Advancements in State-of-Charge (SOC) and State-of-Health (SOH) Estimation Techniques for Battery Management Systems

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Abstract: An overview of the crucial function that state-of-charge (SOC) estimate plays in Battery Management Systems (BMS) for electric vehicles (EVs) is given in the abstract. By tracking the amount of energy that is available, SOC estimate is crucial for guaranteeing effective and secure operation. This paper examines several ways that have been developed for SOC estimation, including as data-driven, model-based, and direct approaches, each with its own advantages and disadvantages. Model-based approaches strike a compromise between accuracy and complexity, but they need accurate battery models, whereas data-driven approaches rely on large training datasets. Despite difficulties in real-time application, emerging technologies like artificial intelligence algorithms and Kalman filters are improving the accuracy of SOC

estimation. The paper also examines state-of-health (SOH) assessment techniques that concentrate on battery performance and longevity, ranging from data-driven methods to electrochemical models. It is expected that forthcoming developments in cloud-based BMS systems and smart BMS applications would surmount present computational constraints and enhance battery management capabilities in electric vehicles.

Keywords: *State-of-charge (SOC), battery management systems (BMS), state-of-health (SOH), electric vehicles (EVs), SOC estimation methods, Kalman filter, data-driven techniques, battery health monitoring.*

I. INTRODUCTION

SOC is crucial for giving vital information, including the amount of energy and/or usable time left to prevent the battery from overcharging or discharging, it is a major worry when it comes to BMS design in EVs. Consequently, there has been a great deal of research done on battery SoC estimate Numerous methodologies have been devised under three categories: direct, model-based, or data-based approaches. While data- and model-based methods have received interest for online implementation, direct methods are suitable only for lab environments. Model-based estimate approaches are more likely to be employed in real-world applications because they logically balance forecast accuracy and complexity [1]. But first, identifying the type of battery is necessary, and this could lead to mistakes. On the other hand, the data-based method does not need a sophisticated battery model; nonetheless, it is challenging for online applications because a significant amount of data is needed to train the model. The SoH-estimation method's direct, model-based, and data-driven methodologies offer some advantages and limitations that are comparable to those of the SoC-estimation methods. Remember that under specific battery-operating settings, the SoH model-based method frequently demonstrates the functional relationship between battery properties and battery aging status. As a result, more testing is still required to verify its feasibility and estimation accuracy using varied electrical current rates, ambient temperatures, and types of lithium-ion batteries [2–3]. Although data-driven SoH techniques necessitate costly training sets of data, they offer a way around these constraints. Therefore, despite the developments in the modern onboard BMS, the restricted processing capabilities prevent the implementation of more sophisticated data-driven algorithms for SoC, SoH, and fault detection, despite the expanding functional demand for BMS. The design and/or deployment of BMS in-cloud apps is being researched as a means of getting around these restrictions [4]. The development is still in its early phases. Using cloud-based solutions is anticipated to provide several benefits, including enhanced accuracy and dependability in battery system diagnostics and local computing simplification.

Lithium battery health has been assessed using a number of metrics, including state-of-charge (SOC), state-of-health (SOH), and remaining usable life (RUL). To indicate the extent of degradation, SOH and RUL are widely utilized. Battery SOH is frequently defined in terms of capacity. A new battery needs to be installed in an electrified vehicle when the SOH is less than 80%. Additionally, a multi-step SOH prediction method based on iterative prediction is proposed for RUL. As a result, precise SOH prediction is crucial for managing battery health.[5]

II. STATE ESTIMATIONS OF BMS AND THEIR DIFFERENT TYPES OF METHODS

Estimates of SOC, SOH, and State were derived from these data. The temperature at the surface is also measured in order to ascertain the heat transfer characteristic and the impact of temperature on the state of charge and discharge of the battery. The two previously mentioned data points have also been used to measure the battery joint state estimation. This integrated state assessment is an essential step to run and maintain the battery effectively and increase its longevity in different applications, such renewable energy storage and electric automobiles. These acquired parameters have been used to describe charging behavior, fault monitoring, fault/abnormal detection, predictive control, and fault diagnostics. The different processes, which are depicted as a block diagram in Figure. 1.[6], include gathering the necessary data, modeling, data collection, and information storage.

