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Review

An Overview of Methods and Technologies for Estimating Battery State of Charge in Electric Vehicles

Taysa Millena Banik Marques [1,†], João Lucas Ferreira dos Santos [2,†], Diego Solak Castanho [1,†], Mariane Bigarelli Ferreira [2,†], Sergio L. Stevan, Jr. [1,†], Carlos Henrique Illa Font [1,†], Thiago Antonini Alves [3,†], Cassiano Moro Piekarski [2,†], Hugo Valadares Siqueira [1,2,*,†] and Fernanda Cristina Corrêa [1,†]

1 Graduate Program in Electrical Engineering, Federal University of Technology—Parana, Ponta Grossa 84017-220, Brazil; taysabanik@alunos.utfpr.edu.br (T.M.B.M.); diegoscastanho@gmail.com (D.S.C.); sstevanjr@utfpr.edu.br (S.L.S.J.); illafont@utfpr.edu.br (C.H.I.F.); fernandacorrea@utfpr.edu.br (F.C.C.)
2 Graduate Program in Industrial Engineering, Federal University of Technology—Parana, Ponta Grossa 84017-220, Brazil; joaolucassantos@alunos.utfpr.edu.br (J.L.F.d.S.); marianebigarellif@gmail.com (M.B.F.); piekarski@utfpr.edu.br (C.M.P.)
3 Graduate Program in Mechanical Engineering, Federal University of Technology—Parana, Ponta Grossa 84017-220, Brazil; antonini@utfpr.edu.br
* Correspondence: hugosiqueira@utfpr.edu.br
† These authors contributed equally to this work.

Abstract: Recently, electric vehicles have gained enormous popularity due to their performance and efficiency. The investment in developing this new technology is justified by the increased awareness of the environmental impacts caused by combustion vehicles, such as greenhouse gas emissions, which have contributed to global warming and the depletion of oil reserves that are not renewable energy sources. Lithium-ion batteries are the most promising for electric vehicle (EV) applications. They have been widely used for their advantages, such as high energy density, many cycles, and low self-discharge. This work extensively investigates the main methods of estimating the state of charge (SoC) obtained through a literature review. A total of 109 relevant articles were found using the prism method. Some basic concepts of the state of health (SoH); a battery management system (BMS); and some models that can perform SoC estimation are presented. Challenges encountered in this task are discussed, such as the nonlinear characteristics of lithium-ion batteries that must be considered in the algorithms applied to the BMS. Thus, the set of concepts examined in this review supports the need to evolve the devices and develop new methods for estimating the SoC, which is increasingly more accurate and faster. This review shows that these tools tend to be continuously more dependent on artificial intelligence methods, especially hybrid algorithms, which require less training time and low computational cost, delivering real-time information to embedded systems.

Keywords: Li-ion battery; state of charge; electric vehicles; estimation

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1. Introduction

Several environmental phenomena, such as global warming, highlight the importance of developing new technologies. Among the various sectors that use fossil fuels, the transport sector is primarily responsible for generating pollutants and greenhouse gas emissions, totaling approximately 20% of global carbon dioxide emissions [1].

This is the case of combustion vehicles, which are seen as the main vehicles responsible for carbon dioxide (CO_2) emissions . In 2017, there was an increase in demand for oil of 1.6%, reaching a consumption of 1.5 million barrels per day, a rate higher than the average of 1% recorded in this decade. Additionally, CO_2 emissions were increased by 1.4% in the same year, reaching the most elevated rate globally, with 32.5 gigatons emitted [2].

These observations opened new perspectives for electric vehicles (EVs), a promising alternative for reducing greenhouse gas emissions. Additionally, they can use a technology based on renewable energy sources [3].

Among the technologies involving EVs, different types of batteries stand out, such as nickel-cadmium (NiCad), nickel–metal hydride (NiMH), lithium iron phosphate ($LiFePO_4$), and lithium-polymer ($Li\text{-}Po_4$) batteries [4]. The SoH and the number of cycles of each battery technology depend mainly on the anodic and cathodic materials used in its construction [5].

Kostopoulos et al. [6] argue that lithium-ion batteries represent the heart of most EVs since this model involves promising features such as high voltage, high energy density, low self-discharge, and long life cycles [7] when compared to other available types [8].

A reliable estimate of the battery SoC is necessary to control charge duration and to prevent failures [7]. SoC estimation is one of the most critical functions in the EV Li-ion BMS. The most used methods consider the measured values, models, load parameters, and algorithms [9].

The estimation of SoC is not precise, and it is not easy to perform. Different studies obtain alternative measurable parameters for calculating battery performance, such as current, voltage, resistance, and temperature [10]. Waag et al. [11] point out charge estimation as a challenge as it involves internal and external conditions to the battery.

Although the literature presents many investigations involving procedures for estimating battery charge, there is a lack of studies that focus on charge estimation methods and models, point out their advantages and disadvantages in a critical way, and direct to future trends; such studies may result in insights for researchers and manufacturers into EV advancements and development.

Thus, this study aims to provide discussions involving the survey of the state of charge of batteries, pointing out the main critical problems, solutions obtained by each method, and the challenges that remain unsolved.

