Power System Technology
ISSN:1000-3673

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Review Paper for SOC Estimation Techniques: Challenges and Future Areas for Improvement

Abdul Rehman[1], Syed Ali Haider Shah[1], Asad Ullah Nizamani[2], Muhammad Ahsan[1], Ahmed Baig Mohammed[3], Awais Sadaqat[4], Muhammad Mehtab Afzal[5], Mateeb Talib Chaudhary[6,*], Muhammad Afnan Aziz Khan[6], Hassan Ahmad Mughees[6]

[1]Department of Electrical Engineering, Cleveland State University, Cleveland, United States,

[2]Department of Chemical Engineering, Lamar University, Texas, United States,

[3]Department of Computer Science, Campbellsville University, Campbellsville, United States,

[4]Department of Electrical Engineering, Bahria University, Pakistan

[5]Department of Civil-Transportation Engineering, Cleveland State University, Ohio, United States,

[6]Department of Electrical Power Engineering, US-Pakistan Center for Advanced Studies in Energy, National University of Science and Technology, Islamabad, Pakistan

[*]Corresponding Author Email: mateebtalib@gmail.com

Abstract

This paper explores the advancements and challenges in State of Charge (SOC) estimation techniques for lithium-ion batteries, particularly within the context of electric vehicles (EVs) and renewable energy systems. As the global demand for sustainable energy solutions grows, accurate SOC estimation becomes essential for optimizing battery performance, enhancing safety, and extending battery life. The paper categorizes various SOC estimation methods into three primary approaches: direct measurement techniques, model-based methods, and data-driven algorithms. Direct measurement techniques, such as Coulomb counting and Open Circuit Voltage (OCV), are straightforward but often lack precision under dynamic conditions. Model-based methods, including Equivalent Circuit Models (ECM) and electrochemical models, provide detailed insights into battery behavior but can be computationally intensive. In contrast, data-driven approaches utilizing machine learning algorithms exhibit promising adaptability and accuracy, albeit relying heavily on large datasets. Despite these advancements, several limitations persist. Current SOC estimation methods are hindered by their dependence on accurate battery models and quality data, which can degrade over time. Furthermore, hybrid

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

methods, which combine strengths from various techniques, introduce complexity and demand substantial computational resources. The integration of SOC estimation techniques in EV applications poses additional challenges due to varying operational conditions, necessitating efficient processing of real-time data from multiple sensors. Emerging trends in Battery Management Systems (BMS) are also examined, highlighting the role of AI and machine learning in improving real-time SOC computations and predictive capabilities. Cloud-based BMS systems are identified as a significant development for remote monitoring and control, enhancing the overall reliability of battery systems. This paper aims to provide a comprehensive overview of SOC estimation techniques, identify ongoing challenges, and suggest future research directions to enhance the effectiveness of battery management strategies in the evolving landscape of energy systems.

Key-words: State of Charge, State of Health, Battery Management, Electric Vehicles, Lithium-ion Batteries.

1. Introduction

Gasoline and diesel, along with other fossil fuels, are extensively used in the global markets and that have contributed most to environmental challenges and climate issues. The use of these fossil fuels in automobiles, industries and for energy production leads to large emission of Carbon dioxide (CO2) and other greenhouse gases that are crucial causes of global warming. This warming causes climate change with serious implications for ecosystem, climatic changes and prudent health. For instance, in 2024, global oil demand was 1.6%, which led to 1.4% of CO2 emissions: relative to burning of fossil fuels demanding, a shift towards sustainable energy [1]. The pollution resulting from the use of the fossil fuels shows how timely efficiency is needed to address the problem of climatic change and move away from the use of the non-renewable sources of energy.

To these factors, much attention has been focused on trying to come up with and implement the use of renewable sources of energy. Technologies like solar energy, wind energy, and energy from water, are now being established as the solutions to the depletion of fossil energy and emission of greenhouse gases. This shift has not only helped in the reduction of the carbon footprints but has also ensured promotion of new related technologies and structures [2]. Some of the most remarkable novelties include electric vehicles and demand-side management based on electricity in its diversified usage rather than focusing merely on the internal combustion engines. This transition proves essential for the promotion of sustainable solutions as well as for managing global consequences connected with traditional approaches to energy organization.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Battery storage, batteries themselves, also remain critical in this change, as batteries are needed for electric vehicles, renewable energy systems and any other application that involves energy storage. Recent advancements in various fields highlight the importance of innovative approaches to enhance system reliability and sustainability. Rehman et al. (2024) discuss AI-driven predictive maintenance for energy storage systems, emphasizing improvements in lifespan and reliability. Additionally, research on satellite selection algorithms aims to optimize receiver processing efficiency. Meanwhile, studies on food retailers' adoption of green supply chain practices in the U.S. reflect a growing commitment to sustainability in retail operations. These insights pave the way for further exploration in SOC estimation techniques [3], [4], [5]. Practical management of batteries is essential to ascertain improved and extended performance. Both SOC and SOH play a vital role in defining how the battery should perform, how safe it is and how efficient it is going to be. SOC stands for state of charge which conveys the amount of the capacity of a battery that is left while SOH is an all-encompassing parameter that conveys the battery health of a battery. Optimal control of these levels is critical to achieving the required power output together with durability of battery supported systems [6].

SOC estimation is one of the critical parameters of Battery Management Systems (BMS), which control charge-discharge cycles, energy consumption, and battery lifetime. SOC is an estimation of the amount of charge currently in a battery which is calculated by several parameters including cell voltage current and temperature. Many SOC estimation methods have been designed to address the requirements of specific battery types and uses. In one way or the other, these techniques can be said to be categorized into direct measurement techniques, model-based techniques and data driven techniques.

The Coulomb Counting method [7], which involves a direct determination of SOC, and the Open Circuit Voltage (OCV) method [8] are two effective methods of SOC estimation. Coulomb Counting measures the cumulative charge from the battery while the OCV method infers SOC using voltage readings when the battery is static. However, these basic approaches often tend to overlook factors like the battery aging, or temperature, that are likely to skew the results. More detailed information can be obtained by model-based methods, like the Equivalent Circuit Models (ECM) [9] or Electrochemical Models [10] which calculate battery behavior according to mathematical models. These kinds of models can capture a large spectrum of internal and external influences of battery performance but can also be resource consuming.

Over the past decade, the usage of data-based approaches has proven to be potential to estimate SOC stocks. These are methods that employ the use of the machine learning algorithms, neural networks and other computational methods [11], [12], [13], [14]. As these approaches use past and current data to update SOC, they can also develop models that accurately predict SOC. The

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

data driven methods are general and can accommodate interactions between battery parameters. But they need extensive data for learning and can be affected by changes in working environment.

As much as research has advanced in SOC estimation, strengths of each the presented method come with their weakness and none of the methods on its own can be used. The techniques can be described as direct measurement methods, although invariable conditions may be inaccurate at certain instances. Despite performing more accurate simulations, model-based techniques can also be operationally expensive. Model-based approaches are quite accurate, as they depend on large amounts of Battery data; however, the methods are sensitive to changes in battery operating conditions. The type of battery and their use continues to change which means that such methods require constant validation to determine their efficiency or otherwise in estimating SOC. Such reviews are useful to provide innovations, to assess performances and to indicate further research avenues [15].

Consequently, this paper presents a review of SOC estimation techniques and takes a critical look at the methods used in quantitative evaluation and the directions that remain unexplored. The review covers all the different categories of methods some of that which ranges from simple direct measurement and estimation methods and extends to sophisticated model and data analytics-based methods. In so doing, this paper proposes an assessment of the advantages and the limitations of each of the mentioned methods to enable the author to provide a comprehensive review of the status prevalent in SOC estimation as well as the impact of such a platform on the battery management systems.

The objectives of this paper are as follows:

- Review and categorize various SOC estimation methods, including direct measurement, model-based, and data-driven techniques.
- Analyze the strengths and weaknesses of each SOC estimation method in terms of accuracy, computational complexity, and real time capability.
- Identify the challenges and limitations associated with existing SOC estimation techniques, focusing on areas such as computational demand, data requirements, and adaptability.
- Suggest future research directions for SOC estimation methods, addressing gaps in the current literature and offering recommendations for improving battery management systems.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

The outline of the paper is as follows:

- **Section 2:** Outlines the methodology for selecting relevant papers, including the literature search strategy and selection criteria.
- **Section 3:** Provides an overview of lithium-ion batteries, covering their basic principles and key characteristics, which made the primary technology for majority of the ongoing SOC estimation research efforts.
- **Section 4:** Explores SOC estimation techniques, categorizing them based on their methodologies and applications.
- **Section 5:** Presents a comparative analysis of these techniques, assessing their accuracy, computational complexity, and suitability for real time applications.
- **Section 6:** Concludes this review paper by discussing the challenges and future directions in SOC estimation.