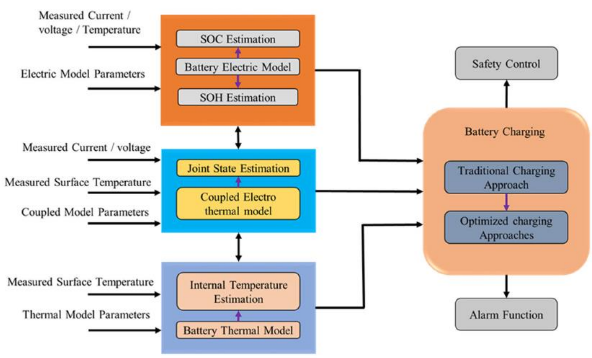

Figure 1. Key Technologies Of BMS

A. The model of equivalent circuits (ECM) is the basis for the SOC estimate approach.

There are two variants of this method: model-based adaptive filter and direct estimation based on the battery model. The former is an open-loop technique that substitutes the real voltage with the analog value calculated by the battery model [7]. It gets over the drawback of OCV not being dynamically acquired online and keeps the easy-to-use, less computational, and handy aspects of the OCV approach. However, the model's correctness and the current measurement have a substantial effect regarding modeL-based direct estimation. The model-based adaptive filter approach is a closed-loop technique. The most commonly published methods are primarily Kalman-filtering techniques and their derivatives, such as synovial observer, H∞ observer, and extended Kalman-filtering (EKF). As early as 2004,[8] assessed SOC using the EKF. The unscented Kalman- filter (UKF) was employed to reduce the inaccuracy brought on through the linearization of the EKF model. With strong resilience, this approach can mitigate the impact of initial SOC and systemic noise on SOC estimate outcomes. However, the accuracy of the model is crucial [8].

B. SOC estimation based on an electrochemical model.

The estimation of battery state of charge was based on the electrolysis-based mechanism modeling and the amount of lithium on each of the electrodes. The extremely high model accuracy provided by the electrolytic model is a major help in improving SOC accuracy. Sadly, the electrochemical model's many parameters and partially coupled differential equations make it unsuitable for use in web-based apps [9].

C. Kalman Filter Method

Batteries can have their SOC estimated uses the same Kalman filter method that is also used to estimate the inner states of any dynamic system. Upon their creation in 1960, the Kalman filters provided a recursive method for resolving optimal linear filters issues related for conditioning observations and predicting. The Kalman filter, in contrast to other estimating techniques, by default offers dynamic error limitations on its own initial state estimates. Through battery system simulation and addition of necessary unknown numbers (e.g., SOC) to the state specification, the Kalman filter predicts these variables. Notably, when a linearization step is required due to the nonlinearity of the battery system, the extended Kalman filter is performed. Despite being a dynamic and online approach, Kalman filtering requires a precise identification of the battery's properties as well as an appropriate model. Accurate initialization and a big processing capacity are also required. Different approaches to estimating state of charge (SOC) have been documented in the literature. One such approach is impedance spectroscopy, which measures cell impedance in real time for each charge and discharge using an impedance analyzer. This method was left out even though it can be used to estimate the SOC and SOH of Li-ion cells since it depends on external measurements made with equipment. Li-ion batteries cannot be used with techniques based on artificial neural networks or the physical characteristics of the electrolytes [10].

III. SOC (STATE OF CHARGE) AND SOH (STATE OF HEALTH) ESTIMATION METHODS

Each of the methods in the above table has advantages of its own, but it also has drawbacks, namely in terms of parameter identification, condition adaptability, and computing complexity.

Table No 1. Comparative table summarizing various SOC and SOH estimation methods

Estimation Approach	Description	Advantages	Disadvantages
Equivalent Circuit Model (ECM)	Simplicity and adequacy in emulating battery dynamics; parameters identified offline.	- Closed-loop self-correction - Online implementation	Offline identified parameters may lead to large errors under varying conditions.
Sliding Mode Observer	Based on ECM, aims for accurate SOC estimation under specific conditions.	- Precise SOC calculation in certain circumstances	Under different functioning situations could result in significant inaccuracies.