This manuscript is organized as follows: this initial section aims to set the scene and present the study's objective; Section 2 presents the methods for the literature review and for building the visual maps and graphs for analysis, Section 3 provides a presentation of battery models and how to control them, SoC estimation methods are discussed in Section 4, Section 5 presents a critical discussion on charge estimation methods, and Section 6 concludes the review.

2. Methodology for Paper Selection

A survey of studies in the literature was carried out using the relevance calculated by the databases as a guideline. The theoretical framework was based on full papers published in databases such as Science Direct®, Scopus®, IEEE®, and MDPI®, searched on 26 September 2022. It delimited the number of articles into 110 for a deeper analysis, with 12 reviews. The other 96 studies had their content analyzed. The combination of keywords used in the searches was "estimation" AND "state of charge" OR "state of health" AND "vehicle." The search was reduced by analyzing only the last ten years, that is, since 2013. These articles were read in full and served as a basis for the analysis carried out in this study.

A mapping of the co-occurrence of the keywords was carried out using the VOSviewer software [12], for relational analysis of the topics that constitute the selected studies. Figure 1 presents the co-occurrence of keywords, in which it is possible to verify the formation of three main clusters of information. The first, in green, indicates the application of the batteries themselves, focusing on vehicles and their models; the second, in red, shows what can be monitored/estimated, especially indicating the SoH of the batteries; finally, in blue, the group presents the need to carry out SoC, indicating the use of different Kalman filters for this purpose as the primary information.

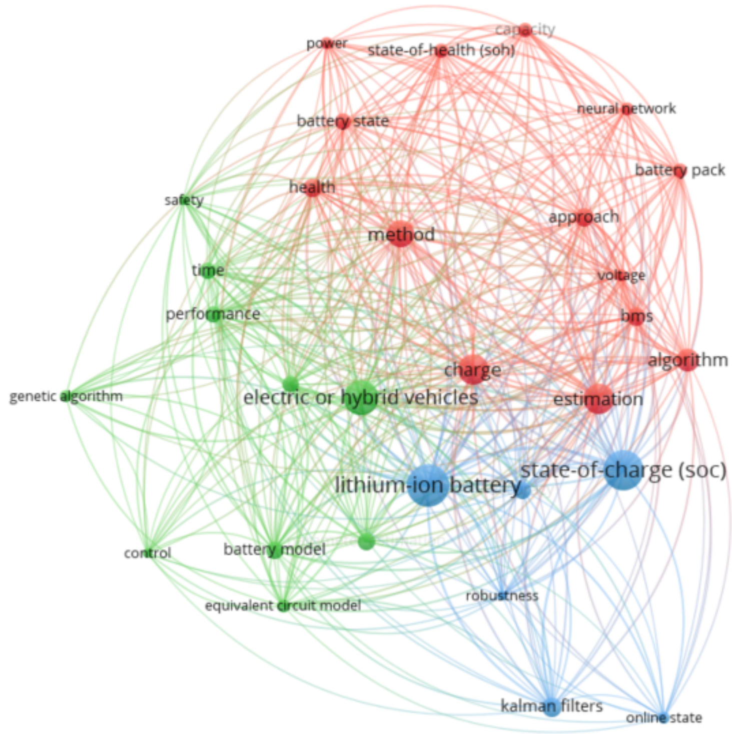

Figure 1. Co-occurrence of terms—final portfolio.

The literature also points out some reviews on battery charge estimation in electric vehicles. Berecibar et al. [3] showed one of the primary studies on estimating the health status of lithium-ion batteries, pointing out that there is no perfect solution for this task. Chen et al. [13] reviewed lithium-ion batteries, introducing a new method of classifying used devices of this kind. Rezvanizaniani et al. [14] presented a review of battery health prognostic and management techniques focused on battery life issues under dynamic operating conditions. Nejad et al. [15] introduced a review of clustered parameter equivalent circuit model structures used in lithium-ion batteries for energy storage applications.

The above-mentioned reviews also clearly show that all of the techniques for SoC estimation still need more development and improvement to reduce measurement error since each one presents advantages and disadvantages. It is also necessary to find more effective methods that can work in real-time, dealing with variations, nonlinearities, different climatic parameters, and parametric conditions that encompass the vehicles. This improvement is of crucial importance to the automobile industry, users, and academia in general, justifying the preparation of the present study.

3. Battery Modelling and Control

The main types of battery modeling found in the current literature to characterize their dynamic behavior are presented and discussed in the sequence:

- **Electrochemical Models**: they are mainly composed of systems of partial differential equations based on batteries' physical and chemical characteristics [16]. To use an appropriate model, one can employ optimization techniques for a set of electrochemical parameters [8];
- **Models Based on Equivalent Circuits**: equivalent circuit models can simulate the static and dynamic behavior of batteries, composed of associations of resistors, capacitors, inductors, and nonlinear components such as Warburg impedance [16,17];
- **Behavioral and Black-Box Models**: Behavioral models and the black-box model (BBM) obtain the output behavior through nonlinear relationships between system inputs, without the need to perform physical or electrical specifications [16].