Overall, it is our hope that this review is useful to battery management and SOC estimation researchers and practitioners alike to benefit from an evaluation of the state-of-the-art and remain motivated for further advancements in the future.

2. Methodology for Paper Selection

A systematic review of the literature was carried out, with purposive criteria from several academic databases being the defining criterion for relevance. Such a theoretical context was used for this review by selecting only full-text papers from leading databases such as Scopus®, IEEE Xplore®, ScienceDirect®, MDPI®, and others.

The search was performed on 2nd June 2024 to capture the latest changes in the field of study in question. The search used a set of keywords such as "estimation"," state of charge", "state of health", "lithium-ion battery", "electric vehicle", "battery management system", "energy storage" and "machine learning". These terms were selected wide enough to cover a range of investigations most related to SOC estimation for LIB for electric vehicles and energy storage application. Specifically, the keywords were chosen in a way that they encompass the basic heuristic approaches to down payment estimation alongside the latest methods relying on AI and ML.

To achieve higher relevance of the articles chosen, the search was supplemented with keywords '2014-Present' as the search filter. Such timescale was chosen as a focus on the most recent trends and innovations, as achieved noticeable progress in SOC estimation within the last decade. The reviewed articles were then scrutinized in order to determine relevance to the topic of the evaluation of SOC estimation methods, sparing the final review of only the most appropriate articles.

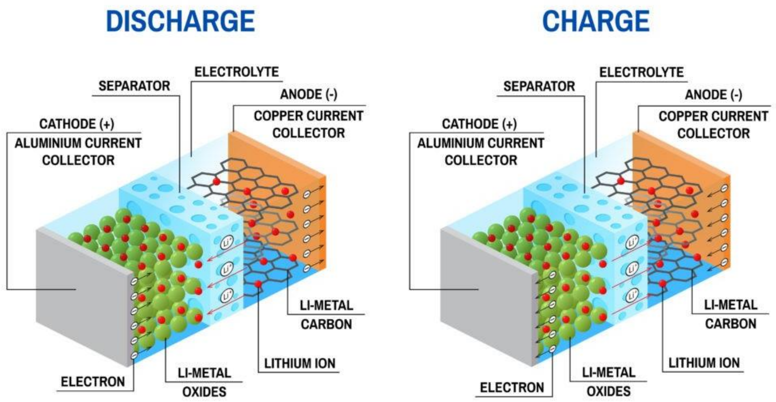
Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

This way, the integration of recent articles provided the evaluations of SOC estimation trends in recent years including the increasing use of machine learning and AI in BMS. Predominantly, this trend represents a transition toward increasingly better and more efficient estimation techniques, which are crucial to enhancing both the performance and durability of Li–ion batteries in contemporary applications like electric vehicles and renewable energy storage devices. It is noteworthy that SOC estimation has emerged as an important subproblem encompassed by the challenges of sustainable energy systems and battery management technologies.

3. Li-ion Batteries

3.1 Background

Lithium-ion (Li-ion) batteries are a type of rechargeable batteries that works fundamentally in the basis of transferring Lithium ions [16]. These systems have come into use in recent decades because of their high energy density, light weight and low self-discharge rates. A common part of Li-ion battery is in the structure that involves cathode or positive terminal, the unfavorable anode, electrolyte, and the separator. Perhaps the most utilized cathode materials are LCO (Lithium Cobalt Oxide), LFP (Lithium Iron Phosphate) and NMC (Lithium Nickel Manganese Cobalt); for the anode, graphite is typically used [17].



(a) (b)

Figure 1 (a): Charging and **(b):** Discharging of Li-ion Batteries [18]

The operation of a Li-ion battery is based on the movement of lithium ions between the cathode and anode during charging and discharging. When the battery is charged, lithium ions move from the cathode to the anode through the electrolyte, where they are intercalated into the anode material. Conversely, during discharge, the lithium ions move back to the cathode, releasing

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

electrical energy in the process. The chemical reactions occurring at each electrode can be represented by Equations (1) and (2).

1. **Charging Reaction** (at the anode):

$$Li^{+} + e^{-} + C \leftrightarrow LiC_6 \qquad (\mathbf{1})$$

2. **Discharging Reaction** (at the cathode):

$$LiC_6 + CoO_2 \rightarrow LiCoO_2 + C + e^{-} \qquad (\mathbf{2})$$

3.2 Characteristics of Lithium Ion Batteries

This charge-discharge cycle is reversible, allowing the battery to be reused multiple times. Several characteristics contribute to the popularity of Li-ion batteries in various applications, especially in consumer electronics and electric vehicles, as shown in **Table 1:**

Table 1: Comparison of Characteristics of Popular Batteries [17], [19]

Characteristic	Lithium-Ion (Li-ion)	Nickel-Cadmium (NiCd)	Nickel-Metal Hydride (NiMH)	Lead-Acid
Energy Density	High (150-250 Wh/kg)	Moderate (40-60 Wh/kg)	Moderate (60-120 Wh/kg)	Low (30-50 Wh/kg)
Cycle Life	Long (500-1500 cycles)	Moderate (1000 cycles)	Moderate (300-500 cycles)	Short (200-300 cycles)
Self-Discharge Rate	Low (1-5% per month)	High (20-30% per month)	Moderate (15-20% per month)	High (5-20% per month)
Charging Time	Fast (1-3 hours)	Moderate (2-4 hours)	Moderate (2-6 hours)	Slow (6-12 hours)
Temperature Range	Wide (−20°C to 60°C)	Limited (−20°C to 50°C)	Moderate (0°C to 45°C)	Moderate (−20°C to 50°C)
Environmental Impact	Moderate	High	Moderate	Low

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Applications	EVs, electronics, renewable energy	Power tools, emergency lighting	Hybrid vehicles, electronics	Automotive, UPS, backup power
Voltage (per cell)	3.2-4.2 V	1.2 V	1.2 V	2 V
Cost	Moderate to high	Low	Moderate	Low
Memory Effect	None	Yes	Minimal	None
Safety	Risk of thermal runaway	Safe, but hazardous materials	Generally safe	Safe, but heavy and bulky

From Table 1, we can surmise that the Li-ion batteries have the following advantages over competing electricity storing technologies:

1. **High Energy Density**: Li-ion batteries provide higher energy density than the other rechargeable battery types such as nickel-cadmium or lead-acid batteries. This implies that the next generation batteries will be able to deliver more energy in a compact and lightweight batter, suitable for mobility as well as electric vehicles.
2. **Long Cycle Life**: With proper management, Li-ion batteries can achieve several hundred to over a thousand charge-discharge cycles before significant capacity degradation occurs. This long cycle life makes them economically viable over extended periods.
3. **Low Self-Discharge Rate**: Li-ion batteries also have a very low self-discharge rate, in a range of 1-5 % of the battery capacity per month. This characteristic makes certain that stored energy is available for longer duration at a given time when the battery is inactive.
4. **Rapid Charging**: The problems of Li-ion batteries include low performance, capability to charge the batteries at higher rates causing quick recharging times than other chemistries. This feature proves especially useful in use case applications like electric vehicles, which require as less downtime as possible.
5. **Environmental Impact**: However, there is an environmental problem with Li-ion batteries being related to mining lithium and other materials necessary for production, but in most cases, systems based on lithium-ion batteries are less environmentally unfriendly than systems based on lead-acid batteries, especially in terms of recycling and total emissions during the life cycle of the battery.
6. **Wide Application Range:** Owing to the flexibility, Li-ion batteries can be used in all forms of applications, including mobile devices, notebooks, and electric cars. This

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

versatility critically points to the need to have accurate SOC estimation to suit the functionality of the SOC in different applications.

7. **Integration with Advanced Technologies:** Battery Management Systems or BMS has evolved as a direct counterpart to the Li-ion technology. These systems apply complex methods of real-time tracking and management of SOC, which allows for the improvement of battery performance qualities and safety.
8. **High Demand for Electric Vehicles:** The usage of electric cars has also led to the quest for realistic battery management system solutions. In addressing the issues of energy management, range estimation, and satisfaction of the user, the SOC estimation is a central point around which all these considerations are formed. Up-to-date knowledge on SOC enables the manufacturer and the user to appraise the battery utility and enhance the driving experience, respectively.

High energy density, long cycle life, fast charging capabilities and low self-discharge rates that characterize Li-ion batteries make it the most suitable battery for SOC estimation techniques. The ever-expanding use of Electric vehicles and increased advocacy for clean electrification underlines the need for proper SOC determination to optimize battery performance and customers' satisfaction. By continuing to study and refine the techniques used in this field, the authors' methods will provide an indispensable contribution to the future of batteries and their uses.

4. SOC Estimation of Lithium-Ion Batteries

4.1 Overview of SOC

One of the important indices when using the rechargeable Battery systems especially lithium-ion battery is the State of Charge [20]. SOC stands for State of Charge which shows the present ability of a battery out of its total ability and is normally in percentages. The research performance can be defined mathematically as stated in equation 3 below.

$$SOC = \frac{Q(t)}{Qmax} \times 100\% \qquad (3)$$

Where $Q(t)$ is the remaining charge at time t and Q_{max} is the maximum capacity of the battery. Accurate SOC estimation is essential for optimizing battery performance, ensuring safety, and prolonging battery life.