Particle Filter	ECM-based method for SOC estimation; suitable for nonlinear systems.	- Effective for nonlinear battery models	Requires careful tuning of parameters; computational complexity.
Kalman Filter Family[11]	Various adaptations (e.g., EKF) for SOC estimation; efficient in handling noise and uncertainties.	- Efficient in noise handling and uncertainty management	Accuracy heavily dependent on initial parameter estimates; offline identification limits adaptability.
Radial Basis Function Neural Network	Data-driven approach for SOH estimation; utilizes real-world datasets for accuracy.	- High prediction accuracy	Dependency on quality and representativeness of training data.
Radial Basis Function Neural Network	Data-driven approach for SOH estimation; utilizes real-world datasets for accuracy.	- High prediction accuracy	Dependency on quality and representativeness of training data.
Extended Kalman Filter (EKF) in 4th Order	Joint estimation of SOC and SOH; offline operation triggered by modeling errors.	- Combined estimation of SOC and SOH	Offline operation limits real-time adaptability to changing conditions.[12-13]
Fractional-Order Model (FOM)	Utilizes fractional calculus for precise battery voltage simulation and SOC estimation; parameters identified online for accuracy in varying conditions.	- Accurate modeling under varying conditions - Online parameter identification	Complexity in modeling due to fractional orders; requires careful parameter tuning.
Fractional-Order Dual-Domain Kalman Filter with Extension	Synchronous estimation of SOC, SOH (including ohmic resistance and capacity); online parameter identification for accurate modeling in any working condition.	- Accurate SOC and SOH estimation under varying conditions - Online parameter identification	Complexity in algorithm implementation; need for robust initialization and noise handling[14]

IV. PARAMETER ESTIMATION

Battery characteristics are hard to predict and change with time and use. An accurate battery modeling is required for precise parameter estimates. Many factors, including open-circuit current and voltage charging control strategies, discharge rate, and state of charge, should be considered in a precise dynamic battery model [15].

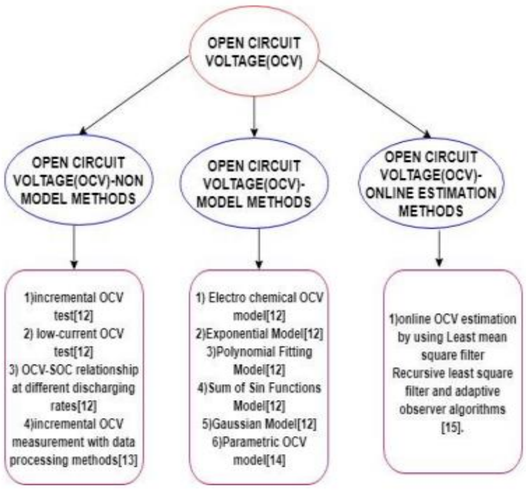

Figure. 2 open circuit voltage methods

A. Open Circuit Voltage (OCV)

One crucial battery metric is “open-circuit voltage”. OCV measures the SOC of the pack of battery and evaluates electronic energy shifts in the electrodes. Therefore, accurate OCV modeling will benefit the battery management system. A flow diagram representing the various open circuit voltage approaches is presented below in figure.2. Because the incremental OCV test offers more accurate and reliable monitoring over a range of loading circumstances, it is therefore a good option for non-model based OCV measurement. For the purpose of predetermining the OCV-SOC relationship, the incremental OCV-test is therefore advised. In the model-based approach, the Gaussian model ($n = 4$) yields the lowest RMSE error; in the online measurement, the adaptive observer provides accurate OCV estimate [16]

B. Current

Current information is pivotal in Battery Management Systems (BMS), particularly for precisely calculating the chargers' State of Charge. The current capacity $Q(t)$ in relation to the nominal capacity Q_n is represented by SOC. which denotes the maximum charge the battery can store.

