IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 11, Issue 12, December 2023

DOI: 10.17148/IJIREEICE.2023.111201

Battery State of Charge Estimation Methods – A Critical Review

P. R. Dhabe[1], Dr. S. R. Paraskar[2], Dr. S. S. Jadhao[3]

Research Scholar, Department of Electrical Engineering, SSGMCE, Shegaon (M.S.), India[1]

Professor, Department of Electrical Engineering, SSGMCE, Shegaon (M.S.), India [2]

Associate Professor, Department of Electrical Engineering, SSGMCE, Shegaon (M.S.), India [3]

Abstract: The automobile sector across the globe has undergone a dramatic change in the last decade. It has started to trust something more, which initially was criticized for its inferior performance – the Electric Vehicle (EV). The battery is one of the most important components of an EV, and the Battery Management System (BMS) continues to be the bottleneck of EVs. However, accurate estimation of the State of Charge (SOC) of batteries is still challenging due to the non-linear characteristics of batteries. This led the scholars to propose various methods of SoC estimation. It now poses a challenge to establish a relationship between the accuracy and robustness of the methods, and their difficulties to implement. This paper publishes an exhaustive literature survey of the SoC estimation methods proposed by various scholars. All the more, it also provides feedback on each method, which will help to make an accurate choice of the SoC estimation method to be implemented. This will, in turn, help in the development of a reliable BMS.

Keywords: Battery Management System (BMS), State of Charge (SoC), Electric Vehicle (EV), Look-up table based estimation, model based estimation, adaptive system based estimation**.**

I. INTRODUCTION

The rise in global crude oil prices and the growing awareness of its environmental impacts have called for increased development in alternative energy storage systems. Battery happens to be an interesting energy storage system owing to its high efficiency. Battery storage system has seen a sharp rise in demand due to its wide use in battery-operated automobiles such as Electric Vehicle and Hybrid Electric Vehicle (HEV). Electric Vehicles are seen to be the new face of future transportation due to zero emissions [1].

Lithium ion Batteries (LiBs) are preferred choice of power supply in EVs due to their superiority over other batteries in terms of high specific energy, high output power and long life cycle [2]. An effective Battery Management System (BMS) in place is vital to ensure safe operation of battery, improved driving range, optimized power management and enhanced service life [2]–[5].

The BMS is responsible to acquire battery's voltage, current and internal temperature data to estimate various states of the battery and protect it from over-charging and over-discharging instances. SoC of a battery, used to represent the remaining capacity, is an important parameter of BMS, and hence it is imperative to have accurate estimation of the SoC to prevent the battery from over-charge, over-discharge and potential reduction in battery life [3].

II. BATTERY MANAGEMENT SYSTEM

A BMS is the equipment designed along with software and hardware to control battery operations at different operating conditions. It consists of controllers, sensors and actuators with an aim to enhance the battery life and guarantee its safety by accurately estimating different states of the battery.

A BMS, all the more, is also capable to interrupt the battery system in case of an abnormal operation. This, it does by closely monitoring the charge and discharge process of the battery and controlling it. A basic function diagram of a BMS is shown in Fig.1.

