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Study of Various State of Charge Estimation Methodsin Electric Vehicle

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ABSTRACT: The need for batteries is rising as new energy electric cars and smart grids emerge quickly. A key component of the battery-powered energy storage system is the battery management system (BMS). The most popular state estimation techniques for BMSs are reviewed in detail in this study. From the viewpoints of remaining capacity and energy estimate, power capability prediction, lifespan and health prognoses, and other important indicators in BMS, the state estimation methodologies are examined. This present paper, through the analysis of literature, includes the state of charge (SOC) reviewed.

Keywords: Electric Vehicle, Battery management system, State of Charge (SOC).

I. INTRODUCTION

One of the most important technologies for the creation of smart grids and new energy electric cars is energy storage technology [1]. Benefiting from the quick rise in new energy electric car production, among all currently used chemical and physical energy storage options, lithium-ion batteries are the ones that are evolving the quickest [2]. The public's perception of electric vehicles has changed recently as a result of the high demands and difficulties that battery management technology must overcome due to the frequent fire accidents involving electric vehicles [3]. The lithium-ion battery management system (BMS), one of the essential elements of electric cars, is essential for the commercialization and manufacturing of electric vehicles. As a result, creating sophisticated and intelligent BMSs for lithium-ion battery packs has been a popular area of research.The primary technological challenges limiting battery technology advancement. These three areas of management technology can be concluded: (1) Due to the extremely nonlinear nature of the lithium battery system, which affects aging on several time and spatial scales (such as nanoscale active materials, millimeter cells, and meter battery packs)(2) The internal states of the battery cannot be determined by a direct measuring method and are easily influenced by ambient factors such as temperature, noise, etc.Power batteries are becoming larger, which decreases the representativeness of measured values and the predictability of battery states, making it difficult to determine the internal states of the battery accurately; (3) the inconsistencies of the battery cells have a direct impact on the performance of the pack, raising the battery's unaddressed risk. Electric cars are mostly unaffected by certain effective safety precautions for small battery systems, and it is challenging to regulate the battery pack accurately and efficiently. Therefore, sophisticated BMSs should be created to address the issues [4,5].

Effective battery management in electric cars is crucial for enhancing driving range, prolonging battery life, lowering costs, and assuring vehicle safety. According to Figure 1, a typical Battery Management System (BMS) in a real-world vehicle is mostly made up of a range of sensors, actuators, controllers, and communication lines. For problem detection, equalization management, and other purposes, more BMSs have been deployed. The sampling circuit's primary function among them is to measure the signals for voltage, current, and temperature. The control circuit then employs a variety of algorithms to estimate the State of Charge (SOC), State of Health (SOH), State of Power (SOP), and State of Life (SOL) of batteries using these signals.

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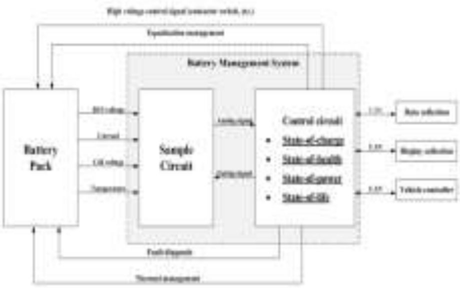

Figure 1. The general function of a battery management system.

A battery management system's battery level of charge functions similarly to a traditional fuel car's fuel meter. The primary purpose of the SOC is to alert the driver of the battery's intuitive status while also preventing issues like overcharging and over-discharging. The estimate of the SOC has been an issue under investigation. Since the battery is an extremely intricate and non-linear electrochemical component, its performance depends on both its internal and external circumstances. At the same time, the battery's performance should consider both the variability of battery performance within the battery pack as well as the performance of the individual battery.The battery's charged status will also face significant difficulties due to battery aging, cycle life, temperature, and other aspects. SOC was first studied by academics and researchers in the 1960s. The SOC estimate of batteries has been the subject of much scientific study over the past 50 years, but a more potent solution is still required. Therefore, to be useful for academics, researchers, and car businesses, this study examines the current SOC estimating techniques.