Charge estimation is intrinsically linked to the battery model and its accuracy. Due to the nonlinear characteristics of batteries, determining the SoC and SoH values is challenging. The estimation error tends to increase in systems in which the model is inaccurate, or measurements cannot be made in real-time. The battery performance will vary according to temperature, operating time, and charging and discharging actions over time [18]. Therefore, it is crucial to develop models that cover all of the possible operating conditions. According to Fotouhi et al. [19], fast and fairly accurate models are preferable rather than complex and highly accurate ones. They also state that EV discharge rates in the modeling are also important.

In this sense, the BMS is the device dedicated to monitoring and controlling the operation of the battery pack to prolong its useful life, operating efficiency, and safety, and to enable the indicators of battery operation [20]. The BMS comprises sensors, controllers, and actuators, connecting large amounts of information read by different models and algorithms [18]. This device must ensure that the operation of the entire battery pack is efficient and, simultaneously, reliable [16]. The BMS estimates indicators such as SoC and SoH in EVs. By estimating the SoH, the user is aware of the current situation of their battery pack and when it should be replaced [20].

When related to EVs, there is particular concern about the safety of the battery bank regarding possible mechanical collisions; fire risks; and the exact estimation of the SoC . Note that many batteries suffer serious charges and discharges, affecting the battery life, particularly lithium-ion batteries [8]. In this way, protection circuits against overloads and deep discharges are emphasized. Such events are the responsibility of the BMS, highlighting the need for indicators such as SoC and SoH [20].

Following these premises, SoC estimation is critical in enabling the safe and efficient use of batteries in EVs. Therefore, the literature presents the development of numerous techniques for its realization, as discussed in the following section.

4. State of Charge Estimation Methods

The literature introduces different approaches for estimating the EV batteries' load, health, and functional status [21]. Among the numerous algorithms and models created for SoC estimation, some stand out for their simplicity of implementation or complexity [18]. This review divides the SOC estimation methods into five categories, which are shown in Figure 2.

In conventional methods, SoC estimation occurs indirectly by combining the physical characteristics of the battery, such as voltage, current, resistance, temperature, and impedance [3,5]. For example, by identifying the critical parameters of the battery pack, an improved control and diagnostic system can be obtained, ensuring the safety and longevity of the battery pack [8]. To perform the SoC estimation techniques based on adaptive filters, nonlinear observers can be used in complex and nonlinear systems [18].

Learning algorithms comprise computational intelligence algorithms, referring to fuzzy logic, neural networks, and bio-inspired optimization metaheuristics. Another possibility is the hybrid approach, in which two or more of these methods are combined to improve the accuracy of SoC estimation [18].

However, Berecibar et al. [3] reported that a perfect technique for SoC estimation has not yet been developed. Additionally, the performance of each one depends on the data available for load forecasting. The following subsections present the most used methods in the literature, describing a summary of the advantages and disadvantages, the problems they solve, and some issues of their performance.