DOI: 10.17148/IJIREEICE.2023.111201

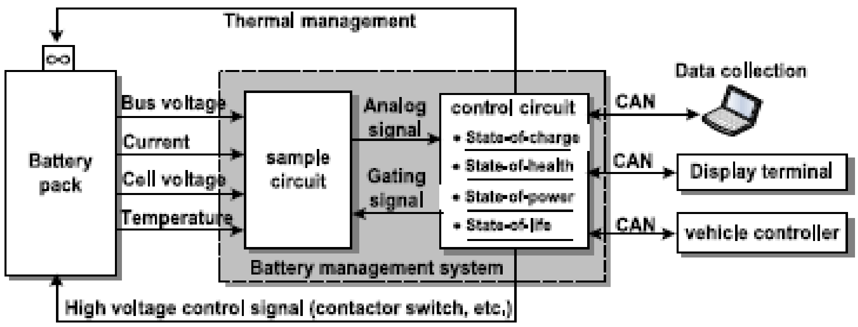

Fig.1 Function Diagram of Battery Management System

The control circuit of a BMS estimates the state of charge (SoC), state of health (SoH) and remaining useful life (RUL) of batteries with the help of advanced algorithms using measured battery current, voltage and temperature. The SoC of a battery can be defined as the percentage of the ratio of remaining capacity to the maximum available capacity. Over a period of time, a battery starts losing its capability to store energy. This deterioration of battery's capability is indicated by State of Health (SoH). Remaining Useful Life (RUL) is an indication of the number of load cycles remaining before the battery reaches its End of Life (EoL). Continuous measurement of voltage, current and temperature of battery enables the estimation of aforementioned battery parameters. However, the accurate estimation of battery parameters, especially SoC, is still a challenging task as battery's behaviour depends on various internal and external conditions. This is further aggravated by the change in battery characteristics over the period of time due to aging and charge-discharge cycles. All the more, the accurate estimation of SoC is hindered by limited battery models and parametric uncertainties. Many SoC estimation techniques proposed by researchers offer poor reliability and accuracy [4], [5]. Some researchers have, in detail, discussed SoC estimation methods along with the future developments and trends [6]–[8]. However, a systematic elaboration of the difficulties and challenges of methods is hard to find in the literature. This research paper aims to present a detailed review of the existing SoC estimation methods bring to the fore an ordered discussion of various SoC estimation metods along with their key challenges and difficulties of implementation. It also discusses the classification of SoC estimation techniques and possible developments likely to take place in the near future.

III. METHODS OF SOC ESTIMATION

The State of Charge (SoC) is a representation of battery's available capacity and is basically used to prevent the battery from being overcharged or undercharged. This in turn reduces the aging effects on the battery. As a result, it has become an interesting area of research and many researchers have proposed various methods for SoC estimation. Since many researchers have proposed methods for SoC estimation which involves combination of two or more techniques, the task of classifying the SoC estimation methods is no simple.

As individual methods have their own limitations, combining more than one technique to reduce the inaccuracies is not uncommon in the latest literatures. A combination of OCV technique, full charge detector and robust extended Kalman filter algorithm (REKF) is proposed in [9]. Despite the difficulty to classify SoC estimation methods due to combination of techniques, this research paper tries to make the classification referring to [10] and the work done by other researchers in the last decade or so. It has classified the SoC estimation methods into two main categories – Direct and Indirect Methods, and then it subcategories these two methods into several other techniques. Each of these methods is discussed along with their challenges and limitations in the following sections.

1. Direct Methods

Direct Method of SoC estimation relies upon measuring the physical properties of battery like current, voltage and temperature, and using an equation to estimate the SoC. The Direct Methods entail directly measuring or calculating SoC without the need for an independent model or system identification. These approaches are commonly preferred due to their straightforwardness and suitability for real-time applications.

1.1 Coulomb Counting (CC) Method

Coulomb Counting (CC) is considered as a standard method of SoC estimation [11]. Since it offers good accuracy for short-term estimations, CC is the most widely used method. According to CC method, SoC is defined by an equation given below [12] as

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 11, Issue 12, December 2023

DOI: 10.17148/IJIREEICE.2023.111201

$$SoC(t) = SoC(t0) + \frac{1}{Cn}\int_{t0}^{t0+t} Ibat\,(d\tau) \times 100\%$$

Where, SoC(t0) is the initial State of Charge of battery, and Cn and Ibat refer to the nominal capacity and Charging/Discharging current of battery respectively. Although CC provides a very simplistic approach, it suffers from the error of initial value. There are also noise errors and errors in the battery current measurement. These errors, in turn, lead to the accumulated errors and the CC method loses its precision and accuracy. Since this method requires the knowledge of initial SoC, which in practice is difficult to acquire, it will give inaccurate estimation of SoC. Hence, it is often used in combination with other algorithms for increasing its accuracy and precision [13].

1.2 Open Circuit Voltage (OCV) Based Estimation

The Open Circuit Voltage method involves continuous measurement of the cell voltage and the corresponding SoC is determined from the look-up table. This method encounters the difficulty of requiring very high resolution sensors and ample amount of time to reach equilibrium for accurate measurement of SoC. Hence, it is practically less effective. Also, The OCV-SoC curve tends to shift upward as the charging current increases [14]. This behaviour of the curve informs that – the higher voltage limit is reached faster when the battery deals with large current, and for the same value of OCV battery does have different values of SoC as shown in fig.2. In addition to this, each cell has different OCV-SoC relationship which further deteriorates the reliability of this method. Hence, the OCV method is often used with methods for estimating SoC. In [15], [16], the authors have proposed a combination of discontinuous discharging method and Extended Kalman Observer method along with OCV-SoC look-up method to estimate the SoC of battery.