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

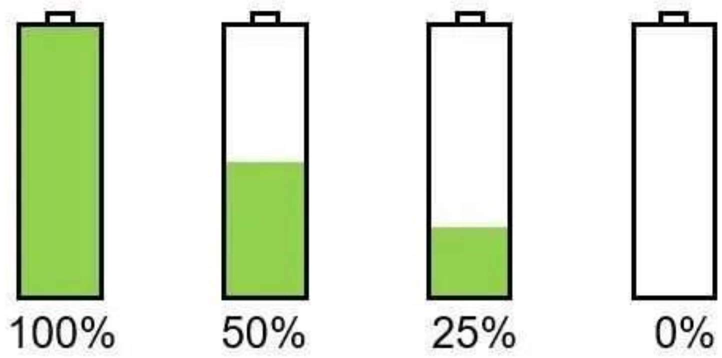


Figure 2: State of Charge Cycle of a Cell [21]

Hence, in some applications like EVs, estimation of SOC is crucial in determining the range of travel, controlling the energy consumption, and, most importantly, in providing information to the users at any one time. Poor SOC estimation can lead to unexpected battery depletion, potentially causing range anxiety among users, making it a significant area of research in battery management systems (BMS).

4.2 Classifications of SOC Estimation Techniques

Depending on the classification criteria, there are several methods of SOC estimation [22] used parameters, the nature of the approach, and the process flow. Every one of these categories has its own pros and cons depending on the situation, problem's complexity or accuracy level needed. It is also important for an analyst to comprehend the type and nature of these techniques for the purpose of choosing an appropriate technique for a particular application that may be EVs, portable electronics or any other.

4.2.1 Parameter Used in Technique

SOC estimation techniques can be categorized based on the dominating parameter used in estimating the battery SOC, including voltage, current, temperature and internal resistances [23]. These parameters are usually assessed from outside the electrochemical cell even though some methods use internal chemical or electrochemical measurements as well. Other methods that are based on voltage include the Open Circuit Voltage (OCV) technique in which SOC is deduced with the help of terminal voltage-SOC characteristics. This relationship is different and exists depending on the kind of battery chemistry involved, which means that the characteristic curves that show how voltage varies with SOC under different conditions must be constructed.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

On the other hand, current-based techniques, like Coulomb counting, use the integration of current over time to estimate the SOC. Since the amount of charge entering or leaving the battery directly affects SOC, this method is relatively simple but suffers from error accumulation over time. Temperature-based techniques are less common, though temperature can influence both voltage and resistance, thereby indirectly affecting SOC estimates. Internal resistance is another popular method for measuring battery SOC as it can be used in conjunction with model-based techniques, where the dynamic behavior of the battery's impedance provides a deeper understanding of the battery's state.

The advantage of classifying SOC techniques by the parameters they use is the flexibility it offers in practical applications. Depending on the available sensors and the computational capacity of the Battery Management System (BMS), different combinations of parameters can be employed. However, the challenge lies in the complexity of accounting for all variables, especially when external conditions, such as temperature, vary significantly during operation.

4.2.2 Based on Nature of Technique

SOC estimation techniques can also be classified by their inherent nature, falling into three broad categories [24]: infrared diagnostics, direct measurements, analytical estimations, and data analysis methods. These four are Coulomb counting and OCV, which entail physical attributes of the battery such as current or voltage then finding their respective value of SOC. Though these techniques are relatively easier to deploy they can be less accurate particularly in dynamic operating environment.

Nominal models include Equivalent Circuit Models (ECMs) and electrochemical models that transform the physical or electrochemical processes of the battery into mathematical models. These models can be very precise if the system parameters are accurately calibrated, but the detail of battery internal mechanisms is needed. Since the physical models require a lot of assumptions, machine learning and artificial neural networks don't rely on these models as they are based on historical data. These methods may perform well for quantitative and even nonlinear relationships between measurable parameters and SOC but for this very reason, their true power and accuracy is highly dependent on the volumes of available training datasets.

Each of these categories offers trade-offs in terms of computational complexity, implementation cost, and accuracy. Direct measurement techniques are quick and easy to deploy, but they often need to be complemented with model-based or data-driven approaches to compensate for their inherent limitations in real-time, dynamic environments.

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

4.2.3 Based on Process Flow (Open Loop vs. Closed Loop)

As with other SOC estimation procedures, techniques can also be categorized by their open-loop or closed-loop functionality [25]. In Coulomb counting, for instance, the algorithm is an open-loop technique since the measurements cannot be corrected using feedback. In these methods, the SOC is estimated by summing up the current in and out of the battery, thus giving a continuous record of the SOC. However small errors in current measurement may, with the passage of time, cause drift from the actual SOC value.

Closed-loop techniques, in contrast, rely on feedback system that constantly updates the SOC estimate depending on the real value and estimate one. Such approaches include Kalman filtering and other observer-based methods have been categorized under this. The main advantage of closed-loop techniques is that it can take corrective action in response to error and uncertainty in the system. For example, if the noise and model error are considered, such as through a Kalman filter, the efficiency of SOC estimate will enhance through time. Nonetheless, the need for special computational methods for the implementation of a closed-loop is often more complicated than in the open-loop case, as well as the design effort needed to incorporate the former.

4.3 Review of Techniques

4.3.1 Direct Measurement Methods

The Two Direct measurement methods include Amp-hour displacement method, which involves determination of the current integrated through its path and the voltage integration method where the SOC of the battery is estimated through the voltage across or through the battery. These methods are very easy to apply, but in most cases, they may not be accurate enough for use in for instance a complex or dynamic environment. From the direct measurement approaches, Coulomb counting and the Open Circuit Voltage (OCV) method are widely used.

4.3.1.1 Coulomb Counting

Coulomb counting is another explicit type of SOC estimation also referred to as charge counting due to their basic approach to estimation. The technique involves summing the current proactively or runoff the battery to get the overall charge that has been used or stored [26]. The basic principle can be expressed by the following equation:

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

$$SOC(t_1) = SOC(t_0) \pm \frac{1}{C_n}\int_{t_0}^{t_1} I(t)\,dt \qquad (4)$$

Where C_n is the nominal battery capacity, $I(t)$ is the instantaneous current, and $SOC(t_0)$ is the initial SOC. This method involves determination of SOC at the start of battery operation and further assumes that the nominal capacity does not vary with time. However, in real world conditions battery capacity decreases as result of its usage, thus without amendments, there will be errors.

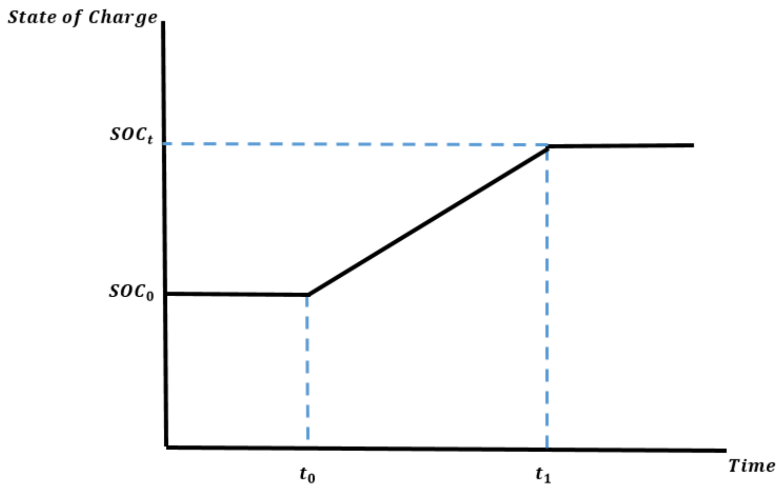


Figure 3: Typical Graph of SOC-Time Graph using Coulomb Counting

Advantages: Coulomb counting is easy to calculate and can be easily embedded in real-time systems because of its simplicity. This yields continuous estimation of SOC and it is especially important in areas where current can be well quantities. Also, the method is effective when using battery under specific current condition like constant current charging or discharging.