II DEFINITION OF SOC

The SOC of the battery refers to the ratio of the current remaining battery capacity to the available capacity under certain conditions (temperature, charge, and discharge ratio, etc.), and its mathematical expression is shown in Equation (1).

$$SOC = \frac{Q_c}{Q} \times 100\% = 100\% - \frac{Q_e}{Q}.$$

Understanding the denominator of Equation (1), which represents the battery capacity, as well as the numerator of the equation, is challenging. The battery capacity as it is defined here is inconsistent. Typically, the denominator of Equation (1) represents the rated capacity, factory capacity, cycle capacity, or current battery real capacity. The most common capacity in the theoretical analysis is rated capacity, which is a traditional definition of the denominator in Equation (1). According to this technique, the rated capacity is treated as a fixed value, and the SOC is calculated by deducting the charge or discharge from the rated capacity.[6]

Currently, most electric cars describe SOC in terms of the amount of electric charge, therefore in this equation, Qc stands for the battery's remaining power at the time of computation n and has the unit Ah; Q stands for the battery's total capacity, and has the unit Ah [7]. The battery charge is Qe.In actuality, the battery typically changes with a variety of conditions, necessitating a modification to this equation [8].The more popular equation is (2).

$$SOC(t) = SOCt_0 - \int_{t_0}^{t} \frac{\eta I}{C_n} d\tau \qquad (2)$$

The battery's nominal capacity denoted as SOC(t), is expressed in Ah in this equation. The coulomb efficiency, also known as the discharged efficiency, is the proportion of a battery's discharge capacity to its charge capacity within a single loop (= Q/Qn). Because there is a certain loss, such as the battery experiencing irreversible side reactions, the input charge frequently is unable to convert all the active compounds into energy. Consequently, the value is typically lower than 100%. The coulomb efficiency of modern lithium-ion batteries is 99.9% or more. The Peukert equation, which combines the observed residual charge and discharge current of the two batteries, may be used to calculate its value.Nevertheless, the coulomb efficiency is challenging to quantify in practice since it is very responsive tothe impact of temperature, battery aging, internal resistance, and charge and discharge current [9].

The status of health (SOH) should be considered while discussing SOC. SOH is a good indicator of how old a battery is. Different types of variables have an impact on SOH. Due to the impact of temperature, ventilation, and self-discharge level while using a battery assembly vehicle,the electrolyte content, and other variations among the batteries in the battery pack may raise to some extent the inconsistencies of battery voltage, internal resistance, capacity, and other characteristics, which will impact the value of SOH. The two have the following relationship.

SOC(t) = SOH(t) − DOD(t). (3)

In Equation (3), SOH(t) is the state of charge. When the battery is a new one, we consider SOH as 100%. DOD(t) (depth of discharge) represents the percentage of discharge of the battery and the rated capacity of the battery. DOD is considered when the discharge of the battery exceeds at least 80% of its rated capacity

III SOC ESTIMATION METHODS

SOC plays a big role in BMS. There are three basic kinds of estimating methodology based on theoretical and experimental properties: look-up table method, model-based estimation techniques, data-driven estimation methods, and filter-based method. Each category uses a different methodology to evaluate the efficacy of SOC. We give a brief conceptual overview of each category in this section.

3.1 Look-up table method: The look-up table method is convenient and straightforward, which measures SOC based on the mapping relationship between characteristic parameters (such as impedance spectroscopy, internal resistance, OCV, etc.) and SOC.