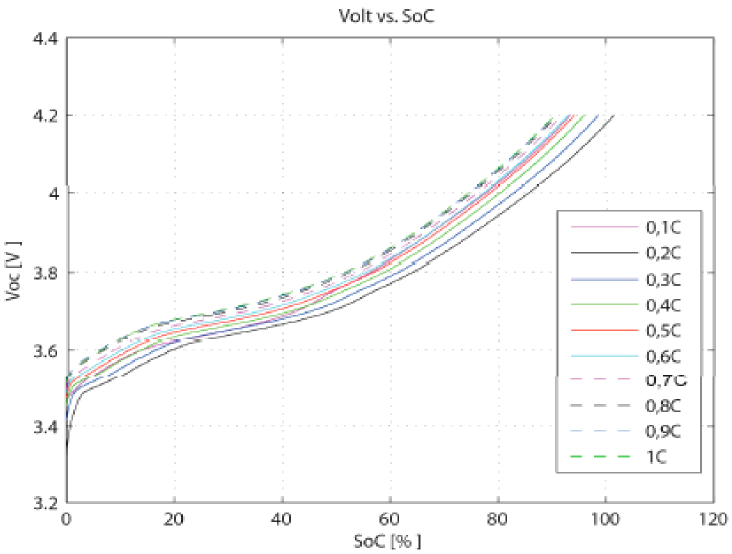

Fig.2 OCV-SoC curve for charging process at different current values

1.3 Impedance Measurement Based Estimation

This method involves the measurement of voltage and current at different frequencies and then computing its complex quotient to be the cell impedance. In [17], Electrical Circuit Model (ECM) is used for battery model and its parameters are calculated from the measured data of impedance which is then represented in the form of a Nyquist graph. This measured impedance is then divided into real and imaginary parts and is plotted against one another. As the parameters of the model become known, the SoC of the battery can then be computed. In [18], the author proposes Electrochemical Impedance Spectroscopy (EIS) approach for estimation wherein the impulse signal is broken down into factors of Fourier series. With this signal of different frequencies, the impedance is found by spectral analysis.

This estimation approach is specifically applicable under uniform charging conditions, making it unsuitable for Electric Vehicles (EVs) subject to inconsistent charging scenarios with varying currents. Furthermore, the method's effectiveness is constrained by its sensitivity to high temperatures, limiting its application to the high-frequency range.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 11, Issue 12, December 2023

DOI: 10.17148/IJIREEICE.2023.111201

2. Model-Based Estimation Methods

As they overcome the logjam of the direct measurement methods, Model-based estimation have become increasingly common. These methods set up a battery model and employ modern algorithms for estimation of battery states using its measured parameters like current, voltage and temperature. This section aims at reviewing only the electrical circuit battery models as they form the reference for most of the other battery modelling methods.

2.1 Electrical Circuit Model-Based Estimation

The three widely used Electrical Circuit Models (ECMs) are illustrated in [19]. The models are chosen owing to their excellent dynamic performance. The first of the models is known as Thevenin model which is a first order R-C model. The Thevenin model comprises of a non-linear voltage source (V_{OCV}) expressed as a function of SoC, battery terminal voltage V_t, charge or discharge current I_b, diffusion resistance (RP_1), a capacitor (CP_1) used to model the polarisation capacitance effects and an internal resistance (R_t). The other model consists of a capacitor added in series with (V_{OCV}). This model characterizes the capacity of charge stored in the battery and also describes the changes in the values of Open Circuit Voltage. The third model is a second order model which adds up a parallel combination of $RP_2 – CP_2$ in series with the first order model. The second order model is shown in Figure 3.

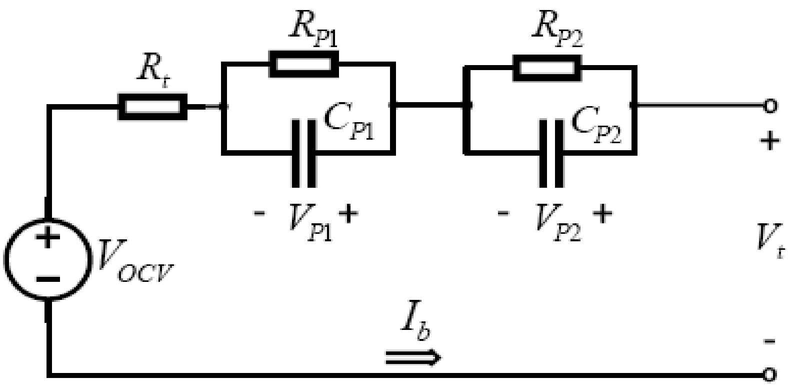

Fig.3 Second Order Electrical Circuit Model

Increasing the number of parallel RC networks proves to improve the precision of battery response estimation. In [19], the author has shown the second order model to be the most accurate as it has superior dynamic performance. In [20], the author compares the continuous and discrete time equations of second order model and draws an inference that there are sensitivity issues encountered in transformation of discrete parameters and hence makes the discrete time method less efficient. Accurately parameterizing the model for new batteries is a resource-intensive process, typically confined to laboratory settings. However, this approach is marked by high costs, time-consuming procedures, and often proves impractical for obtaining all requisite parameters. Moreover, the model falls short of providing a comprehensive description of the battery's electrochemical processes and lacks the capability to account for inherent inaccuracies.

2.2 Electrochemical Model-Based Estimation

An electrochemical model considers the internal electrochemical processes within the battery, providing a more detailed and accurate representation of its behaviour. It takes into account factors like electrode kinetics, ion diffusion, and temperature effects, allowing for a comprehensive understanding of the battery's state.