Limitations: The main disadvantage of Coulomb counting is that the calculation of the SOC increases with time cause of cumulative errors. Because they depend on current sampling and/or initial SOC estimation, various slight discrepancies, such as the inability to predict capacity loss, can significantly alter estimated SOC values. However, since Coulomb counting is not very accurate at determining the state of charge it is usually applied with other algorithms, such as Kalman filtering [27]. A second limitation is that Coulomb counting cannot consider self-discharge, that is charge loss in the absence of current. He added that it is not sufficient in long-term applications where the battery is on standby or dormant for a long time.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

4.3.1.2 Open Circuit Voltage (OCV) Method

The Open Circuit Voltage (OCV) method is another commonly used SOC estimation technique. In this method, the battery's terminal voltage is measured when it is in a fully relaxed state, meaning there is no load or charging current flowing through it. The SOC is then determined by correlating the measured voltage with an SOC-OCV characteristic curve, **[5]**, which varies for different battery chemistries. The relationship between OCV and SOC can be expressed as:

$$SOC = F(OCV) \qquad (5)$$

Where $F(OCV)$ is the function or curve that defines the relationship between OCV and SOC for a particular battery. It gives a highly accurate reading when the battery is calmly charged or discharges but has a low chance of success when the battery is charging or discharging actively. The relaxation period may take several hours and thus the applicability of this method is in actual time scenarios very little.

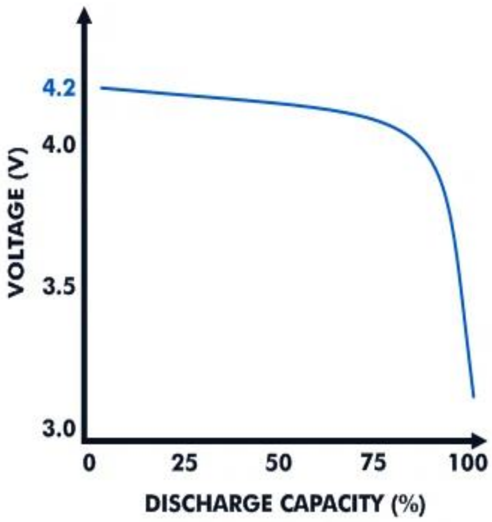


Figure 4: Typical OCV-SOC Graph showing how OCV Falls with Capacity Discharged

Advantages: The OCV method is highly accurate under stable conditions, such as when the battery is at rest for an extended period. It is also a non-invasive technique, requiring no additional sensors beyond the voltage measurement. This makes it cost-effective and relatively easy to implement in systems where long periods of rest are available.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Limitations: The primary limitation of the OCV method is its dependency on the battery being in a relaxed state. In most real-world applications, such as electric vehicles, batteries are rarely idle for long enough to allow for accurate OCV measurements. Additionally, the OCV-SOC relationship is nonlinear, as shown in Figure 4, [28], especially at the extremes of SOC (near 0% and 100%), making the method less accurate in those regions. Temperature variations also affect the OCV reading, requiring temperature compensation to improve accuracy.

4.3.2 Model-Based Estimation Techniques

Model-based estimation techniques involve constructing mathematical models that represent the physical and electrochemical processes inside the battery. These models are used to estimate SOC by solving equations that describe the battery's dynamic behavior. Two popular model-based approaches are Equivalent Circuit Models (ECMs) and electrochemical models.

4.3.2.1 Equivalent Circuit Models (ECM)

Equivalent Circuit Models (ECM) represent the battery as a combination of electrical components, such as resistors, capacitors, and voltage sources, which mimic the battery's dynamic behavior. The simplest ECM is the Thevenin model [29]**,** which consists of a voltage source representing the OCV, a series resistance accounting for internal resistance, and one or more RC networks modeling the battery's transient behavior.

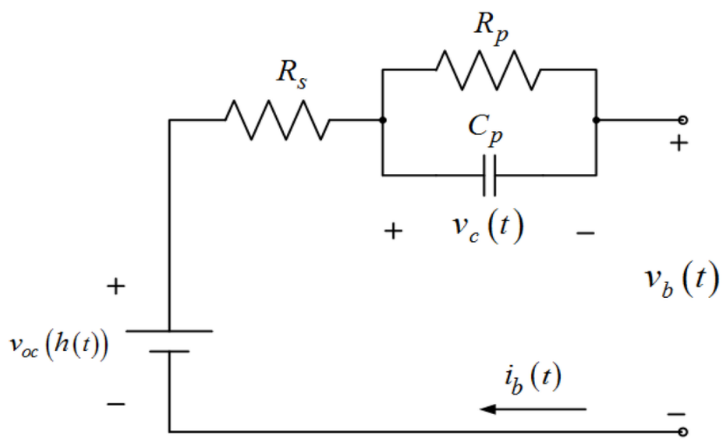


Figure 5: ECM Model of a Li-Ion Battery

The Thevenin model can be described by the following equations:

$$V(t) = OCV - I(t)R_s - V_{RC}(t) \qquad (6)$$

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Where, $V(t)$ is the terminal voltage, R_s is the series resistance, $I(t)$ is the current, and $V_{RC}(t)$ is the voltage across the RC network. The SOC can then be estimated by solving the model equations using measured current and voltage data, along with the known battery parameters.

Advantages: As compared to other methods ECMs are computationally efficient and estimates, SOC under dynamic operating conditions with reasonable accuracy. They can be easily incorporated in real-time systems and are commonly utilized in EV applications as they are able to simulate both one-time and temporary cycles of the battery. ECMs also allow for the incorporation of temperature within the reaction kinetics which increases the performance of the bioreactors in environments of varying temperature.

Limitations: While there are some drawbacks, the major drawback of the ECMs is that they are only as accurate as the parameters chosen, like resistance and capacitance. These parameters may be time variant because of aging, temperature, and other factors leading to deterioration of the model [30]. Another issue is that ECMs only represent the battery electrochemical behavior and therefore can be off in the reproduction of battery internal mechanisms.

4.3.2.2 Electrochemical Models

Electrochemical models are somewhat more accurate than the classical acoustic ones as being based on the description of the battery's inner chemical processes such as lithium ions diffusion of within the electrodes and the electrolyte [31]. These parameterized models are derived from first principles, for example the Nernst equation [32] and Butler-Volmer equation [33] which characterize the electrochemical reactions that go on within the battery.

One such electrochemical model is the DFN model developed by Doyle et al [34], which accounts for diffusion of lithium-ion concentration in the solid and liquid phase. The model entails finding the solution of coupled partial differential equations (PDEs), that describe the diffusion of Li ions and, the electrode processes.

Advantages: Battery electrochemical models are accurate with high precision, which gives them an added advantage of interpreting the internal state of a battery including SOC, SOH and capacity fade. They are more exploitable in research & development applications that will require characterization of internal battery behavior. In the same respect, these models can also be applied in enhancing battery design with a view of enhancing performance in particular applications.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Limitations: However, this is the most complex drawback of all electrochemical models. Real-time implementation of the real-time solution of the PDEs is very demanding and computer intensive. Also, with these models, there is an information requirement in terms of the battery material properties as well as the electrochemical characteristics, which may not be well known [35]. Consequently, electrochemical models are often combined with other models to maintain a good level of detail and at the same time, not demand excessive amounts of time and resources; for instance, with ECMs [36].

4.3.3 Data-Driven Estimation Techniques

Data-Driven Estimation Techniques Despite technological advancement in evaluation and estimation techniques, the nature of actual situation constraint, timing factor, and a progressive risk pattern are some of the challenges which make data-driven estimation techniques applicable in a project.

Consequently, data-driven SOC estimation schemes build the relationship between demonstrable parameters such as voltage, current and temperature, and SOC using historical data and machine learning methods [37]. Unlike some of the other techniques described above, these non-invasive techniques do not need a precise physical representation of the battery system and are therefore relatively versatile with respect to battery chemistry and conditions.

4.3.3.1 Machine Learning Approaches

This section focuses on the Machine Learning which can be used, classified and evaluated in the following subsections:

Machine learning (ML) techniques entail use of algorithms that are fed with big data so as to identify dependency between input parameters and SOC, [38]. Methods, including decision trees [39], random forests [40], and gradient boosting [41], have been used in SOC estimation with reasonable accuracy.

That is why, ML models are most effective in scenarios where the battery operates under condition changes, because it can describe relationships between variables in detail, [42]. Though these models are hit and correct, the accuracy of these models depends on the quality and diversification of the data used for training. Traditional ML techniques also need to be updated with fresh data after some time: to adjust for battery degradation or otherwise different operating conditions [43].

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Advantages: ML approaches offer high accuracy and adaptability without requiring detailed knowledge of the battery's internal processes. They can be used in various systems of different battery types and usages suitable for use in electric cars and renewable energy. Further, the conventional SOC can also be modelled while training the ML models for other battery conditions including SOH and state of power (SOP).

Limitations: The major challenge of using ML approaches is that they greatly rely on large, high-quality data [43]. Depending on the richness of the training set, should it contain all possible running conditions, the model may decline in accuracy when the battery is in a new territory. In addition, the training of the models might be time consuming, and the models might possess high complexity in terms of computations, and thus, it may be necessary to apply hardware supports for real time implementation of the models.

4.3.3.2 Neural Networks and Deep Learning

Previous methodologies, such as, artificial neural networks (NNs), and the more recent DL techniques, have been preferred in SOC estimation because of their applicability to depict more intricate correlation systems of input parameters and SOC [44]. NNs have a number of connected layers which are called the nodes, or neurons that take the input and learn from it, thanks to backpropagation [45].