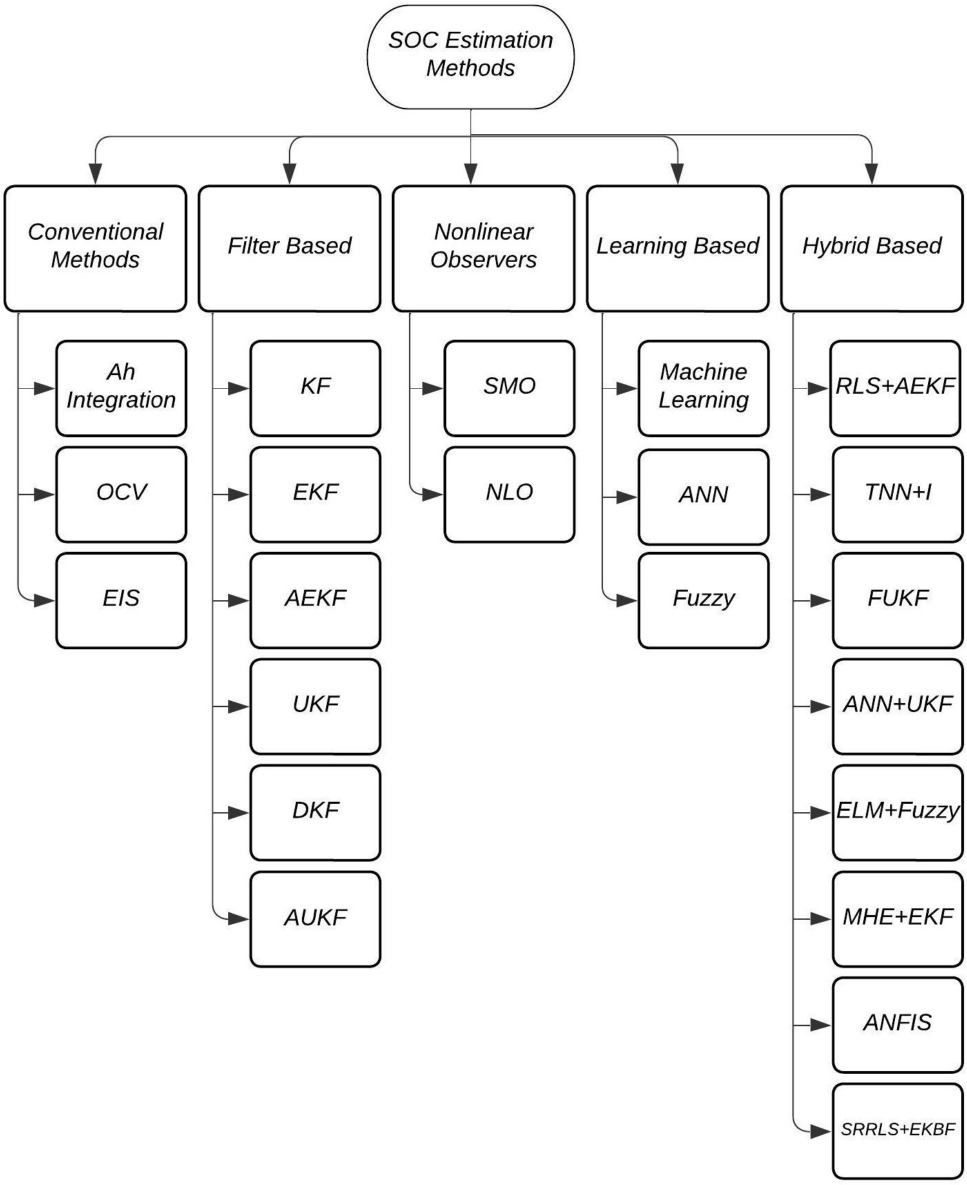

Figure 2. Classification of SOC estimation methods.

4.1. Conventional Methods

The Coulomb count (CC) method, also known as the Ampere-hour (Ah) integration method, is usually applied to perform SoC and SoH estimation. It is based on the product of current and discharge time [3]. The method compares the total charge of the battery concerning the charge released or stored. The CC is simple to implement, but its accuracy depends on the sensor. The error accumulated during the measurements cannot be discarded. Still, predicting the amount of SoC load is difficult, so an incomplete load can generate a large amount of error [20].

The electrochemical impedance spectroscopy (EIS) is a method to perform SoC estimation, in which small current signals with different frequencies are applied to the battery. This strategy is suitable for offline analysis as the estimate takes some time to be completed [20].

The open-circuit voltage (OCV) method is widely used to perform an initial estimate of the SoC for a static or uncharged battery. Nevertheless, these conditions are not always observed during its use as it does not allow for the use of the technique in real time. Therefore, this method is usually applied together with the Ah method to determine the initial SoC prediction [9].

Chen et al. [22], in their work, mathematically model batteries and perform simulation tests with electrochemical models to estimate charge capacity. On the other hand, Dong et al. [23] use the ampere-hour integration, a conventional estimation method, to estimate the battery charge. They performed simulations, but there was no error calculation in their work. Maltezo et al. [24] present a battery management system for lead-acid battery banks used in electric vehicles. The measurement of the state of charge and state of health of the battery is derived from its charging voltage, no-load voltage, charging current, and temperature during experimentation. Additionally, Khan et al. [25] used electrochemical impedance spectroscopy as a reference for optimization with another method, the pseudo-random binary sequence. Hardware was programmed for testing, and the accuracy reached was 98%.

4.2. Methods Based on Filtering Algorithms

The Kalman filter (KF) is a technique capable of predicting the behavior of complex systems, such as the SoC of a battery. Although successful and widely used, it presents a high computational cost and difficulty in representing nonlinear systems [18]. The implementation of this technique, when applied to SoC estimation, can be divided into two main parts. In the first, the prediction of the output variable of the current state is performed; in the second, the estimate is updated to minimize the error [3]. The method presents good accuracy and is not sensitive to the initial SoC and associated noise. It requires several parameters as input, such as voltage, current, capacity, Coulomb efficiency, self-discharge rate, initial SoC value, and battery model.

The technique is based on partial derivatives and Taylor Series expansion to linearize the nonlinear behavior of the battery pack, allowing it to operate in nonlinear systems. Despite not presenting the best estimation values, the method is adaptable to the different battery models used for simulations. However, this method presents drawbacks as it works effectively only with first- and second-order nonlinear models; the calculated errors could be more satisfactory. The articles [26–31] worked with the Kalman filter and some variations. They made simulations and validations with different conduction cycles to verify the robustness of the method. References [32–38] operated with the extended Kalman filter to estimate SoC and SOH. In particular, the authors [32,33,39] used the least square method to find the best set of parameters to be applied in the estimation. Using the autoregressive model with exogenous input (ARX) to find battery parameters, Ko and Choi [40] used the extended Kalman filter (EKF) with a 10 Ah cell (HW 38120 L/S).

Zheng and Zhang [41] focused on the effects of temperature on SoC estimation using EKF. In testing the algorithm, the authors applied different temperatures to check the performance. Seo et al. [42] proceeded with similar steps, but they used a new battery model. Wang et al. [43] carried out their studies with the EKF measuring the internal resistance of the battery in real-time, while Lin et al. [44] made EKF with dynamic noise adjustments. Zhou et al. [45] tested the estimation of SoC by EKF with stress tests using conduction cycles. [46] compared the EKF with the performance of the proportional integral observer method and concluded that EKF performed better.

