estimate the SOC based on this relationship. However, the OCV technique requires a lengthy holding period, and the IR method is highly temperature dependent. Significantly affected by temperature. Both the observer and filter methods are fundamentally model-based, with the observer method utilizing modern control theory to estimate battery SOC. First, by analyzing the ECM characteristics of the battery, the battery state space model expression including the SOC is established. Then, using the control theory observer design method, the state observer is designed to estimate the SOC value. This procedure is difficult to implement because it requires expert-level knowledge of automatic control and mathematical matrix theory. The filtering method is mainly based on the characteristics of correction and recursion of various filters. It has excellent measurement precision and can measure dynamic SOC. The intelligent algorithm is independent of the model, has high recognition accuracy when sufficient data is available, and is appropriate for computer implementation. These two methods are currently the most popular research topics in SOC estimation [55-60].

Category	Specific method
Filter method	particle filter, KF, unscented KF, extended KF, H∞ filter, etc.
Intelligent algorithm	neural network, fuzzy logic, SVM, genetic algorithm, etc
Observer method	nonlinear observer, sliding mode observer, proportional integral observer, etc.
Traditional methods	AHI, OCV, IR, etc.

TABLE.5.SOC Estimation Method

5.1 Filter methods in SOC estimation-

The KF method has advantages such as real-time performance monitoring in online recursive modeling, less demand for storage capacity during operation, and closed-loop control. KF, extended KF (EKF) [38], and unscented KF [39] are commonly used in research. The KF is a popular adaptive filter for linear models, but it is inappropriate for nonlinear models. The EKF technique, an extension of the KF method, can be applied to complex and nonlinear models. However, because the EKF method needs to linear the approximation of It is not accurate to calculate nonlinear functions using the first- or second-order terms of the Taylor formula and the Jacobian matrix. To overcome these shortcomings, the unscented KF has been not only does it not require the calculation of the Jacobian matrix, but it also provides more accurate SOC estimations than the EKF. However, the statistical information of battery noise (such as model and measured noise covariance) is presumed to be accurate in each of the previously mentioned KF methods. If the noise statistics are inaccurate, the estimation of SOC based on the above KF will be unstable or even divergent, and the adaptation speed will be too sluggish [40]. To solve these problems, the adaptive KF, adaptive EKF [41], and adaptive unscented KF [42-44] are used online noise statistics estimations incur additional calculation costs. Only when the statistical properties of system noise are predicted can the KF filtering algorithm produce more accurate estimations. Therefore, the actual precision of KF filtering in SOC estimation cannot frequently satisfy engineering specifications. If accurate prior system information cannot be predicted, it is necessary to increase the value of the noise covariance matrix when designing the KF in order to increase the utilization weight of real-time measurement and decrease the utilization weight of one-step prediction. This practice is commonly referred to as adjusting. However, tuning is blind, and it is impossible to predict by how much the noise covariance matrix must be increased to obtain the highest estimation precision. In addition, if the measurement noise and process noise of the system are not white noise, or if there is deviation, the Kalman filtering effect will be severely diminished or even divergent. Both noise and measurement noise are presumed to be zero-mean Gaussian white noise in the KF estimation model. In practical applications, it is challenging to actualize this assumption due to environmental interference noise, which may explain the biased distribution and negatively impact the accuracy and convergence behavior of SOC estimation using s KF. To address this issue, particle filter and unscented particle filter methods [45,46] are studied to estimate battery SOC. Due to the large number of computational requirements and the high memory consumption, these filters are unsuitable for online SOC estimation in real-world applications. The H filtering algorithm is also used to estimate the state of charge (SOC) of batteries requires the noise signal of the system to be online noise statistics estimations incur additional calculation costs. Only when the statistical properties of system noise are predicted can the KF filtering algorithm produce more accurate estimations. Therefore, the actual precision of KF filtering in SOC estimation cannot frequently satisfy engineering specifications. If accurate prior system information cannot be predicted, it is necessary to increase the value of the noise covariance matrix when designing the KF in order to increase the utilization weight of real-time measurement and decrease the utilization weight of one-step prediction. This practice is commonly referred to as adjusting. However, tuning is blind, and it is impossible to predict by how much the noise covariance matrix must be increased to obtain the highest estimation precision. In addition, if the measurement noise and process noise of the system are not white noise, or if there is deviation, the Kalman filtering effect will be severely diminished or even divergent. Both noise and measurement noise are presumed to be zero-mean Gaussian white noise in the KF estimation model. In practical applications, it is challenging to actualize this assumption due to environmental interference noise, which may explain the biased distribution and negatively impact the accuracy and convergence behavior of SOC estimation using KF. To address this issue, particle filter and unscented particle filter methods [45,46] are studied to estimate battery SOC. Due to the large number of computational requirements and the high memory consumption, these filters are unsuitable for online SOC estimation in real-world applications. The H filtering algorithm is also used to estimate the state of charge (SOC) of batteries. [49,50].