An extension to the neural network is made through deep learning where more layers and neuron are put in place to capture more features. CNNs and RNNs [46], [47] have been used for SOC estimation, especially where time series data needs to be incorporated such as in electric vehicles.

Advantages: An NN and a DL model provide the best solution when it comes to finding outliers in large datasets. Because of this, the models can capture highly nonlinear dependence of SOC on input parameters, and thus are appropriate for application in complex and rapidly changing conditions. In corporately, DL models can directly learn the features without features extraction or engineering processes.

Limitations: The main weakness of NNs and DL is that these models require vast amounts and large sets of data and quite extensive computation. Model training deeply is computationally resource consuming, and deploying models for real-time systems often may call for specialized architecture, namely GPUs [47]. Furthermore, NNs are often used as “black-box model”, [47], this means that they do not give any kind of information about physical mechanisms, which influence the battery’s behavior.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

4.3.3.3 Fuzzy Logic

The methods employing Fuzzy logic technique of SOC estimation incorporates linguistic variables to manage vagueness and imprecision of the SOC of the battery [48]. In fact, in this approach, SOC is defined as a combination of fuzzy rules that, with the help of the input parameters such as voltage, current and temperature describe SOC. These are global rules adopted by human beings who wish to estimate SOC given that the data collected is either inaccurate or noisy.

Advantages: Fuzzy logic is most appropriate for use in zones that characterized battery functioning in highly unpredictable circumstances, including in marginal climates or when acquiring data from sensors. The method is also computationally efficient to implement and is therefore well suited for real time operation. In addition, fuzzy logic is also can be integrated with another paradigm of methods, for example, model-base methods for increasing the accuracy of systems.

Limitations: Notably, the main issues to do with the use of fuzzy logic is that experts have to define the fuzzy rules [49]. However, the use of fuzzy logic models can be less precise compared to other model-based techniques when the battery works in various or stochastic regimes [50].

4.3.3.4 Support Vector Machine (SVM)

Another learning algorithm that has been used for SOC estimation is Support Vector Machine (SVM). SVM is a type of supervised learning algorithm that creates a hyperplane that best defines the data to classify it into different sets [51]. By regarding state of charge SOC estimation, SVM can be applied in the classification of battery states from voltage current and temperature inputs [52].

Advantages: SVM provide reasonable accuracy and generalization across a range of applications and where the link between parameters and SOC is non-linear. He's also fairly easy to complement and does not need as much computing resources as the deep learning methods.

Limitations: The major weakness of Support Vector Machines is that their performance depends greatly on the kernel function that defines the shape of the hyperplane line [53]. Furthermore, analytically, SVM is considered an inflexible model compared to some other approaches of data mining techniques like neural networks; it maybe lacks efficacy specifically in intricate or fluctuating environments [54].

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

4.3.4 Filter-Based Estimation Techniques

Filter-based SOC estimation techniques use mathematical filters to process noisy sensor data and provide an accurate estimate of SOC [55]. These techniques are widely used in dynamic applications, such as electric vehicles, where real-time SOC estimation is critical. The most common filter-based methods are Kalman filtering, particle filtering, and H-infinity filtering.

4.3.4.1 Kalman Filtering

Kalman filtering, in general, is a recursive filter which estimates the state of a system for example SOC by employing a series of noisy measurements [56]. In detail, the Kalman filter uses a model to predict the system state and correct prediction with an error between the served and forecasted values. The algorithm gives real time variation to the SOC estimate, which makes it very efficient when operating in ever changing conditions [57].

Kalman filter is important in SOC estimation because it can accommodate noisy information from the sensors as well as uncertainties in the model [58]. It also gives a means for modeling battery aging and temperature changes, thereby enhancing the accuracy with which the SOC of the battery is estimated [59].

Advantages: Kalman filtering gives very good real time converging result and accustomed to noisy and uncertain data, so it is therefore very useful wherever the battery system operates in dynamic environment. Therefore, it is computationally efficient and may also be deployed in low power systems like Battery Management Systems (BMS).

Limitations: The principal drawback of the Kalman filter is that its application involves constructing an accurate model of the battery dynamics. The filter not only depends on the model presented in this paper but also relies on the other samples in the database, so if the model used here is not well calibrated, the filter might give wrong SOC estimates [60]. Moreover, the applicability of Kalman filters is relatively low in cases of highly nonlinear battery conditions, e.g., at the low and high ends of SOC.

4.3.4.2 Particle Filtering

Particle filtering is a more sophisticated kind of filtering technique which utilizes samples, or particles to portray the potential states of the system [61]. The SOC is estimated according to the average of particles and each one of them is filtered with weight depending on how close the measured data fits [62]. The above approaches of particle filtering require more

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

computational effort as compared to the Kalman filtering; it is especially suitable for strongly nonlinear systems[63]

Advantages: Particle filtering is a very versatile and can work with nonlinear and non-Gaussian systems, and therefore can be applied to battery systems even though conventional filters do not hold. It also offers the possibility to predict not only SOC but also SOH and capacity fade as well.

Limitations: The main disadvantage of particle filtering is a high computational cost associated with implementation of such a strategy. The algorithm is based on a need for a large number of particles to get good accuracy which can be time-consuming and in real-time forcing. Further, the efficiency of the particle filter is determined by the proposal distribution, according to which the particles are created.

4.3.4.3 H-Infinity Filtering

The second method employed in this research is H-infinity filtering, is a powerful estimation method via minimizing the maximum estimation error instead of assuming the error distribution is Gaussian as in the Kalman filter [64]. This makes H-infinity filtering most suitable for use where the battery operates under conditions of high uncertainty or when it is under attack, for instance, through fluctuations in temperature or high discharge rates [65]

Advantages: The H-infinity filtering also presents great results in terms of model uncertainties and external disturbance and consequently, in those scenarios where the Battery is submitted to unfavorable conditions. It also helps in introducing a way to take care of the worst expectations of the human estimate that in turn enhances the quality of the SOC estimate.

Limitations: The main disadvantage of H-infinity filtering is a high level of its complexity. The algorithm lends itself to a detailed understanding of the battery and can be very demanding and complex in real time systems [66]. Also, H-infinity filtering may give lower SOC accuracy than other algorithms in the situation when the system performs in the nominal mode [67].

4.3.5 Hybrid Estimation Techniques

For the final SOC estimation, techniques are hybrid that encompass merits of various methods providing a unified solution to SOC estimation problem [68]. These methods propose to combine the advantages of one technique over the other to increase the efficiency, accuracy, reliability and flexibility of the solution. Hybrid methods are particularly useful in complex

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

and dynamic battery systems, such as those in electric vehicles (EVs), where a single technique might not provide the best performance across all conditions.

4.3.5.1 Combination of Data-Driven and Model-Based Methods

The data-driven and model-based techniques are used together and in this the characteristics of both the approaches are combined and thus advantageous of both approaches are achieved [69]. There is one type of approach, which involves the application of the ECM to capture the physical characteristics of the battery and the subsequent machine learning, for instance, a neural network or SVM to modify the estimate of SOC based on the model [70].

For example, an ECM can be employed for estimating the voltage and current of the battery and a neural network can adapt the value of SOC based on the past values about a learned pattern. This approach can enhance SOC estimation performance in various operating points, especially when model-based approaches may prove inadequate because of parameter changes and or unmodeled effects [71].

Advantages: The integration of conventional and model-based gives an improved estimate of SOC since it leverages on the model's physical insights but supplements the shortcomings of a model with actual data. This method is not sensitive to the condition of the battery which include aging and temperature and is universal to all chemistries as well as configuration.

Limitations: The main difficulty of the methods is the higher order compared to the first order when using hybrid methods. It should be noted that the model-based and data-driven portions of the proposed system can take considerable time to fine-tune and execute [72]. Moreover, each of the hybrid methods relies on the quality of the training data, as well as the accuracy of the models that are available; these are not always possible to achieve.

4.3.5.2 Adaptive Filtering Techniques

Adaptive filtering stands as an improved form of traditional filtering like Kalman filtering whereby the model parameters are adjusted with time due to changes in the battery operating conditions [73]. These techniques are developed to address the variance and variation inherent in real-world battery systems and more so in EV applications, where characteristics of batteries can evolve with time through aging, temperature change and different loading patterns [74].

These are the extended Kalman filters (EKF) [75], [76], [77], [78], Unscented Kalman Filter (UKF), [79], [80] and particle filters [81] of the adaptive filtering techniques. In these methods, the filter not only estimates SOC but also adjusts the parameters of the system model according

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

to registers received from the battery, thus keeping the SOC estimate always correct in accordance with the current state of the battery. For example, adaptive particle filters can change the number of particles or their importance depending on the battery's behavior, which leads to the improvement of the accuracy of the SOC estimate.