This metric is crucial for assessing how much energy remains available for use, guiding decisions on charging and discharging cycles to optimize battery performance and longevity. Various methods are employed to measure current, each with specific applications:

- Shunt Resistor: This method calculates current flow using Ohm's law, where the voltage drop across a known resistor (shunt) is proportional to the current passing through it. It is widely used for its simplicity and reliability in accurately measuring current.
- Hall Effect Current Sensor: This sensor measures the magnitude of the magnetic field that is generated by current flowing through a conductor using the Hall Effect principle. It allows for non-contact measurement of current and is, therefore, suitable for applications where isolation from high voltage or electrical contact may not be possible.
- Unknown Input Observer: This is a far better method that estimates cell current when input signals are unavailable or uncertain. The UIO makes use of the system dynamics, coupled with available measurements like voltage and temperature, to provide enhanced accuracy of the current estimation as compared to traditional techniques. In this way, it becomes very useful for those applications in which the sensor data may not be availed continuously [17]

C. State of Charge (SOC)

The ratio of current capacity (Q(t)) to nominal capacity (Qn) is known as SOC. Nominal capacity refers to the maximum charge that a battery is capable of holding. The following is the mathematical formula for SOC:

$$SOC\ (t) = \frac{Q(t)}{Q_n}$$

D. State of Health (SOH)

State-of-health is the most significant remaining capacity available out of the charge-discharge cycle. The SOH can be obtained from the following equation:

SOH (%) = (Qactual / Qrated) × 100.

Where Qactual is the actual capacity of the battery, Qrated is the rated capacity [18].

Determining the State of Health (SOH) of batteries is essential for understanding their internal resistance and capacity degradation over time. This assessment is facilitated through three primary approaches: model-free, model-based, and data-driven techniques. Model-based approaches utilize established battery models to predict changes in capacity and internal resistance as indicators of SOH. These methods rely on mathematical representations of battery behavior under various operating conditions, providing insights into degradation patterns and remaining lifespan.

Electrochemical Impedance Spectroscopy (EIS) represents a key model-based technique that directly measures capacity and resistance changes. By analyzing impedance spectra, EIS offers detailed insights into the electrochemical processes within the battery, aiding in precise SOH assessment. In contrast, data-driven techniques leverage real-time operational data such as temperature, voltage, and current readings to infer the SOH. Machine learning algorithms, for instance, process large datasets to identify patterns correlating with battery degradation, thereby estimating SOH without explicit battery models. Each approach—model-free, model-based (including EIS), and data-driven—offers distinct advantages and limitations in SOH estimation. Model-based methods provide detailed insights but require accurate model parameters and controlled test conditions. Data-driven techniques excel in handling diverse operational scenarios but depend heavily on the quality and breadth of available data. Advancements in these methodologies continue to refine SOH estimation accuracy, paving the way for improved battery management strategies across various applications, including electric vehicles and renewable energy systems.

V. Emerging Technologies in BMS

Battery management systems (BMS) are constantly evolving to keep pace with advancements in battery technologies and meet the increasing demands of various applications. Several emerging technologies are being explored and developed to enhance the performance, safety, and efficiency of BMS. Here are some of the notable emerging technologies in BMS [19].

A. Advanced Algorithms for State Estimation:

- Kalman Filtering: A lot of usage of these Kalman filters is applied in state estimation within the BMS. The variants that are fast emerging amongst them, however, turn into an Extended Kalman Filter and an Unscented Kalman Filter. These variants help achieve a more accurate estimation of the state’s due to considerations introduced towards nonlinear and uncertain system dynamics.
- Particle Filters: Particle filters, also known as Monte Carlo filters, are more accurate since they propagate a set of particles through the model of the battery and update their weights based on measurements.
- Artificial Intelligence Techniques: It believes that algorithms of machine learning, such as neural networks and support vector machines, are being applied for BMS state estimation, health prediction, and performance optimization.

B. Wireless and Cloud-based BMS Solutions:

- Wireless Sensor Networks: The wireless integration of sensors in the BMS dispenses with the necessity for cables; this system reduces the complexity and the related installation costs of it. It provides support to real-time data acquisition and added flexibility when looking at the parameter monitoring of the batteries.
- Cloud-based Monitoring and Control: BMS can leverage cloud computing for storing, analyzing, and remotely monitoring data. The cloud-based BMS makes it possible to achieve central control, predictive maintenance, and real-time access to any place where battery performance data is required.