3.1.1 Open-circuit voltage (OCV) look-up table method: The battery voltage after a prolonged period of idleness without load is known as the OCV, and it has a nonlinear relationship to SOC [10]. The method's entire implementation procedure is provided in Reference [11]. The OCV-SOC table is created by measuring the OCV under various SOC situations. In actuality, the OCV and OCV-SOC table are used to calculate the SOC. The procedure is straightforward and uncomplicated, but the battery must be left standing for a considerable amount of time to guarantee that the measured voltage is identical to OCV. These elements are added to the OCV-SOC chart [12] in consideration of how temperature, material, and aging affect the connection between OCV and SOC. To determine battery SOC, Pecht et al. [13] created an off-line OCV-SOC-Temperature table. Additionally, the hysteresis effect of OCV is a crucial element in determining OCV accuracy [14]. For LiFePO4 batteries, the hysteresis effect may be recognized as the difference in OCV under the same SOC during charging and discharging [15]. Therefore, an inaccurate OCV-SOC relationship without considering the hysteresis effect may lead to unacceptable SOC errors.

3.1.2 Impedance look-up table method: The two variables impedance and SOC are related. The impedance look-up table technique is established by applying a certain frequency of current to the battery, which identifies several SOC-related parameters by nonlinear fitting or a parameter identification algorithm [16]. The impedance characteristics include constant phase element, internal ohmic resistance, polarisation capacitance, polarisation resistance, and inductance [17]. These techniques could result in substantial prediction errors if the impedance amplitude is minimal. Battery aging may have an impact on the SOC look-up table method's accuracy, according to reference [18]. Additionally, non-linear variations in impedance and SOC may be caused by the current, the surrounding temperature, and other variables [19]. The effects of the current ratio, aging, and temperature on impedance need to be consideredto guarantee the accuracy of the SOC estimate. the drawback of the look-up table approach is that the battery must be rested for a long period to maintain the stability of the internal electrochemistry and allow for reasonably accurate measurement of the parameters. Additionally, the precision of the SOC table has a significant impact on the dependability of SOC measurement. As a result, the approach is inappropriate for applications requiring real-time and high-precision SOC estimation, such as those in aviation, aerospace, and military.

3.2 -hour integral method: Compared with the above methods, the ampere-hour integral method is more straightforward, where the SOC of the battery is calculated by current integration [20].

Although this approach is straightforward, it has drawbacks. The sensor error will build as a result of the open-loop computation, which might result in a more significant SOC error. Additionally, variations in rated capacity and Coulomb efficiency can be brought on by aging and temperature, which has an impact on how accurately SOC is calculated. Additionally, the look-up table approach is used to establish the initial SOC, allowing any beginning errors to propagate through the whole SOC computation process. To increase its resilience, this strategy is typically paired with the model-based method or the data-driven method.

3.3 Filter-based method; Typically, the filter-based method can be roughly categorized into: LKF, EKF, AEKF, SPKF, UKF, and AUKF.

3.3.1 Linear Kalman Filter(LKF): The Kalman Filter (KF) has been a popular tool for estimating battery conditions for a while [21]. It may be thought of as a two-step recursive process that begins by forecasting the system state and output and ends by modifying the system state in response to output errors [22]. KF cannot be utilized directly with the OCVfunction because of its nonlinear nature. A technique of SOC estimate of LIB employing an LKF based on local linearization was put out in Reference [23]. Because of the piecewise linearization of the OCV function, LKF may be used to estimate the SOC. A hybrid estimate approach of SOC and SOF based on LKF was proposed by Chen et al. [24]. A combination technique of SOC and capacity estimate was proposed by Wei et al. [25]. Recursive least squares and the LKF are used, respectively, to estimate the SOC and capacity. For battery SOC estimates, many KF versions have been utilized recently.

3.3.2 Extended Kalman Filter(EKF): EKF is a suboptimal filter since its fundamental tenet is to linearize the nonlinear system and conduct Kalman filtering [26]. Based on the linearization concept of nonlinear functions, the EKF increases the nonlinear OCV function with partial derivatives [27]. The SOC estimate approach, which is based on a reduced-order battery model and EKF, was suggested in Ref. [28] to address the issue that the model parameters are susceptible to change as a result of the battery's nonlinear behavior. According to experimental findings, SOC errors are under 2%. A dual-time scale EKF was used to construct a SOC estimate method for the battery pack in Ref. [29]. The cell was calculated after the average SOC.