Electrochemical models provide a higher level of accuracy by considering the complex electrochemical reactions occurring within the battery. Also, electrochemical models can account for temperature variations, offering a more robust SoC estimation in diverse environments. However, electrochemical models can be computationally intensive and accurate SoC estimation relies on precise model parameterization, which can be challenging. For an instance, an electrochemical model discussed in [21] comprises six non-linear partial differential equations which require numerical solution.

3. Adaptive System-Based Estimation Methods

In recent times, the progress in artificial intelligence has led to the creation of diverse adaptive systems designed for SoC estimation. These newly developed techniques encompass a range of methodologies, including back propagation (BP)

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⩰ Peer-reviewed & Refereed journal ⩰ Vol. 11, Issue 12, December 2023
DOI: 10.17148/IJIREEICE.2023.111201

neural networks, radial basis function (RBF) neural networks, fuzzy logic approaches, support vector machines, fuzzy neural networks, and Kalman filters. What sets these adaptive systems apart is their intrinsic self-designing nature, enabling automatic adjustments in response to evolving system conditions. Given the impact of various chemical factors on batteries and the nonlinearity inherent in SoC, adaptive systems emerge as effective solutions for accurate SoC estimation.

3.1 Back Propagation Neural Network-Based Estimation

A Neural Network operates on a mathematical algorithmic model to handle the intricate characteristics of a complex neural network or parallel processing. This technology excels at processing data and discerning relationships among various initial complex factors. Within the realm of Neural Network algorithms, the Back Propagation (BP) Neural Network stands out for its ability to solve non-linear systems, featuring a simpler topology compared to conventional Neural Network methods [22]. The BP Neural Network structure comprises three layers: the input layer, hidden layer, and output layer. The input layer incorporates parameters such as battery voltage, current, resistance, and ambient temperature, while the number of hidden layers is contingent on the desired system accuracy. The output layer generates an estimated SoC value. The primary objective of this method is to minimize the error value. However, the system error is contingent on factors such as the quantity of training data and the methodology employed in experiments. Training data, crucial for SoC estimation, is typically derived from charging and discharging battery experiments. The effectiveness of this training method is evident in minimizing error functions. However, errors may escalate if the BP Neural Network lacks sufficient training information from SoC values [23]. To mitigate this, it becomes imperative to utilize a substantial amount of training data from diverse batteries to achieve an accurate SoC value. This is crucial because the discharge characteristics of batteries may vary, even if they share the same type and manufacturer, owing to differences in the electrolyte quantity [24].

3.2 RBF Neural Network-Based Estimation

The RBF neural network proves to be an effective methodology for estimating systems with incomplete information, particularly adept at analysing relationships within a given set. It excels in comparing one major (reference) sequence with other sequences, offering valuable insights into diverse scenarios. The application of the RBF neural network extends to SoC estimation, as demonstrated through experimentation with battery data. Results indicate that the model's operational speed and estimation accuracy align with practical demands, underscoring its valuable applications [25].
In a study documented in [25], the SoC estimation method utilizing the RBF neural network relies on input data such as terminal voltage, discharging current, and battery temperature. This approach effectively estimates SoC for $LiFePO_4$ batteries across varying discharging conditions. The experimental data obtained closely aligns with the model's predictions, validating its reliability and accuracy in SoC estimation.

3.3 Fuzzy Logic-Based Estimation

Fuzzy Logic (FL) serves as a problem-solving methodology designed to streamline complex input data characterized by noise, vagueness, ambiguity, and imprecision. This method employs objective rules to discern the actual value within the input data. The operational principle of a Fuzzy Logic technique can be delineated into four fundamental stages [26]:

a) Fuzzification**:** During this initial stage, the measured values of the system undergo a transformation into linguistic fuzzy sets. These sets are then categorized into membership functions, each indicating the degree of belonging to a specific logical set.
b) Fuzzy Rule Base**:** The development of a fuzzy rule base constitutes the second stage, drawing on professional expertise and insights into the system's operational methods. This rule base serves as a foundation for guiding the fuzzy logic process.
c) Inference Engine**:** In the inference engine stage, all fuzzy rules are systematically converted into fuzzy linguistic outputs. This transformation is pivotal in deriving meaningful insights from the input data based on the established fuzzy rule base.
d) Defuzzification**:** The final stage involves translating the linguistic fuzzy rules into analog output values. Defuzzification is the process through which the abstract and linguistic outcomes are transformed into concrete and quantifiable results.

By navigating through these four stages, Fuzzy Logic methodologies provide a structured approach to handling complex input data, extracting valuable insights, and generating meaningful output values. Fuzzy Logic (FL) systems possess the capability to make generalizations about any system through cycle number estimation.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 11, Issue 12, December 2023

DOI: 10.17148/IJIREEICE.2023.111201

This is particularly advantageous in battery tests where describing the battery's state as either "High" or "Low" may be more straightforward than obtaining a precise numerical value.