C. Application of Smart Battery Management Systems (BMS) in Electric Vehicle (EV) Technology

This table highlights the various advantages that Smart BMS brings to EV applications, from efficiency gains and safety improvements to environmental benefits and technological advancements.

Table 2 Advantages of Smart Battery Management Systems (BMS) in Electric Vehicle (EV) applications

Advantage	Description
Enhanced Efficiency	Optimizes battery performance, extends driving range, and reduces energy consumption.
Improved Battery Life	Monitors and manages SOC, SOH, and RUL, extending battery lifespan through optimized charging and discharging cycles.
Safety Enhancement	Prevents issues like thermal runaway, overcharging, and over-discharging, ensuring safe operation of batteries.
Cost Savings	Reduces operational costs through energy efficiency improvements and optimized maintenance schedules.
Environmental Benefits	Contributes to sustainability by reducing carbon footprint through efficient energy use and battery recycling.
Integration with Renewable Energy	Facilitates integration of renewable energy sources, enhancing grid stability and promoting clean energy usage.
Advanced Monitoring and Control	Real-time monitoring and control capabilities improve system reliability and performance.
Technological Innovation	Drives innovation in battery technology and management systems, leading to continuous improvements in EV performance [21]

VI. CONCLUSION

Finally, accurate SOC and SOH estimation enhance battery efficiency and increase driving life of the battery in an EV. All these methods of SOC estimation ranges from a bag of mixed advantages and disadvantages, discussed in this review. Model-based techniques are robust in their estimation accuracy under controlled conditions; however, they require extensive a priori model construction efforts. On the other hand, data-driven methods are more flexible but require vast and representative training datasets. Further reaching developments in technology, such as sophisticated algorithms and wireless battery management system solutions, can balance remaining limitations and support enhanced efficiency, safety, and life expectancy in the context of management procedures. Taking into account climatic variations and possible changes in technical requirements, proper exploitation of the potential linked to EV battery systems will require sustained research and development in these areas.

Conflict of Interest: The corresponding author, on behalf of second author, confirms that there are no conflicts of interest to disclose.

REFERENCES

[1] Di Luca G, Di Blasio G, Gimelli A, Misul DA. Review on Battery State Estimation and Management Solutions for Next-Generation Connected Vehicles. Energies. 2024; 17(1):202. https://doi.org/10.3390/en17010202.

[2] Ren, Z.; Du, C. A review of machine learning state-of-charge and state-of-health estimation algorithms for lithium-ion batteries. Energy Rep. 2023, 9, 2993–3021. [Google Scholar] [CrossRef]

[3] Li, W.; Rentemeister, M.; Badeda, J.; Jöst, D.; Schulte, D.; Sauer, D.U. Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. J. Energy Storage 2020, 30, 101557. [Google Scholar] [CrossRef]

[4] Yang, S.; Zhang, Z.; Cao, R.; Wang, M.; Cheng, H.; Zhang, L.; Jiang, Y.; Li, Y.; Chen, B.; Ling, H.; et al. Implementation for a cloud battery management system based on the CHAIN framework. Energy AI 2021, 5, 100088. [Google Scholar] [CrossRef].

[5] Lin, J., Yan, G., & Wang, C. (2021, September). Li-ion battery state of health prediction based on long short-term memory recurrent neural network. In Journal of Physics: Conference Series (Vol. 2010, No. 1, p. 012133). IOP Publishing.

[6] Kumar, R. R., Bharatiraja, C., Udhayakumar, K., Devakirubakaran, S., Sekar, S., & Mihet-Popa, L. (2023). Advances in batteries, battery modeling, battery management system, battery thermal management, SOC, SOH, and charge/discharge characteristics in EV applications. Ieee Access.