SOC was calculated using the disparity between the solitary and typical cells. The findings indicated that the pack SOC error is under 2%. the direct accuracy of the rated capacity has an impact on the accuracy of SOC estimate findings. SOC and capacity were simultaneously calculated by EKF in Ref. [30], and SOC error was further decreased. A reliable estimate SOC approach employing EKF for the battery was put out in Reference [31] SOC was corrected by using the modelling error as a constant bias state vector. The linearization of the OCV function and the model parameters both affect how accurate the EKF is[32]. To estimate battery SOC, numerous better techniques have been put forth. These techniques may be categorized into two groups: (1) model improvement, and (2) algorithm improvement. The battery's thermal-electrochemical model was created in Reference [33]. Temperature is used to adjust the model parameters, and EKF calculated the SOC. An improved SOC estimating approach based on EKF that considered the impacts of various currents, SOCs, and hysteresis effects on the model parameters was developed.

The suggested approach can mitigate the impact of truncation mistakes. A multi-time scale estimation approach based on EKF is suggested and used to estimate the SOC and SOH of batteries together. The filter with greater performance than EKF is used to estimate SOC to lower the estimation error.

3.3.3 Adaptive Extended Kalman Filter (AEKF): The covariance of the two types of noise in the AEKF is adaptive. The divergence or bias of the algorithm is avoided by AEKF thanks to the adaptive covariance of process noise and measurement noise. An online OCV estimate technique was developed in Ref. [34] utilizing AEKF, and SOC was calculated by consulting the OCV-SOC table. The correlation between SOC and the chemical makeup of various battery types was examined. Then, using a multi-parameter closed-loop feedback system, AEKF determined the precise estimation of SOC.

According to the findings, the highest SOC error is less than 3%. The accuracy of the SOC estimates is hampered by the battery's aging. In Ref. [35], a novel approach to estimating SOC of LIB based on AEKF was put out. A straightforward optimization approach is used to update the battery aging model, and AEKF predicted the SOC for various battery ages.

The findings indicated that the SOC error is under 4%. The battery SOC was calculated using AEKF based on the fractional-order model since it provides a better explanation of the behavior of the battery. A hybrid estimates technique of SOC and capacity based on the AEKF multi-time scale framework is presented in Ref. [36] to address the issue of current measurement offset interference to SOC estimation, which significantly enhances the robustness and accuracy of SOC estimation.

3.3.4 Sigma-Point Kalman Filter (SPKF): Since the nonlinear element of the OCV-SOC function is omitted for EKF, the linearization of the function is enlarged close to the previous mean, which results in a clear SOC estimate mistake. As a result, EKF struggles to deliver enough performance in applications that demand high SOC prediction accuracy. The SOC estimate methods based on SPKF software were proposed. The findings showed that SPKF could provide SOC estimate accuracy that was greater than EKF. A SOC estimate approach based on an electrochemical model and employing an adaptive square root sigma point Kalman filter (ASRSPKF) with equality constraints was presented in Ref. [37]. The results show that ASRSPKF has outstanding performance. Compared with AEKF, its accuracy is improved by 30%, and its convergence time is shortened by 88%.

3.3.5 Unscented Kalman Filter (UKF): The traceless transformation and conventional KF are the ancestors of UKF. Under the linear assumption, nonlinear system equations may be applied to the conventional Kalman filter through traceless transformation. UKF does not ignore higher-order terms due to linearization, so it has high estimation accuracy. The battery model's parameters are temperature-sensitive. In Ref. [38], the temperature was used to adjust the model parameters before UKF was used to predict SOC. Several enhanced UKF algorithms were created to enhance the performance of traditional UKF. In Ref. [39], the battery model was trained using an RBF network, and the SOC was calculated using SRUKF. The findings indicated that SRUKF and EKF both had greater SOC estimate accuracy. The square root unscented Kalman filter employing spherical transform (Sqrt-UKFST) was created to predict battery SOC in Ref. to lessen the computation needs of the unscented transformation in UKF. RMSE and maximum error grew by 37% and 44%, respectively, in comparison to EKF. Compared to UKF, the calculating need is 32% lower. The fuzzy inference technique was used to optimize UKF to increase its robustness. The more reliable modified UKF algorithm has a SOC error under the UDDS condition that is within 1.76 percent.