However, the computational expense associated with this method is substantial. Due to the requisite for a distinct and consistent battery characteristic rule, coupled with the substantial variation in battery parameters throughout the lifetime of Lithium-ion Batteries (LiBs), the accuracy of SoC estimation may be compromised. Specifically, if the proposed SoC estimation relies on static battery characteristics, this approach becomes practically unfeasible for LiBs employed in Electric Vehicles (EVs). Notably, the aging of the battery is not taken into consideration, further limiting the applicability of this method.

3.4 Support Vector Machines-Based Estimation

The Support Vector Machine (SVM) has found widespread application in pattern recognition, excelling particularly in classification across various domains. Interestingly, the SVM has also proven effective in addressing regression problems, a task inherently more challenging than classification. When employed as a nonlinear estimation system, the SVM exhibits greater robustness compared to a least-squares estimation system, showcasing insensitivity to minor changes [27].

In a study by Hansen and Wang [27], the application of SVM for estimating the SoC in lithium-ion batteries was investigated. The SVM-based estimator not only overcomes the limitations associated with the Coulomb counting SoC estimator but also delivers accurate SoC estimates, presenting a promising advancement in battery management technology.

3.5 Kalman Filter-Based Estimation

Utilizing real-time road data for the estimation of Battery SOC poses inherent challenges due to potential difficulties and costs associated with measurement. However, in a study outlined in [28], the application of the Kalman filter method is demonstrated to offer reliable SoC estimations through real-time state estimation. Kalman Filtering is a powerful and widely used technique for estimating the SoC of a battery. It combines mathematical modeling with real-time measurements to provide accurate and dynamic SoC estimates.

The two primary variations of Kalman Filtering used for SoC estimation are the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). Overview of the Kalman Filtering technique for SoC estimation is as below:

a) Battery Model: Kalman Filtering relies on a mathematical model of the battery's behavior. This model can be a simple equivalent circuit model or a more complex physics-based model, depending on the accuracy desired.
b) State Variables: The SoC is considered a state variable in the Kalman Filter, which is continually estimated and updated. Other state variables might include the battery's internal resistance, capacity, or voltage.
c) System Dynamics: The battery model is used to describe how the SoC and other state variables change over time in response to factors like charging, discharging, temperature, and aging. These dynamics are typically described by a set of differential equations.
d) Measurement Model: The Kalman Filter combines the battery model with real-time measurements, such as voltage and current, to estimate the state variables. The relationship between the state variables and the measurements is described by a measurement model.
e) Prediction Step (Time Update): In the prediction step, the Kalman Filter uses the battery model and the system dynamics to predict how the state variables (including SoC) will change over a short time interval (a time step). This prediction includes an estimate of the SoC.
f) Update Step (Measurement Update): In the update step, the Kalman Filter compares the predicted state variables, including the predicted SoC, with the actual measurements taken from the battery (voltage and current). The filter calculates a correction factor that minimizes the difference between the predicted and measured values, and this correction is used to update the state variables, including SoC.

Iterative Process: The Kalman Filter iteratively performs the prediction and update steps at a high frequency, continually refining the SoC estimate based on new measurements.

Yatsui and Bai [29] introduced a SoC estimation method for lithium-ion batteries based on the Kalman filter. Through experimental validation, the effectiveness of the Kalman filter in online applications was substantiated.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.021 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 11, Issue 12, December 2023
DOI: 10.17148/IJIREEICE.2023.111201

Barbarisi et al. [30] proposed an extended Kalman filter (EKF) for estimating concentrations of key chemical species averaged across the thickness of the active material. This approach utilizes terminal current and voltage measurements to derive the SoC of the battery.

In the realm of SoC estimation, an innovative method is presented in [31] based on the unscented Kalman filter (UKF) theory and a comprehensive battery model. Results indicate the superiority of the UKF method over the extended Kalman filter method in accurately estimating SoC for batteries. Sun et al. [32] further contribute to this field by introducing an adaptive UKF method for estimating SoC in lithium-ion batteries used in electric vehicles. The adaptive adjustment of noise covariance during the SoC estimation process is implemented through the concept of covariance matching within the UKF framework.

The Kalman Filter based algorithms encounter challenges associated with heightened complexity, elevated computational costs, and instability. The method incorporates intricate matrix operations, potentially leading to numerical instabilities and complicating the implementation of the algorithm on standard, cost-effective microcontrollers. Kalman Filter (KF) methods exhibit a strong dependence on battery models and sensor precision, accompanied by limitations such as accuracy in linearization and the stability of filters derived from Jacobian matrices.The efficacy of KF variants hinges on prior knowledge of the model and the covariance of measurement noise. Any inaccuracies in system modeling and noise covariance may detrimentally impact filter performance, resulting in sub-optimal convergence or sluggish adaptation. KF performance is notably compromised in the presence of substantial uncertainties regarding model structure, physical parameters, noise levels, and initial conditions.