Advantages: Adaptive filtering is accurate and proven to be very robust in real-time dynamic application such as management of EV batteries. It also shows that these proposed techniques can mitigate changes in battery parameters and calculate a precise SOC even under the worst and highly fluctuating conditions.

Limitations: This station enjoys numerous benefits, but adaptive filtering techniques do entail high computational cost in systems that are complex, including high-dimensional, high-volume systems [82]. Moreover, the filter's filter performance also depends on the quality of the first model and the calibration of adaptable parameters, which poses problems in some processes.

5. Comparative Analysis of SOC Estimation Techniques

The SOC estimation techniques are therefore comprehensively reviewed to reveal accuracy, computational costs, and applicability to all types of batteries. Either of the methods has its characteristic advantages and drawbacks, and, in general, none of the methods suits all kinds of batteries. The type of chemistries used in the method implemented also determines the technique applied for a particular battery type and utilization whether in electric vehicles, portable electronics or grid storage systems, and the battery's chemical type, usage conditions, and phase of its lifecycle [83]. As mentioned in Section 4, various approaches for SOC estimation are present here, and this section gives a detailed comparative study of the various techniques. The methods are assessed based on several key factors:

1. **Accuracy**: How closely the technique estimates the actual SOC.
2. **Computational Complexity**: The level of computational resources (e.g., processing power, memory) required to implement the method.
3. **Real-Time Capability**: The ability to provide SOC estimates in real time, which is particularly important in dynamic applications like EVs.

5.1 Accuracy Comparison

Most of the SOC estimation techniques achieve varying results based on the technique employed, operating condition, and battery properties. The model-based techniques like equivalent circuit models (ECMs) are reasonable accurate in most cases although they are not highly accurate under dynamic conditions in view of parameter changes. The inclusion of

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

machine learning-based approaches show more promise for higher accuracy because the discovered relations can generalize from data samples and change when new conditions are encountered. However, van develop in complexity and need huge training set of data and are also affected by the quality of data fed to it. For example, Coulomb Counting is easy, theoretically accurate, accurate in stable environment, although it has accumulated errors, especially when the initial SOC assessment is inaccurate. On the other hand, Kalman filtering techniques such as EKF or UKF are more accurate when SOC is identified and calculated in real time using flowing data taking into consideration between noise and variable battery parameters.

The highest accuracy is obtained when solutions from both model-based and data-driven approaches are used, most especially in mutable systems such as EVs, which undergo frequent changes in operation. These methods can improve significant random or systematic errors inaccuracy of the physical model when being applied in practice because of using the data-oriented approach.

5.2 Computational Complexity

Practicality is also an essential consideration when evaluating a SOC estimation technique owing to resource limitations that characterize portables or embedded devices. Coulomb Counting, for example, is significantly less complex and will not drain battery power in a system, thus making it possible to work on low-powered systems. However, such methods cause improved errors if used for successive data sets. Electrochemical models and ECMs are relatively demanding as they solve differential equations of internal battery dynamics. These methods are typically applied in systems where computational capabilities do not represent an issue, for example in EVs or in stationary energy storage systems.

Machine learning and deep learning specifically are computationally expensive to implement because of the training exercise as well as the eventual data analysis. Although these methods can give very high accuracy, they may be too computationally heavy for real-time applications and thus suffer when implemented in low end embedded systems. It is always seen that the hybrid cracks are more time-consuming than the other approaches as they incorporate the characteristics of both Model based and Data Driven approaches. Nonetheless, the use of these methods becomes improving generally due to development in hardware and optimization algorithms for real-time applications.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

5.3 Real-Time Capability

Real-time capability may be defined as the capacity of an SOC estimation method to update SOC information continuously and instantaneously during the dynamic use of the Battery. Of all the techniques described above, it is notable that Coulomb Counting is quite effective because it affords the monitoring of SOC in real time by way of integrating current continuously over time. This particular method provides a way for SOC estimate to changed instantaneously depending on current flowing into or out of the battery; useful in applications that demand responses. In contrast, the Open Circuit Voltage (OCV) Method fails in real-time application because its readings can only be taken when the battery is non-operational or at a standstill, this is not feasible during normal charging or discharging cycles. This limitation puts it out of bounds for dynamic systems where monitoring is continuously required.

However, a parameter estimation solution together with suitable filters such as the Kalman-PRLS filter as well as the error Kalman filter placed on the Equivalent Circuit Models (ECM) gives real time estimating proficiency. This allows them to respond to conditions fluctuating and obtain the correct SOC at times of power cycling. However, there is a high increase of the computational demands, accompanied by the increases in the complexity of the model. Electrochemical Models are not functional in real time. These models are more appropriate when used in research where precision is considered ultimate, but their computational needs make them unfit for real-time applications.

Real-time SOC estimation has been applying Machine Learning techniques at a growing rate. Using this approach once a model has been trained it can learn from the data and make the estimates as and when needed as opposed to batch processes as required in dynamic models. However, they are computationally intensive, especially in the training process though they can be implemented readily. Nevertheless, Neural Networks also have real-time evaluation characteristics, one can have real SOC predictions as soon as the training is complete. However, like machine learning methods, they require a call for high computational resources and thus might be a problem in environments with limited resources. Among the identified Kalman Filters, the real-time performance of the constant gain Kalman Filter and the Extended Kalman Filter (EKF) can be attributed to recursive estimation. They can track and estimate SOC sufficiently while working under different conditions; however, they need an improved initial model to perform their work properly. Particle Filters are also capable of giving real-time estimation but are constrained by high computational burden. On one hand, their capability to address nonlinearities makes them useful in dynamic contexts, while on the other, the high level of implementation may limit it. Last, Hybrid Techniques, which integrate the features of several methods, let these methods provide SOC estimates in real-time successfully. However,

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

they are typically the most computationally intensive, as well as the most analytically complex, systems that call for complex synthesis of multiple methods for optimal performance.

5.4 Summary of Comparison of Techniques

The comparison of each technique is provided in Table 2.

Table 2: Detailed Comparison of SOC Estimation Techniques

Technique	Parameter Used	Main Method	Classification	Accuracy	Computational Complexity	Real-Time Capability	Most Suitable Applications	Advantages	Disadvantages
Coulomb Counting	Current	Integration over time	Open Loop	**Moderate**	**Low**	**Yes**	Consumer electronics, low-power devices	Simple, low computational requirements, works in real time	Prone to cumulative errors, requires accurate initial SOC
Open Circuit Voltage	Voltage	Voltage-SOC relation	Open Loop	**Moderate**	**Low**	**No**	Stationary battery systems, UPS systems	Simple, no real-time measurements needed, low-cost	Only accurate at rest, cannot be used during charging/discharging
ECM	Current, Voltage	State-space model	Model-based	**High**	**Moderate to High**	**Yes**	EVs, high-performance	High accuracy, adaptable to	Computationally demanding, requires parameter

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Technique	Parameter Used	Main Method	Classification	Accuracy	Computational Complexity	Real-Time Capability	Most Suitable Applications	Advantages	Disadvantages
							applications	different applications	identification
Electrochemical Model	Voltage, Current	Complex equations	Model-based	**Very High**	**High**	**No**	Research applications, advanced EVs	Most accurate, detailed internal battery representation	Extremely high computational demand, impractical for real-time
Machine Learning	Current, Voltage, Temp	Data-driven learning	Data-driven	**High**	**Very High**	**Yes**	Smart grids, predictive maintenance	Learns from data, can adapt to nonlinear behavior	Requires large datasets, computationally intensive
Neural Networks	Multiple (incl. Temp)	Data-driven learning	Data-driven	**Very High**	**Very High**	**Yes**	Advanced EV systems, energ	Can model complex systems,	Requires training and significant computati

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Technique	Parameter Used	Main Method	Classification	Accuracy	Computational Complexity	Real-Time Capability	Most Suitable Applications	Advantages	Disadvantages
							y management	highly adaptive	onal resources
Kalman Filter (EKF)	Voltage, Current	Recursive estimation	Filter-based	**High**	**Moderate to High**	**Yes**	EVs, robotics, drones	High accuracy in dynamic systems, adaptive filtering	Requires accurate modeling, computationally demanding
Particle Filter	Current, Voltage	Bayesian estimation	Filter-based	**Very High**	**High**	**Yes**	Autonomous vehicles, high-stakes applications	Very accurate, handles nonlinear systems	Extremely high computational demand, complex to implement
Hybrid Techniques	Multiple	Combination	Hybrid	**Very High**	**Very High**	**Yes**	High-performance EVs, aerospace	Combines strengths of multiple techniques, highly	Highest computational demand, complex to design and implement

Power System Technology
ISSN:1000-3673

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Technique	Parameter Used	Main Method	Classification	Accuracy	Computational Complexity	Real-Time Capability	Most Suitable Applications	Advantages	Disadvantages
								accurate	

Color Scheme for Table

- Least Favorable Characteristic
- Less Favorable Characteristic
- Favorable Characteristic
- Most Favorable Characteristic

6. Conclusion

In conclusion, the present paper has discussed how advanced the SOC estimation techniques have come in recent years, there are still few issues that hinder their performance as well as their practical usability. These challenges must be addressed to further improve the accuracy, robustness, and efficiency of SOC estimation methods, particularly in applications such as electric vehicles (EVs) and renewable energy systems.