3.3.6 Adaptive Unscented Kalman Filter (AUKF): AUKF is an improvement over UKF that allows for automated noise covariance adjustment in SOC estimate. In Ref. [40], the AUKF was used to estimate battery SOC. The AUKF state model was updated in real-time while model parameters were online discovered using the recursive least squares approach.

The findings demonstrated that the joint estimation technique could lower the SOC estimate error. The effectiveness of AUKF, AEKF, UKF, and EKF in SOC estimate based on a 2nd order RC model has been evaluated by Mara et al. [41]. The outcomes showed that AUKF performed the best. Only 0.028% was the absolute average error. An enhanced AUKF based on Sage-Husa maximum posterior estimate was suggested for SOC estimation to calculate the error covariance adaptively.

3.4 Observer-based method: Based on the observed values of the system's external variables, the state observer can determine the estimated values of the state variables. Luenberg presented the idea and building approach of the state observer to realize state feedback or other demands for control systems. State feedback technology may now be used practically, and many parts of control engineering have benefited from the introduction of the state observer. g. In recent years, observer-based methods such as the Luenberger observer (LO),the proportional-integral observer (PIO), and the H-infinity/H∞ observer (HIO) have been used extensively for battery state estimation.

3.4.1 Luenberger Observer (LO): The LO is frequently employed in time-varying, nonlinear, and linear systems. An adaptive Luenberger observer (ALO) based technique for online battery pack SOC estimation was put in. A stochastic gradient technique was used to change the observer gain. A LO for SOC estimate was created based on a nonlinear fractional battery model. The Lyapunov direct technique can guarantee global asymptotic stability.

3.4.2 PI Observer (PIO): It is effective to estimate the state of systems with unknown input disturbances using the PIO. In Ref. [127], a PIO-based SOC estimate approach based on a straightforward RC battery model was developed. An observer based on a dual-circuit was created by Tang et al. The capacity error and starting error were addressed by the parameters-normalized PIO, and the impact of the drifting current was limited by the current integrator. The experiment's findings demonstrated that even when the initial SOC was unknown, this method's calculation complexity was low but its accuracy was great.

3.4.3 H-infinity/H∞ Observer (HIO): The resilience of the erroneous starting system state and unknown disruption from inaccurate or unidentified statistical features of modeling and measurement mistakes can be ensured by the HIO. An approach using an HIO and a hysteresis model was suggested in Ref. [42] to account for the mode uncertainties caused by current, temperature, and aging. For the SOC estimation of a battery pack, Zhu et al. [43,44] created an HIO with dynamic gain that may lessen the negative effects of the non-Gaussian model and measurement errors. In addition, the observer design criterion was formed as the linear matrix inequality (LMI) for easy computation. Liu et al. [45] developed an HIO using a switched battery model to estimate the Electromotive force (EMF) for SOC. The switched model considered the relaxation effect and the relationship between EMF and SOC.

3.5 Data-driven based method: The data-driven approaches treat the battery as a "black box" and use a significant quantity of quantifiable input and output data to learn about its internal dynamics. Neural networks (NN), fuzzy logic, genetic algorithms (GA), support vector machines (SVM), and others are often used in data-driven-based approaches for SOC estimates.