5.2 Intelligent algorithms in SOC estimation-

Even though there has been a lot of development in modern sensor technology, it is still not possible to do an accurate measurement of SOC anywhere other than in a laboratory in a very specific setting. Nevertheless, the SOC is commonly estimated using the battery's voltage, current, and temperature. This is due to the fact that the SOC has a strong correlation with these observable characteristics. Estimating SOC based on observations is typically done with the help of intelligent algorithms, which are the high-order algorithms that are employed the most. SVM and artificial neural networks are two examples of intelligent algorithms that are frequently utilized in the process of SOC estimation [7,38,51].However, both techniques suffer from two flaws, both of which negatively impact the accuracy of SOC estimation. To begin, the input data consist of the feature information that was extracted from the original data. This process requires human design, which in turn necessitates a significant amount of personnel and expert-level knowledge. Second, the model structure employs a superficial learning architecture, which lacks adequate analytical capability and makes it difficult to manage high-dimensional data. Deep learning, an essential component of machine learning, provides effective solutions to the aforementioned problems. One can construct a deep neural network (DNN) using a multilayer nonlinear transformation and extract complex feature information from input data using deep learning technology. Several SOC estimation techniques based on DNNs have been proposed recently. In [52], a SOC estimator was built using a multilayer perceptron network and trained using signals measured at various ambient temperatures. The outcomes demonstrated that the trained model can decrease the SOC estimation error. On the basis of this investigation, the benefits of using a network with long short-term memory (LSTM) to extract time information from time series data have been examined. Tian Y et al. and Yang F et al. Gated cyclic unit (GRU) networks, a variant of the recurrent neural network (RNN), have also been applied to SOC estimation. In [18,55], a GRU structure was incorporated into an RNN to enhance the modeling capability of the nonlinear behavior of lithium-ion batteries, and two models using current and voltage signals as inputs were developed to estimate the SOC. It was proposed and used to estimate the SOC of two lithium-ion battery data sets at different ambient temperatures [56,57] using a simple estimation model based on the GRU. The above RNN-based method offers three advantages over the conventional SOC estimation technique: The RNN can transfer the battery measurement data directly to the SOC value without the need for additional battery models based on the operating parameters. 2. The RNN can learn the weight and deviation using the gradient descent algorithm, which is quite distinct from the mathematical model that requires considerable effort to explicitly design and parameterize. 3. The RNN with a set of network parameters can estimate SOC under a variety of ambient temperatures, whereas other traditional methods require models with distinct parameter sets for various working conditions. Various SOC methods withs its principle is given below in the table 2.

Method	Principle
AHI	Integrates the current beneath the known initial SOC value.
OCV	Nonlinear relationship between OCV and SOC
IR	Relationship between internal resistor and SOC
Observer method	Principle of control theory observer
Filter method	State equation and measurement equation recursion
Intelligent algorithm	Intelligent algorithm with the capability to simulate nonlinear battery characteristics

TABLE 2: Methods with principle

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VI. THE PROSPECTS FOR SOC ESTIMATION

Since energy storage systems have been highlighted in applications for portable electronics and hybrid electric vehicles, the accuracy of SOC estimation becomes increasingly crucial. The accuracy of estimates has steadily increased, and intensive research and development efforts are likely already underway. In order to increase SOC estimates further, additional research is anticipated to include the following enhancements.

(i) Conduct additional research on hybrid methods, such as combining the direct measurement method with the bookkeeping estimation method, in order to accomplish accurate online SOC estimation.

(ii) The existing estimation procedure should be applied to multiple battery types. Conduct additional research on the ubiquitous practical application of the methods.

(iii) Conduct additional research to enhance the SOC estimation system's ability to account for the effect of battery deterioration.

(iv) Study more innovative artificial intelligence methods and enhance their training algorithms to improve the accuracy of SOC estimations. In addition, the focus of future research will be on the development of novel methods for navigating complex terrain.

To further enhance the estimation performance of the neural network method, it is necessary to investigate and incorporate optimal search methods for the optimal number of neurons in the hidden layer.

Perform additional investigation on adaptive parameter estimation. The models can automatically adjust to varying battery types, discharging conditions, and battery age.

(vii) Make the assessment system and performance measurement standard for the SOC estimation method as accurate as possible.

VII. CONCLUSION

This paper critically reviews SoC estimation methodologies presented by researchers, presenting the fundamentals and main drawbacks of each method. From the review of the different approaches, it can be concluded that the hardest part of obtaining a battery SoC estimation is to build a model that reflects the reality inside the battery, including the impact of temperature dependencies on internal resistance and capacity fading. It is also possible to draw the conclusion that the precision of the SoC estimation may be impacted by factors such as the inaccuracy of the modeling, the uncertainty of the parameters, the imprecision of the sensors, and the measurement noise. Other elements, such as self-discharge, effects of age, imbalance between cells, capacity fade, and temperature impacts, all have an impact on the performance of the battery. In order to estimate the SoC, with the latter two models being routinely used in LIB SoC estimation in BEVs. However, the precision of these approaches is limited, and this might become an issue when attempting to monitor the state of the LIB in the most effective way. To establish the status of the system, another option is to employ estimating methods that are based on look-up tables, ampere-hour integrals, filter-based, observer-based, or data-driven algorithms. These methods do cause some mistake, but they enable for a higher level of accuracy to be achieved when estimating the state of LIBs. They can also demand a big amount of processing power, which can extend the process of collecting an estimated state by a significant amount of time. Research should concentrate on optimizing estimate methodologies that enable SoC estimation without requiring a considerable amount of computer resources in order to advance the state of the art in SoC estimation. Additionally, the accumulation of errors should be reduced by enhancing the fundamental understanding of battery operation. The estimation error should be minimized by emphasizing on capacity-induced error, initial SoC error, current measurement error, and voltage measurement error. In order to accomplish this, numerous obstacles must be surmounted. Using internal optical fiber sensing, multi-state estimation, estimated model parameter accuracy, and operating conditions could mitigate such obstacles. Overall, substantial progress remains to be made in this field of study, but the convergence point is nearing.

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