6.1 Limitations of Current Techniques

It is important to realize that the current approaches to SOC estimation share some of the primary drawbacks of accurate battery models and quality data. Simulation-based methods are based on equivalent circuit models and electrochemical models, called ECM and ESM respectively, which in turn need accurate estimates of the battery parameters that can degrade with time and usage conditions of the battery. This means that SOC cannot be estimated

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

independently of SOH as discussed in [83], [84]. Because the internal resistance of a battery rises as the battery ages, its SOH deteriorates, and so does its maximum capacity or rating; if the battery models are not refreshed, the SOC estimates are contaminated with errors.

It must be understood that data-driven methods including machine learning and neural networks highly rely on big, diverse data. The weakness of the training data is that other operating conditions possibly could be missed, so the model cannot give accurate SOC estimations when the battery works in conditions beyond the training range. Furthermore, these techniques demand high computational cost and may not be feasible when used in a low power device such as portable or embedded devices.

Indeed, the hybrid methods, which provide better accuracy and flexibility, include more problems to implement and require more computational resources. These methods need to be tuned and calibrated with an aim of rationing the strengths between the model based and the data driven based approaches, which can be complex when designing real time systems.

One of the main drawbacks is that few practical methods used for estimating SOC stock have been tested and validated. Sometimes they are optimal in certain conditions but decline in other conditions and therefore does not allow one to compare the efficiency of the various methods. There is a lack of metrological reference data and quantitative criteria for validating SOC estimation methods in terms of accuracy, stability, and computational cost for various chemistries of batteries and different working conditions.

6.2 Integration of SOC Estimation Methods in EV Applications

The problem of SOC estimation is more complex when integrating SOC estimation techniques for specific applications such as EV because of these varying operating conditions. SOC estimation is influenced by EV batteries high charging and discharging rates as well as temperatures as well as power requirements that they undergo regularly. Furthermore, the battery capacity decays over time hence impacts the accuracy of SOC estimation when using this kind of battery.

To overcome these challenges, the SOC estimation methods engaged in EVs must be capable enough to deal with the real time data from the different sensors such as current sensor, voltage sensor, and temperature sensor. The estimation algorithms must also be efficient in terms of computational complexity because real-time BMS require a minimal and efficient computation.

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Another area is the application of adaptive filters, including EKF or particle filters able to update SOC estimate according to the changes in battery usage conditions. Moreover, the combination of the model-based approach and data-driven approaches that allows achieving higher accuracy than purely model-based methods and yet being less computationally expensive is emerging in EV applications.

There is therefore pressure on SOC estimation techniques that should accommodate new chemical configurations of EV batteries like solid structures, which boast of high energy relative densities and safety measures as compared to lithium-ion batteries. To advance SOC estimation for these new battery technologies, further research is required to support the reliability of the EV systems.

6.3 Emerging Trends in Battery Management Systems (BMS)

The emergence of advanced battery management systems (BMS) is of paramount significance to the enhanced performance and reliability of current battery systems in such applications as EVs and RECSs. One of the major issues of current and future BMS development is the combination of intricate SOC estimations with other functions that are typically incorporated into the BMS, including SOH and SOP monitoring.

AI and machine learning have become crucial components of the state-of-the-art BMS since they allow for improved computation of the SOC of the battery in real time. Machine learning algorithms also improve battery management by predicting its future behavior from data received from the battery system without the need for physical samples. Other methods, including neural network as a tool of deep learning, are also being considered as promising for analysis of nonlinear dependency between SOC and other battery characteristics.

Another new frontier is cloud BMS that can enable online supervising and regulating of battery systems at various sites. This approach allows for timely collection and evaluation of the data in real-time that would be useful for SOC estimation as well as for monitoring the health status of batteries and deciding on when to service or replace them.

Next to Artificial Intelligence and Cloud Computing, progress in sensor technology extends the overall capacity of BMS to assess battery characteristics in real time. Temperature, voltage, and current sensor have high precision in SOC estimation, and new sensor technologies will provide better performance improvement to next generation BMS.

The emerging trends of Li-ion battery SOC estimation research from 2015 to 2024 is summarized in Table 3.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Table 3: Summary of Emerging Trends for All Techniques

SOC Estimation Technique	Emerging Research Trends	Challenges	Benefits of Research Trend
Coulomb Counting	- Advanced current sensing techniques	- Accurate current sensing is complex and expensive	- Improved SOC accuracy
	- Adaptive Coulomb counting methods	- High computational demand for real-time adjustment	- Better compensation for capacity fade and self-discharge
	- Capacity degradation modeling		
OCV-Based Estimation	- OCV-SOC relationship under dynamic conditions	- OCV behavior varies with temperature and SOC dynamics	- Enhanced SOC accuracy in dynamic and varying conditions
	- Effect of temperature on OCV-based estimation	- Slow response in real-time scenarios	- More reliable real-time applications
Equivalent Circuit Model (ECM)	- Adaptive parameter identification for ECM	- Identifying accurate model parameters in real-time	- Increased adaptability to operational conditions
	- Temperature compensation techniques	- Temperature sensitivity in ECM accuracy	- Improved accuracy over varying temperatures
Electrochemical Models	- Reduced-order electrochemical models	- Simplification may sacrifice accuracy	- Feasible real-time applications with reduced computation
	- Lithium-ion diffusion modeling	- Complex diffusion modeling can be computationally intensive	- Enhanced understanding of diffusion behavior
Machine Learning-Based Methods	- Transfer learning for SOC estimation	- Data availability and variability across systems	- Applicability to diverse systems
	- Ensemble learning techniques	- Model complexity may increase training time	- Improved estimation accuracy by leveraging multiple models
Neural Networks	- Explainable neural networks	- High computational costs	- Better understanding and control of SOC estimation models

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

SOC Estimation Technique	Emerging Research Trends	Challenges	Benefits of Research Trend
	- Deep reinforcement learning for battery management systems	- Lack of interpretability in black-box models	- Enhanced learning and optimization for battery management
Fuzzy Logic-Based Techniques	- Fuzzy logic in hybrid SOC techniques	- Complex rule definition for large-scale systems	- Flexibility in handling uncertain and imprecise data
	- Optimization of fuzzy rules for SOC estimation	- Computational intensity for real-time applications	- Improved hybrid SOC estimation accuracy
Support Vector Machine (SVM)	- SVM for SOC estimation in hybrid systems	- Kernel function selection can be difficult	- Robust SOC estimation in hybrid systems
	- Kernel optimization in SVM-based SOC estimation	- High computational cost for large datasets	- Higher accuracy with optimized kernel functions
Kalman Filter-Based Techniques	- Extended Kalman filtering for nonlinear SOC estimation	- Nonlinearities are difficult to model	- Better SOC estimation in nonlinear systems
	- Adaptive Kalman filtering for battery aging	- Battery aging behavior is hard to predict in real-time	- Adaptive filters ensure longevity in SOC estimation
Particle Filtering	- Particle filtering for multi-parameter estimation	- High computational costs for real-time applications	- Accurate multi-parameter SOC estimation
	- Optimization of particle filter proposal distribution	- Complex optimization of proposal distribution	- Better estimation under uncertainty and noise
H-Infinity Filtering	- H-infinity filtering for robust SOC estimation	- Complexity in tuning H-infinity parameters	- Improved robustness in extreme environments
	- Comparison of Kalman and H-infinity filtering	- High computational demand	- Better resilience to model uncertainties
Hybrid Estimation Techniques	- Hybrid machine learning and model-based SOC techniques	- Combining model-based and ML techniques increases complexity	- Improved adaptability to changing conditions

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

SOC Estimation Technique	Emerging Research Trends	Challenges	Benefits of Research Trend
	- Adaptive hybrid systems for dynamic environments	- Difficult integration of multiple data sources	- Enhanced accuracy by leveraging both models and data-driven techniques
Adaptive Filtering	- Adaptive Kalman filtering for battery aging	- Computationally expensive to adapt in real-time	- More accurate SOC estimation for aging batteries
	- Particle filter-based adaptive SOC estimation for EVs	- Requires continuous recalibration	- Higher accuracy for EV applications with varying operational conditions

6.4 Research Gaps and Opportunities

Despite these advances in SOC estimation techniques, this research indicates that there are still five critical research gaps that have been identified that offers the potential for further study and improvement. A potential area of future study, therefore, relates to the determination of SOC in other types of batteries and more specifically in novel chemistries such as solid state and lithium-Sulphur batteries. These chemistries possess different electrochemical characteristics than conventional lithium-ion batteries; therefore, the current SOC quantization methodologies could be unsuitable.