3.6 Fuzzy Neural Network-Based Estimation

The Fuzzy Neural Network (FNN) has found extensive applications, particularly in identifying unknown systems. In the realm of nonlinear system identification, the FNN demonstrates effectiveness by adeptly fitting nonlinear systems through the calculation of optimized coefficients within its learning mechanism.

In the field of SoC estimation, two prominent types of fuzzy-based neural networks frequently appear in the literature: the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the Local Linear Model Tree [12]. These models primarily employ direct open-loop SoC estimation. ANFIS, specifically, combines the strengths of fuzzy systems and adaptive networks within a unified intelligent paradigm. By integrating the flexibility and subjectivity of fuzzy inference systems with the optimization prowess and learning capabilities of adaptive networks, ANFIS excels in modeling, approximation, nonlinear mapping, and pattern recognition. Its applications include modeling cell characteristics, online correction of other SoC estimation techniques for enhanced accuracy, and direct retrieval of the estimated SoC value [33], [34].

However, implementing direct open-loop SoC estimation introduces inaccuracies into the process. The approach demands a substantial volume of training data and involves extensive computations. Given the inherent open-loop nature of this method, adapting to the aging state of the battery becomes unfeasible. Moreover, the considerable volume of training data required significantly restricts its widespread applicability.

IV. CONCLUSION

This paper provides a critical examination of the State of Charge (SoC) estimation methodologies presented by scholars in the recent past, elucidating the core principles and principal limitations of each approach. Only methodologies extensively employed in recent years are discussed, excluding those less prevalent. Through this review, it becomes evident that the most challenging aspect of achieving accurate battery SoC estimation lies in constructing a model that authentically represents the internal dynamics of the battery, encompassing temperature dependencies on internal resistance and capacity degradation. It is also observed that the precision of SoC estimation can be influenced by several factors, including modeling imperfections, uncertainties in parameters, inaccuracies in sensors, and measurement noise. Additional factors impacting battery performance, and consequently the estimation methods, involve self-discharging, aging effects, cell imbalances, capacity fade, and temperature influences. Regardless of the methodology employed, there is an inherent trade-off in battery modeling, necessitating a balance between accuracy and computational complexity.

The literature underscores that the aging of Lithium-ion Batteries (LiBs) is influenced by various parameters, including temperature, time, SoC, cycle number, charge rate, and depth of discharge. The inclusion or exclusion of these parameters in battery models significantly affects the accuracy of SoC estimation. Notably, SoC estimation techniques that continuously update model parameters can effectively address the aging phenomenon.

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.021 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 11, Issue 12, December 2023

DOI: 10.17148/IJIREEICE.2023.111201

In the context of real-time EV applications, it is essential to develop a model that strikes a balance between simplicity and accurate SoC estimation. The Electrical Circuit Model (ECM) stands out as particularly suitable for online estimation. In this model, adaptive filter-based and artificial intelligence-based approaches are employed to achieve highly precise SoC estimations. However, a notable drawback of the ECM is its lack of a detailed physical-chemical explanation for microscopic movements within the battery. Conversely, the electrochemical model, while having the potential to illustrate charge transfer and unveil electrochemical mechanisms, is deemed overly complex for online calculations. Through the review, it becomes evident that adaptive filter-based algorithms prove more fitting for EV applications. In contrast, approaches based on artificial intelligence are considered less suitable due to their demanding computational requirements and/or offline learning processes. In addressing optimization challenges within filter-based techniques, there is a growing trend towards employing artificial intelligence-based optimization techniques. This shift is motivated by the simplicity, flexibility, derivation-free mechanism and effectiveness.

Establishing an accurate SoC estimation algorithm relies fundamentally on the battery modeling process. However, existing battery modeling methods, as proposed in the literature, exhibit limitations in terms of accuracy, especially under specific conditions. Additionally, these methods often impose restrictions on assessing aging, hindering continuous model updates. Consequently, there is a pressing need for further research in this field. To enhance the accuracy and practicality of battery modeling, there is a call for exploring practical battery construction and integrating adaptive control technology, expert system theories, and artificial intelligence into the modeling process. It is crucial to acknowledge that none of the reviewed methods emerges as entirely efficient and reliable. While a method may be comprehensive and accurate for a specific application and set of conditions, it might fall short of accuracy in different scenarios. Given these considerations, the selection of an appropriate algorithm ultimately rests with the designer, contingent upon their understanding of the specific application. The information provided in this paper shall serve as a valuable resource to aid designers in choosing the most suitable approach for their particular context.

.