Refs. [47–50] worked with the adaptive extended Kalman filter (AEKF). Shen et al. [51] used a dual-extended Kalman filter to obtain more precision and reduce errors caused by the sensor. Wang et al. [52] applied a hierarchical adaptive extended Kalman filter to estimate SOC and made tests with the urban dynamometer driving schedule (UDDS) cycle.

Tran et al. [53] addressed an autoregressive-exogenous model to define the parameters for SoC estimation by dual EKF. These parameters were updated online. Xiong et al. [54] applied a Robust EKF, which showed better results than the traditional EKF. They performed tests considering urban driving cycles, showing accurate error values even with the imprecise initial SoC. Wu et al. [55] used the adaptive forgetting factor recursive augmented least squares algorithm (AFFRALS) to find the best parameters of an affine iterative adaptive extended Kalman filter (AIAEKF), which performed better than EKF, even with unknown SoC.

Su et al. [56] compared the EKF with the multiple model adaptive estimation method based on a bank of Kalman filters, which showed more accurate results and a faster conversion rate. Liu et al. [57] used the least square method to find the parameters of an extreme gradient boosting method (XGBoost). Takyi-Aninakwa et al. [58] used robust long short-term memory (LSTM) to adjust the model and applied it in a squared gain EKF to eliminate noise.

The performance of adaptive extended Kalman filter (AEKF) is significantly dependent on the identification of lithium-ion battery model parameters and the noise information. In this sense, Wu et al. [59] used auto-tuning multiple forgetting factors recursive least squares (AMFFRLS) to find the best parameters to estimate the SoC by EKF. The authors proposed an adaptive timescale dual extended Kalman filter (ATSDEKF) with a sliding window forgetting factor approximate total recursive least squares (SWFFATRLS) to update the battery capacity. The same research group applied multiple linear regression to find the better initial parameters of an adaptive forgetting factor adaptive Kalman filter (AFFAKF) to manage and estimate the SoC and perform the correction of the current and next measurements, even without the exact current values Wu et al. [60].

He et al. [61] applied the unscented Kalman filter (UKF) in the aforementioned task, while Zheng et al. [62] used a double Kalman filter and UKF with an extended Kalman filter. The EKF was responsible for updating the parameters, and the UKF was responsible for estimating the SoC. Fu et al. [63] used forgetting factor recursive least squares to find the simulation parameters of the cubature Kalman filter (CKF) to estimate SoC. Zeng et al. [64] worked with two fuzzy UKF and a bayesian identification algorithm to find the best parameters to estimate the battery's charge and the system's SoH. The process included tests in conduction cycles within the Matlab software. Yun et al. [65] used something similar: a variable bayesian unscented Kalman filter coupled with a variable bayesian square-root cubature Kalman filter to estimate battery SoC. Liu et al. [66] proposed an adaptive square root unscented Kalman filter that overcame the EKF and UKF and proved to be more accurate and stable, and they presented a better self-adaptive response to the system. Lv et al. [67] addressed the adaptive UKF for finding noise that affected the system when using only UKF in SoC estimate tasks. Zheng et al. [68] found the parameters of the UKF by the deviation compensation recursive least squares method. Miao and Gao [69] proposed an adaptive fractional-order UKM, using an augmented vector method to find the parameters. Biswas et al. [70] proposed the augmented unscented Kalman filter (AUKF), which proved more accurate than the UKF. The model also provided automatic parameter adjustment according to driving cycle tests.

In the work from Bhuvana et al. [71], the comparative efficiency and complexity of the EKF, the UKF, and the CKF concerning battery internal state estimation were realized. The results clearly showed that the CKF-based method significantly increases the efficiency of the state estimation compared to the others. As the implementation on an embedded platform is always a trade-off between complexity and accuracy, the use of the CKF-based SoC estimation method was suggested. The results of the work from Linghu et al. [72] indicated that compared with the UKF and the adaptive CKF, the adaptive fifth-degree CKF could achieve higher state-of-charge estimation accuracy and better overcome the impact of significant measurement error and initial error.

4.3. Methods Based on Nonlinear Observers

The sliding mode observer (SMO) is a technique that guarantees stability and robustness in measurement, even in the presence of uncertainties and noise. The resulting model is an equation of state such that the system output is decomposed into observer equations following the stage. The SMO is based on the exhaustive study of battery behavior, so it is possible to select the appropriate parameters of the SMO, such as switching gains and uncertainty limits [73].

The nonlinear observer (NLO) method can perform SoC estimation from a set of nonlinear observation equations, using models based on a first-order RC equivalent circuit.

In the NLO, performing a high computational cost matrix calculation is unnecessary, presenting robustness against measurement errors and uncertainties [74]. When compared to SMO, this method can improve accuracy and convergence time. However, obtaining an adequate gain matrix to reduce the error is difficult.

Othman et al. [75] proposed a simple and fast online adaptive observer for the SoC estimation of the lithium-ion battery. It was confirmed that the computation time of the proposed algorithm is reduced by approximately 2.5 times compared to the extended Kalman filter-recursive least square (EKF-RLS) method. Despite the reduction in computation time, the errors are comparable to the latter. The low computational cost is significant when considering the need to accurately estimate the SoC of a large number of cells in a battery pack of an EV. Brembeck [76] presented a new highly automated framework for generating model based observers based on different types of Kalman filters extended with constraint handling algorithms for the use in embedded application.