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3.5.1 Neural Network (NN) method: Another subset of artificial intelligence is the neural network. It is based on a straightforward simulation of the human brain and accepts training mostly using input and output samples to match the mapping function relations. By adjusting the model weight and deviation, it increases the model's accuracy. Two steps may be distinguished in this procedure. The first is a procedure known as positive calculation, which primarily involves calculating each unit from the input layer to the output layer.The propagation of erroneous echos is the second.The input layer in Figure 2 primarily consists of battery performance indicators including current, voltage, temperature, and internal resistance. The estimated SOC of the battery is represented in the output layer.The system's activation mechanism is the secret layer. According to Xia Kegang et al.'s research, Figure 3 depicts the neural network algorithm's fundamental processing flow. The procedure is reliable and accurate, according to the findings of the experiments.

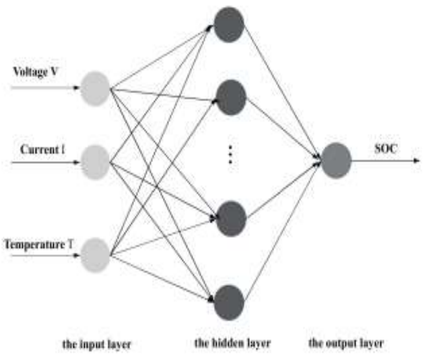

Figure 2. SOC estimation principle of neural network.

The benefit of this approach is that it is quick and simple to estimate the SOC appropriately.The experiment shows that the convergence speed and precision of the parallel and global searching strategies are better.The drawbacks of this approach are also readily apparent, mostly due to the need for a substantial quantity of training data to complete the training system

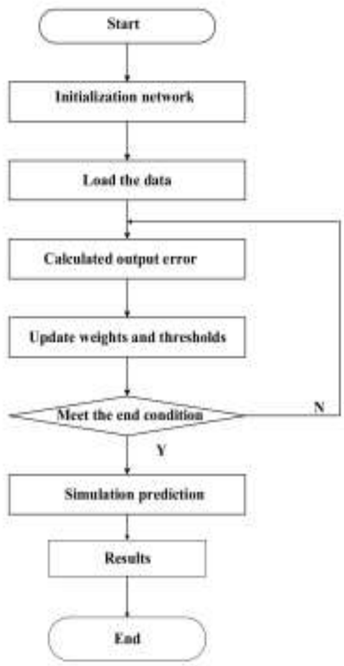

Figure 3: Process of neural network.

Its accuracy is significantly influenced by training data and training techniques. It also requires more research since its method is very complicated and requires a lot of calculations in practice.

3.5.2 Fuzzy Logic method: To account for the battery's nonlinear dynamics, a fuzzy NN (FNN) basic battery model was developed. To estimate the SOC, Lee et al. [46] developed a learning system made up of learning controllers, FNNs, and cerebellar-model-articulation-controller networks. A simple-structure merging FNN for SOC estimation was createdby combining a reduced-form genetic algorithm (RGA) with a B-spline membership function (BMF)-based FNN.

3.5.3 Genetic Algorithm (GA): For further SOC estimate, the GA is often utilized to determine the battery model parameter. A unique SOC estimate approach was created by Chen et al. [47] using genetic algorithms and the grey model (GM). Higher precision and repeatability were brought using a genetic algorithm.

3.5.4 Support Vector Machine (SVM): The SVMs are a group of connected supervised learning techniques that may accurately and universally estimate any multivariate function. In Ref. [48], an improved SVM for a regression-based SOC estimate approach was put forward. The outcomes demonstrated that this approach was both easier to use and more precise than that based on artificial neural networks (ANNs). To calculate battery SOC,integrated least-square support vector machines (LSSVM) with adaptive unscented Kalman filters (AUKF). The battery model can be accurately established and updated even with limited training samples

IV CONCLUSION

In the field of electric vehicles, lithium batteries have become a research hotspot with their advantages. SOC estimation, as a very important and challenging part of the battery management system, will remain a research hotspot in the future. This review discusses the current SOC estimation in combination with specific research and classifies the existing methods, which is of great significance to future research.

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