REFERENCES

[1]. K. M. Amanathulla and A. S. Pillai, “An Extensive Comparison of State of Charge Estimation of Lithium Ion Battery — Towards Predictive Intelligent Battery Management System for Electric Vehicles,” in *2020 International Conference on Futuristic Technologies in Control Systems & Renewable Energy (ICFCR)*, Sep. 2020, pp. 1–5. doi: 10.1109/ICFCR50903.2020.9249992.

[2]. F. Zhu, G. Liu, C. Tao, K. Wang, and K. Jiang, “Battery management system for Li-ion battery,” *J. Eng.*, vol. 2017, no. 13, pp. 1437–1440, 2017, doi: 10.1049/joe.2017.0569.

[3]. R. Xiong, H. He, F. Sun, and K. Zhao, “Online Estimation of Peak Power Capability of Li-Ion Batteries in Electric Vehicles by a Hardware-in-Loop Approach,” *Energies*, vol. 5, no. 5, Art. no. 5, May 2012, doi: 10.3390/en5051455.

[4]. Y. Xing, E. W. M. Ma, K. L. Tsui, and M. Pecht, “Battery Management Systems in Electric and Hybrid Vehicles,” *Energies*, vol. 4, no. 11, Art. no. 11, Nov. 2011, doi: 10.3390/en4111840.

[5]. R. Xiong, Q. Yu, L. Y. Wang, and C. Lin, “A novel method to obtain the open circuit voltage for the state of charge of lithium ion batteries in electric vehicles by using H infinity filter,” *Appl. Energy*, vol. 207, no. C, pp. 346–353, 2017.

[6]. R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, “Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles,” *IEEE Access*, vol. 6, pp. 1832–1843, 2018, doi: 10.1109/ACCESS.2017.2780258.

[7]. M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, “A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations,” *Renew. Sustain. Energy Rev.*, vol. 78, no. C, pp. 834–854, 2017.

[8]. Z. Li, J. Huang, B. Y. Liaw, and J. Zhang, “On state-of-charge determination for lithium-ion batteries,” *J. Power Sources*, vol. 348, pp. 281–301, Apr. 2017, doi: 10.1016/j.jpowsour.2017.03.001.

[9]. C. Fleischer, W. Waag, Z. Bai, and D. U. Sauer, “Self-learning state-of-available-power prediction for lithium-ion batteries in electrical vehicles,” in *2012 IEEE Vehicle Power and Propulsion Conference*, Oct. 2012, pp. 370–375. doi: 10.1109/VPPC.2012.6422670.

[10]. W. Waag, C. Fleischer, and D. U. Sauer, “Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles,” *J. Power Sources*, vol. 258, pp. 321–339, Jul. 2014, doi: 10.1016/j.jpowsour.2014.02.064.

[11]. “Adaptive Battery Management and Parameter Estimation Through Physics-Based Modeling and Experimental Verification | IEEE Journals & Magazine | IEEE Xplore.” Accessed: Aug. 16, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/7462263?reload=true

[12]. C. Fleischer, W. Waag, Z. Bai, and D. U. Sauer, “Adaptive On-line State-of-available-power Prediction of Lithium-ion Batteries,” *J. Power Electron.*, vol. 13, no. 4, pp. 516–527, 2013, doi: 10.6113/JPE.2013.13.4.516.

[13]. “A novel adaptive technique for Li-ion battery model parameters estimation | IEEE Conference Publication | IEEE Xplore.” Accessed: Aug. 17, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/7856769

[14]. J. P. Rivera-Barrera, N. Muñoz-Galeano, and H. O. Sarmiento-Maldonado, "SoC Estimation for Lithium-ion Batteries: Review and Future Challenges," *Electronics*, vol. 6, no. 4, Art. no. 4, Dec. 2017, doi: 10.3390/electronics6040102.

[15]. "Reduction of parameters in a Lithium ion cell model by experimental validation of relationship between OCV and SOC | IEEE Conference Publication | IEEE Xplore." Accessed: Aug. 17, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/7916800

[16]. S. Nejad, D. T. Gladwin, and D. A. Stone, "On-chip implementation of Extended Kalman Filter for adaptive battery states monitoring," in *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*, Oct. 2016, pp. 5513–5518. doi: 10.1109/IECON.2016.7793527.

[17]. U. Westerhoff, T. Kroker, K. Kurbach, and M. Kurrat, "Electrochemical impedance spectroscopy based estimation of the state of charge of lithium-ion batteries," *J. Energy Storage*, vol. 8, pp. 244–256, Nov. 2016, doi: 10.1016/j.est.2016.09.001.

[18]. Z. Yang, D. Patil, and B. Fahimi, "Online estimation of capacity fade and impedance of lithium-ion batteries based on impulse response technique," in *2017 IEEE Applied Power Electronics Conference and Exposition (APEC)*, Mar. 2017, pp. 1229–1235. doi: 10.1109/APEC.2017.7930852.