Tran et al. [77] proposed a model-based approach using a nonlinear state observer and an online parameter identification algorithm. A battery model based on an ARX was used with recursive least squares (RLS) for parameter identification, in an effort to guarantee reliable estimation results under various operating conditions. The validity and feasibility of the proposed algorithm were verified by an experimental setup of six Li-ion battery cells connected in a module in series. It was found that, when compared with a simple linear state observer (LSO), an NLO can further reduce the SoC error by 1%.

4.4. Methods Based on Learning Algorithms

Artificial neural networks (ANN) are characterized by adaptability and self-learning. ANNs can be used in many systems with a reasonable approximation, including complex nonlinear cases. Still, a database that describes the system's dynamics is required. Regarding SoC estimation tasks when using ANNs, the most usual inputs are voltage, current, and temperature [78]. The drawback of the ANN for SoC estimation is the need for a significant computational effort and the amount of memory required for its implementation and tuning. It requests a large dataset with all of the parametric variations that may occur during the load and unload cycles and different temperatures at which batteries can operate [79,80]. Kang et al. [81] worked with a radial basis function neural network to remove the effects of battery degradation in the SoC estimation. Furthermore, it compared the created model with a conventional neural network and performed tests with conduction cycles to verify robustness.

Gao et al. [82] proposed a SoC estimation method based on self-recurrent wavelet neural network and compared the method with a conventional neural network, a backpropagation neural network (Multilayer Perceptron—MLP), and a wavelet neural network. Zhang et al. [83] mention the use of a backpropagation neural network and a particle swarm algorithm to optimize the network. Bezha and Nagaoka [84] also used backpropagation ANN to estimate SoC values, varying the number of network inputs (voltage, current, cycles, and temperature) to find a more robust model. The neural architecture is not mentioned in both cases, but the authors are dealing with an MLP [85]. Gu and Wang [86] used an extreme learning machine to model the SoC of the battery and the recursive least squares algorithm to perform the online estimation. With beetle antennae search the authors optimized the network to have better parameters. In the work from Ströbel et al. [87], the battery's temperature is estimated using an MLP with electrochemical impedance spectroscopy. The Bayesian regularization backpropagation, and Levenberg-Marquardt backpropagation, was used to adjust the model.

Ezemobi et al. [88] used ANN to estimate battery health under different load conditions. Hamida et al. [89] employed ANN with the artificial hummingbird optimization technique (AHOT) to find the optimal parameters for the network. The articles [90,91] worked with a nonlinear autoregressive neural network with exogenous inputs (NARX) to estimate the SoC and SoH of the battery, considering as markers the accuracy of the estimate, the duration of the network training, the robustness to noise, and the imprecision of the initial estimate. The proposed model is a combination of five artificial neural networks. Lipu et al. [92] applied a time-delay neural network (TDNN) optimized by an improved firefly algorithm (iFA), whereas SoC accuracy is subject to the proper parameter value. The iFA determines the optimal value of the free parameters of the ANN.

Some investigations proposed deep learning approaches to deal with the battery challenges. The authors [93–95] used an MLP with an LSTM considering a set of different inputs to estimate SoC and SoH values. Focusing on low temperatures, Cui et al. [96] proposed a convolutional neural network with a bidirectional weighted gated recurrent unit (CNN-BWGRU) to estimate SoC.

Fuzzy logic is one of the most important areas of computational intelligence used to model complex and nonlinear systems [97]. The design of a fuzzy system is composed of a fuzzification unit responsible for translating the actual inputs into fuzzy sets, and a group of fuzzy rules that correlates the inputs and outputs. An inference mechanism named defuzzification corresponds to the inverse fuzzification process, in which fuzzy output variables are converted into actual output variables. Fuzzy logic emulates the human capacity for rational decision-making even in ambiguous and uncertain situations [98,99]. However, its implementation requires a large number of mathematical operations and available memory, as well as a processing unit. Hou et al. [100] used an ANN (indeed an MLP) endowed with backpropagation to select the parameters and then proposed a fuzzy neural network to estimate the state of charge.

Algorithms from other nature were presented in recent studies. Gruosso et al. [101] estimated the state of charge without using a battery current sensor, creating a virtual sensor with system information. The proposal addressed a principal component analysis (PCA) with support vector regression (SVR). Surya et al. [102] created an equivalent cell model with a support vector machine (SVM). The articles [103,104] worked with XGBoost and supervised regression modeling to estimate the state of charge and health without the initial battery charge values.

4.5. Hybrid Methods

Hybrid methods can be defined as strategies that use two or more techniques to perform SoC estimation. This approach considerably increases accuracy and efficiency but at a higher computational cost than single algorithms.

Li et al. [105] worked with an equivalent circuit model (ECM), applying an RLS method to find the system parameters of an adaptive EKF to estimate the SoC. They also aggregated the Elman neural network (ELM) to predict the battery capacity, validating the results with vehicle driving cycles. Shen et al. [106] applied a transformer neural network (TNN) with an innovative immersion and invariance (I&I) adaptive observer to reduce the oscillations in the predictions found by the ANN. Zhang and Zhang [107] used a fuzzy method with UKF(FUKF) to find an estimator free of system and measurement noise. Ref. [108] applied an ANN (an MLP) to estimate the SoC and UKF to reduce the percentage of errors.