[7] Zhou, D.M.; Zhang, K.; Ravey, A.; Gao, F.; Miraoui, A. Online Estimation of Lithium Polymer Batteries State-of-Charge Using Particle Filter-Based Data Fusion with Multimodels Approach. IEEE Trans. Ind. Appl. 2016, 52, 2582–2595. [Google Scholar] [CrossRef]

[8] Li, C.; Cui, N.; Wang, C.; Zhang, C. Simplified electrochemical lithium-ion battery model with variable solid-phase diffusion and parameter identification over wide temperature range. J. Power Sources 2021, 497, 229900. [Google Scholar] [CrossRef].

[9] Zhou L, Lai X, Li B, Yao Y, Yuan M, Weng J, Zheng Y. State Estimation Models of Lithium-Ion Batteries for Battery Management System: Status, Challenges, and Future Trends. Batteries. 2023; 9(2):131. https://doi.org/10.3390/batteries9020131.

[10] Murnane, M., & Ghazel, A. (2017). A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries. Analog devices, 2, 426-436.

[11] J. Lv, B. Jiang, X. Wang, Y. Liu, and Y. Fu, ‘‘Estimation of the state of charge of lithium batteries based on adaptive unscented Kalman filter algorithm,’’ Electronics, vol. 9, no. 9, p. 1425, Sep. 2020.

[12] C. She, Z. Wang, F. Sun, P. Liu, and L. Zhang, ‘‘Battery aging assessment for real-world electric buses based on incremental capacity analysis and radial basis function neural network,’’ IEEE Trans. Ind. Informat., vol. 16, no. 5, pp. 3345–3354, May 2020.

[13] W. X. Duan, C. X. Song, Y. Chen, F. Xiao, S. L. Peng, Y. L. Shao, and S. X. Song, ‘‘Online parameter identification and state of charge estimation of battery based on multitimescale adaptive double Kalman filter algorithm,’’ Math. Problems Eng., vol. 2020, no. 12, Dec. 2020, Art. no. 9502605.

[14] L. Ling and Y. Wei, "State-of-Charge and State-of-Health Estimation for Lithium-Ion Batteries Based on Dual Fractional-Order Extended Kalman Filter and Online Parameter Identification," in IEEE Access, vol. 9, pp. 47588-47602, 2021, doi: 10.1109/ACCESS.2021.3068813.

[15] Yasser Diab, François Auger, Emmanuel Schaeffer and Moutassem Wahbeh,‖Estimating lithium-ion battery state of charge and parameters using a continuous-discrete extended Kalman filter,‖Energies,vol.10.no.8,pp.1-19,July 2017.

[16] Wen-Yeau Chang,‖The state of charge estimating methods for battery: A review,‖Hindawi Publishing Corporation, ISRN Applied Mathematics, Article ID 953792, pp. 1-7, July 2013.

[17] Technologies In Battery Management System-A Review Hamsavarthini.Y, INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 9, ISSUE 01, JANUARY 2020.

[18] Lipu, M.S.H.; Hannan, M.A.; Hussain, A.; Hoque, M.M.; Ker, P.J.; Saad, M.H.M.; Ayob, A. A Review of State of Health and Remaining Useful Life Estimation Methods for Lithium-Ion Battery in EVs: Challenges and Recommendations. J. Clean. Prod. 2018, 205, 115–133. [Google Scholar] [CrossRef]

[19] "Lithium-Ion Batteries: Advanced Materials and Technologies" edited by Christian Julien and Bruno Scrosati. 6. "Battery Management Systems: Design by Functional Safety Principles" by Patrick Schweizer, Massimo Fiorini, and Davide Mora.

[20] Review on Battery Management Systems Dr.G.Balaji, 2023 IJCRT ,Volume 11, Issue 6 June 2023 ,ISSN: 2320-2882

[21] Hossain Lipu MS, Miah MS, Ansari S, Wali SB, Jamal T, Elavarasan RM, Kumar S, Naushad Ali MM, Sarker MR, Aljanad A, et al. Smart Battery Management Technology in Electric Vehicle Applications: Analytical and Technical Assessment toward Emerging Future Directions. Batteries. 2022; 8(11):219. https://doi.org/10.3390/batteries8110219.