[19]. Q. Wang, J. Wang, P. Zhao, J. Kang, F. Yan, and C. Du, "Correlation between the model accuracy and model-based SOC estimation," *Electrochimica Acta*, vol. 228, pp. 146–159, Feb. 2017, doi: 10.1016/j.electacta.2017.01.057.

[20]. B. Xia, X. Zhao, R. De Callafon, H. Garnier, T. Nguyen, and C. Mi, "Accurate Lithium-ion battery parameter estimation with continuous-time system identification methods," in *2016 IEEE Energy Conversion Congress and Exposition (ECCE)*, Milwaukee, WI, USA: IEEE, Sep. 2016, pp. 1–8. doi: 10.1109/ECCE.2016.7854811.

[21]. V. R. Subramanian, D. Tapriyal, and R. E. White, "A Boundary Condition for Porous Electrodes," *Electrochem. Solid-State Lett.*, vol. 7, no. 9, p. A259, 2004, doi: 10.1149/1.1773751.

[22]. C. Dong and G. Wang, "Estimation of power battery SOC based on improved BP neural network," in *2014 IEEE International Conference on Mechatronics and Automation*, Tianjin, China: IEEE, Aug. 2014, pp. 2022–2027. doi: 10.1109/ICMA.2014.6886014.

[23]. Ch. Ehret, S. Piller, W. Schroer, and A. Jossen, "State-Of-Charge Determination for Lead-Acid Batteries in PV-Applications," in *Sixteenth European Photovoltaic Solar Energy Conference*, 1st ed., H. Scheer, B. McNelis, W. Palz, H. A. Ossenbrink, and P. Helm, Eds., Routledge, 2020, pp. 2486–2489. doi: 10.4324/9781315074405-109.

[24]. S. Jeon, J.-J. Yun, and S. Bae, "Comparative Study on the Battery State-of-Charge Estimation Method," *Indian J. Sci. Technol.*, vol. 8, no. 26, Oct. 2015, doi: 10.17485/ijst/2015/v8i26/81677.

[25]. W.-Y. Chang, "The State of Charge Estimating Methods for Battery: A Review," *ISRN Appl. Math.*, vol. 2013, pp. 1–7, Jul. 2013, doi: 10.1155/2013/953792.

[26]. N. Khayat and N. Karami, "Adaptive techniques used for lifetime estimation of lithium-ion batteries," in *2016 Third International Conference on Electrical, Electronics, Computer Engineering and their Applications (EECEA)*, Beirut, Lebanon: IEEE, Apr. 2016, pp. 98–103. doi: 10.1109/EECEA.2016.7470773.

[27]. T. Hansen and C.-J. Wang, "Support vector based battery state of charge estimator," *J. Power Sources*, vol. 141, no. 2, pp. 351–358, Mar. 2005, doi: 10.1016/j.jpowsour.2004.09.020.

[28]. L. Xu, J. Wang, and Q. Chen, "Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model," *Energy Convers. Manag.*, vol. 53, no. 1, pp. 33–39, Jan. 2012, doi: 10.1016/j.enconman.2011.06.003.

[29]. M. W. Yatsui and H. Bai, "Kalman filter based state-of-charge estimation for lithium-ion batteries in hybrid electric vehicles using pulse charging," in *2011 IEEE Vehicle Power and Propulsion Conference*, Chicago, IL, USA: IEEE, Sep. 2011, pp. 1–5. doi: 10.1109/VPPC.2011.6042988.

[30]. O. Barbarisi, F. Vasca, and L. Glielmo, "State of charge Kalman filter estimator for automotive batteries," *Control Eng. Pract.*, vol. 14, no. 3, pp. 267–275, Mar. 2006, doi: 10.1016/j.conengprac.2005.03.027.

[31]. N. Ding, K. Prasad, T. T. Lie, and J. Cui, "State of Charge Estimation of a Composite Lithium-Based Battery Model Based on an Improved Extended Kalman Filter Algorithm," *Inventions*, vol. 4, no. 4, p. 66, Nov. 2019, doi: 10.3390/inventions4040066.

[32]. F. Sun, X. Hu, Y. Zou, and S. Li, "Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles," *Energy*, vol. 36, no. 5, pp. 3531–3540, May 2011, doi: 10.1016/j.energy.2011.03.059.

[33]. M. A. Awadallah and B. Venkatesh, "Accuracy improvement of SOC estimation in lithium-ion batteries," *J. Energy Storage*, vol. 6, pp. 95–104, May 2016, doi: 10.1016/j.est.2016.03.003.

[34]. H. Dai, P. Guo, X. Wei, Z. Sun, and J. Wang, "ANFIS (adaptive neuro-fuzzy inference system) based online SOC (State of Charge) correction considering cell divergence for the EV (electric vehicle) traction batteries," *Energy*, vol. 80, pp. 350–360, Feb. 2015, doi: 10.1016/j.energy.2014.11.077.