Zahid et al. [109] proposed a subtractive clustering-based neuro-fuzzy architecture (SC-ANFIS), in which the neuro-fuzzy set learning features from the dataset and adjusts the parameters. In the work by Rahbari et al. [110], the adaptive network-based fuzzy inference system (ANFIS) is used together with teaching learning-based optimization (TLBO). Shen et al. [111] used moving horizon estimation (MHE) with EKF, and Poloei et al. [112] used a moving window least mean square approach (LMS) with EKF to estimate the state of charge. Arasaratnam et al. [113] applied a dual bayesian estimation scheme with a square-root recursive least-squares (SRRLS) estimator and an extended Kalman–Bucy filter (EKBF) to determine the SoC.

Finally, Table 1 summarizes the most relevant information among the charge estimation methods described in this section, grouping them by method and indicating the main published results with root mean square error (RMSE) and mean absolute error (MAE) values, advantages and disadvantages, important considerations, and limitations.

Table 1. Charge estimation methods.

Charge Estimation Methods	Method	Main Results	Advantages	Disadvantages	Considerations and Limitations	References
Conventional Methods	Ah, OCV, and EIS	Those that show error values have an RMSE of 1.65%, which is a hybrid model with machine learning	No need for an algorithm to implement [18]	Battery needed to be in resting mode for long time [18]	Authors who did not present errors performed simulations or measurement tests. The hybrid algorithm obtained results from physical tests with an embedded algorithm	[22–25]
Kalman Filter-Based	KF, EKF, AKF, UKF, DKF, and AUKF	MAE—range of values 0.0426% to 2.22%, RMSE—range of values 0.0044% to 4.58%; these vary depending on the filter used	Acceptable accuracy, dealing with white noise [18]	Need for an accurate enough battery model, extensive time and computational memory, and a complicated algorithm to implement [18]	The method's accuracy is linked to the accuracy of the battery model. Such processes need longer execution time and memory because they have a more complex algorithm	[26–72]
Nonlinear Observed-Based	SMO, NLO	MAE—0.928% and RMSE—1.7%	Acceptable accuracy and robustness against modeling uncertainties [18]	Difficult for online application due to the complicated computational algorithm [18]	The authors performed physical tests. Still, nonlinear methods are difficult to apply online due to the algorithm's complexity	[73–77]
Learning-Based	Techniques of machine and deep learning, ANN and their variations, fuzzy logic	MAE—range of values 0.001929% to 3%, RMSE—range of values 0.018% to 3%; these vary depending on the filter used	Powerful ability to approximate nonlinear functions [18]	Need for a large number of data to train the algorithm applicable for all operating conditions [18]	Applicable for all operating conditions but need a large number of data for algorithm training; they also require more processing time and cost	[78,81–84,86–104]
Hybrid-Based	RLS + AEKF, TNN + I, FUKF, ANN + UKF, ELM + Fuzzy, MHE + EKF, ANFIS, and SRRLS + EKBF	RMSE—range of values 0.01119% to 3%; these vary depending on the filter used	They reduce the cost of the system but also make the estimation results more effective and reliable [18]	Combining two or three methods is a laborious task and has high complex computation [18]	The combination of the two strategies increases the accuracy of the system	[105–113]

5. Discussion and Future Directions

After carefully reading over a hundred works, a relevant analysis can be conducted regarding the current state of the methods applied to battery charge estimation in electric vehicles. Li-ion batteries are currently the most used due to several factors, such as the energy density, number of cycles, and high voltage. Thus, these batteries are currently the most viable for EV applications despite their high cost.

Most of the studies on SoC prediction present results obtained from experiments carried out in the laboratory with distinct variables, such as temperature, controlled charge and discharge rate, and the use of these techniques in only one or two batteries. So, the current literature on the SoC estimation method needs a model and/or technique to overcome this task. The techniques are applied in an ideal scenario that should have the ability to be calibrated through practical experiments so that it can consider all of the natural characteristics found by the EV.

Lin et al. [114] point out that good battery charging performance directly influences consumers' interest in recognizing and accepting electric vehicles. In this sense, developing a more intelligent and efficient battery charge state management method is essential. To achieve this development, a process that performs the following characteristics is needed:

- Automatic calibration through hands-on experiments (self-tuning over time);
- Online estimation method, accuracy, and reliability;
- Scalable for huge batteries or with different configurations;
- Process of simple, practical implementation;
- A model that requires less computational effort;
- Operate in other temperature conditions;
- Operate well with battery nonlinearities;
- Take into account the loss of capacity that the battery has to store energy (SoH) over the cycles;
- Low circuit volume that does not take up too much physical space.

By analyzing the data in Table 1, it can be observed that despite the good RMSE values, the observation-based nonlinear methods are unable to operate in real-time, which is precisely what the industry requires. The same applies to conventional methods when they require information about the physical states of the battery, which is not feasible for continuous use.

Although they present higher RMSE values compared to the two previously mentioned methods, the filter-based and learning-based methods allow for the real-time estimation of SoC, which favors their application in an industrial context.

Among the methods verified during this review, the Kalman Filter stands out for being distributed over the study period, especially in the first investigations. Thus, adaptations have emerged to reduce noise errors or increase its use in applications in which more complex and nonlinear functions are proposed.

Learning-based methods stood out in this topic, especially in recent years. The most prominent methods are neural networks and fuzzy methods. However, it is important to mention that the training time and the computational cost have still been obstacles to fully accepting the application in embedded systems.

Hybrid algorithms offer a viable solution by combining the advantages of different methods, effectively addressing the limitations of each approach. By leveraging the strengths of multiple techniques, these algorithms can improve response times, minimize errors, and enhance overall performance. This results in real-time capabilities and increased robustness, making hybrid algorithms a valuable choice in various applications.

The ideal method should be able to estimate the SoC at different rates of charge, discharge, battery configurations, and technologies, with temperature variations that occur during the day and throughout the year. It is crucial to observe that the season and weather phenomena change the characteristics of batteries. Therefore, the model used should be able to determine how much charge is left in the EV under all of these conditions.

The selection of the most suitable technique relies on several factors, including the battery type, data availability, computational resources, and desired level of accuracy. Choosing the optimal technique involves considering the specific requirements of the application; considering the available resources; and striking a balance between accuracy, complexity, and cost. Evaluating and comparing various techniques within the context of the particular battery system under consideration is often advantageous.

Finally, the future perspectives indicate using modern components to improve existing solutions and make changes to obtain better battery models and algorithms that require less training time and lower computational costs, allowing for real-time actions in embedded systems.

6. Conclusions

Battery management in hybrid electric vehicles has become a topic of great interest in recent years. In this sense, alternative energy sources have become more than necessary. Considering these issues, this review discusses the importance of good power system management to obtain maximum battery use. The battery models are briefly discussed.

This review sought to approach the methods and algorithms for charge estimation, discussing how they work, their benefits, their disadvantages, and the error estimate. There is no complete method for estimating SoC and SoH values. Note that there are different approaches according to the battery model used and the treatment of variables.

It is possible to identify a pattern in the studied methods in which the researchers use the Kalman filter at first, including its different adaptations/variations. In the second place, the methods based on a learning algorithm are often addressed. From this perspective, it is clear that the trend will likely be toward applying hybrid estimation methods built on the models mentioned above, extracting the benefits of each and making them work together. The benefits that such methods seek are a more accurate and real-time charge estimation, with reduced errors and shorter response and convergence time. With this, battery management can be more effective, extending its useful life and giving greater control over changes.

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Abbreviations

The following abbreviations are used in this manuscript:

AEKF	Adaptive extended Kalman filter
AFFAKF	Adaptive forgetting factor adaptive Kalman filter
AFFRALS	Adaptive forgetting factor recursive augmented least squares algorithm
Ah	Ampere-hour
AHOT	Artificial hummingbird optimization technique
AIAEKF	Affine iterative adaptive extended Kalman filter
AKF	Adaptive Kalman filter
AMFFRLS	Auto tuning multiple forgetting factors recursive least squares
ANFIS	Adaptive network-based fuzzy inference system
ANN	Artificial neural network
ARX	Autoregressive model with exogenous input
ATSDEKF	Adaptive timescale dual extended Kalman filter
AUKF	Augmented unscented Kalman filter
BBM	Black-box model
BMS	Battery management system
CC	Coulomb count
CKF	Cubature Kalman filter
CNN-BWGRU	Convolutional neural network with a bidirectional weighted gated recurrent unit
CO_2	Carbon dioxide
DKF	Dual Kalman filter
ECM	Equivalent circuit model
EIS	Electrochemical impedance spectroscopy
EKBF	Extended Kalman–Bucy filter
EKF	Extended Kalman filter
ELM	Elman neural network
EV	Electric vehicle
EVs	Electric vehicles
FUKF	Fuzzy unscented Kalman filter
I&I	Immersion and invariance
iFA	Improved firefly algorithm
KF	Kalman filter
Li-$FePO_4$	Lithium iron phosphate
Li-Po_4	Lithium-polymer
LMS	Moving window least mean square approach
LSO	Linear state observer
LSTM	Long short-term memory
MAE	Mean absolute error
MHE	Moving horizon estimation
MNN	Multilayer neural network
NARX	Nonlinear autoregressive neural network with exogenous input
NiCad	Nickel-cadmium batteries
NiMH	Nickel–metal hydride
NLO	Nonlinear observer
OCV	Open-circuit voltage
PCA	Principal component analysis
RLS	Recursive least square
RMSE	Root mean square error
SC-ANFIS	Subtractive clustering-based neuro-fuzzy architecture
SMO	Sliding mode observer
SoC	State of charge
SoH	State of health
SRRLS	Square root recursive least squares
SVM	Support vector machine
SVR	Support vector regression

SWFFATRLS	Sliding window forgetting factor approximate total recursive least squares
TDNN	Time-delay neural network
TLBO	Teaching learning-based optimization
TNN	Transformer neural network
UDDS	Dynamometer driving schedule
UKF	Unscented Kalman filter
XGBoost	Extreme gradient boosting

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