There is scope in future work to refine the SOC estimation techniques to incorporate consideration of battery degradation over the course of time. As batteries are utilized and age, their ability to hold charge reduces and the internal resistance rises if not corrected cause poor SOC measurement. What is required, in fact, are methods that can adjust to these changes in real time, for instance affine projection, or adaptive filtering technique, or machine learning algorithms, so that SOC estimation is accurate throughout the lifetime of a battery.

The use of a variety of SOC estimation methods, multicomponent hybrid estimation studies that involve both model and data-driven approaches as well, also offer a clear avenue for future research. Such methods may use better traits of various methods to enhance outcomes and overcome shortcomings in changeable situations.

Last but not the least, there is a lot of scope for standardizing and validating SOC estimation techniques. The creation of standards for comparing and critiquing methods will help proponents of various approaches to more effectively disseminate the best practices and methods to the rest of the industry.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

References

[1] "Oil Market Report - July 2024 – Analysis - IEA." Accessed: Sep. 30, 2024. [Online]. Available: https://www.iea.org/reports/oil-market-report-july-2024

[2] "Renewable Energy | MIT Climate Portal." Accessed: Sep. 30, 2024. [Online]. Available: https://climate.mit.edu/explainers/renewable-energy

[3] A. Rehman, S. Ali Haider Shah, A. Ullah Nizamani, M. Ahsan, A. Baig Mohammed, and A. Sadaqat, "AI-Driven Predictive Maintenance for Energy Storage Systems: Enhancing Reliability and Lifespan," *Power System Technology*, vol. 48, no. 3, pp. 686–701, Sep. 2024, doi: 10.52783/PST.859.

[4] "Advances in Satellite Selection Algorithms: Reducing... - Google Scholar." Accessed: Sep. 30, 2024. [Online]. Available: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Advances+in+Satellite+Selection+Algorithms%3A+Reducing+Receiver+Processing&btnG=

[5] "Food Retailers' Adoption of Green Supply Chain... - Google Scholar." Accessed: Sep. 30, 2024. [Online]. Available: https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Food+Retailers%E2%80%99+Adoption+of+Green+Supply+Chain+Practices+in+the+US%3A+A+Case+from+the+US+using+the+GSCM+Model&btnG=

[6] M. R. M. Kassim, W. A. W. Jamil, and R. M. Sabri, "State-of-Charge (SOC) and State-of-Health (SOH) Estimation Methods in Battery Management Systems for Electric Vehicles," *2021 IEEE International Conference on Computing, ICOCO 2021*, pp. 91–96, 2021, doi: 10.1109/ICOCO53166.2021.9673580.

[7] A. Basia, Z. Simeu-Abazi, E. Gascard, and P. Zwolinski, "Review on State of Health estimation methodologies for lithium-ion batteries in the context of circular economy," *CIRP J Manuf Sci Technol*, vol. 32, pp. 517–528, Jan. 2021, doi: 10.1016/J.CIRPJ.2021.02.004.

[8] R. Xiong, Q. Yu, and L. Y. Wang, "Open circuit voltage and state of charge online estimation for lithium ion batteries," *Energy Procedia*, vol. 142, pp. 1902–1907, Dec. 2017, doi: 10.1016/J.EGYPRO.2017.12.388.

[9] J. Meng, M. Boukhnifer, D. Diallo, and T. Wang, "A New Cascaded Framework for Lithium-Ion Battery State and Parameter Estimation," *Applied Sciences 2020, Vol. 10, Page 1009*, vol. 10, no. 3, p. 1009, Feb. 2020, doi: 10.3390/APP10031009.

[10] J. Wang, J. Meng, Q. Peng, T. Liu, and J. Peng, "An electrochemical-thermal coupling model for lithium-ion battery state-of-charge estimation with improve dual particle filter framework," *J Energy Storage*, vol. 87, p. 111473, May 2024, doi: 10.1016/J.EST.2024.111473.

[11] M. Ismail, R. Dlyma, A. Elrakaybi, R. Ahmed, and S. Habibi, "Battery state of charge estimation using an Artificial Neural Network," *2017 IEEE Transportation and*

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Electrification Conference and Expo, ITEC 2017, pp. 342–349, Jul. 2017, doi: 10.1109/ITEC.2017.7993295.

[12] S. El Fallah *et al.*, "Advanced State of Charge Estimation Using Deep Neural Network, Gated Recurrent Unit, and Long Short-Term Memory Models for Lithium-Ion Batteries under Aging and Temperature Conditions," *Applied Sciences 2024, Vol. 14, Page 6648*, vol. 14, no. 15, p. 6648, Jul. 2024, doi: 10.3390/APP14156648.

[13] D. Darbar and I. Bhattacharya, "Application of Machine Learning in Battery: State of Charge Estimation Using Feed Forward Neural Network for Sodium-Ion Battery," *Electrochem 2022, Vol. 3, Pages 42-57*, vol. 3, no. 1, pp. 42–57, Jan. 2022, doi: 10.3390/ELECTROCHEM3010003.

[14] M. Haroon Bukhari, A. Javed, S. Ali Abbas Kazmi, M. Ali, and M. Talib Chaudhary, "Techno-economic feasibility analysis of hydrogen production by PtG concept and feeding it into a combined cycle power plant leading to sector coupling in future," *Energy Convers Manag*, vol. 282, Apr. 2023, doi: 10.1016/j.enconman.2023.116814.

[15] J. P. Rivera-Barrera, N. Muñoz-Galeano, and H. O. Sarmiento-Maldonado, "SoC Estimation for Lithium-ion Batteries: Review and Future Challenges," *Electronics 2017, Vol. 6, Page 102*, vol. 6, no. 4, p. 102, Nov. 2017, doi: 10.3390/ELECTRONICS6040102.

[16] Y. Chen *et al.*, "A review of lithium-ion battery safety concerns: The issues, strategies, and testing standards," *Journal of Energy Chemistry*, vol. 59, pp. 83–99, Aug. 2021, doi: 10.1016/J.JECHEM.2020.10.017.

[17] N. Nitta, F. Wu, J. T. Lee, and G. Yushin, "Li-ion battery materials: present and future," *Materials Today*, vol. 18, no. 5, pp. 252–264, Jun. 2015, doi: 10.1016/J.MATTOD.2014.10.040.

[18] "(34) Understanding the Self-charge and discharge mechanism of a lithium-ion battery | LinkedIn." Accessed: Sep. 30, 2024. [Online]. Available: https://www.linkedin.com/pulse/understanding-self-charge-discharge-mechanism-battery-singal/

[19] W. Liu, T. Placke, and K. T. Chau, "Overview of batteries and battery management for electric vehicles," *Energy Reports*, vol. 8, pp. 4058–4084, Nov. 2022, doi: 10.1016/J.EGYR.2022.03.016.

[20] S. Yang and E. W. Kim, "Neural network based SOC estimation during cycle aging using voltage and internal resistance," *ITEC Asia-Pacific 2019 - 2019 IEEE Transportation Electrification Conference and Expo, Asia-Pacific: New Paradigm Shift, Sustainable E-Mobility*, May 2019, doi: 10.1109/ITEC-AP.2019.8903777.

[21] "State of Charge - Battery Design." Accessed: Sep. 30, 2024. [Online]. Available: https://www.batterydesign.net/battery-management-system/state-of-charge/

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

[22] M. Zhang and X. Fan, “Review on the State of Charge Estimation Methods for Electric Vehicle Battery,” *World Electric Vehicle Journal 2020, Vol. 11, Page 23*, vol. 11, no. 1, p. 23, Mar. 2020, doi: 10.3390/WEVJ11010023.

[23] B. Yang *et al.*, “Classification, summarization and perspectives on state-of-charge estimation of lithium-ion batteries used in electric vehicles: A critical comprehensive survey,” *J Energy Storage*, vol. 39, p. 102572, Jul. 2021, doi: 10.1016/J.EST.2021.102572.

[24] W.-Y. Chang, : M Brünig, and E. Di Nardo, “The State of Charge Estimating Methods for Battery: A Review,” *Int Sch Res Notices*, vol. 2013, no. 1, p. 953792, Jan. 2013, doi: 10.1155/2013/953792.

[25] K. Das and R. Kumar, “A Comprehensive Review of Categorization and Perspectives on State-of-Charge Estimation Using Deep Learning Methods for Electric Transportation,” *Wirel Pers Commun*, vol. 133, no. 3, pp. 1599–1618, Dec. 2023, doi: 10.1007/S11277-023-10830-5/METRICS.

[26] 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,” *Renewable and Sustainable Energy Reviews*, vol. 78, pp. 834–854, Oct. 2017, doi: 10.1016/J.RSER.2017.05.001.

[27] B. E. Lebrouhi, Y. Khattari, B. Lamrani, M. Maaroufi, Y. Zeraouli, and T. Kousksou, “Key challenges for a large-scale development of battery electric vehicles: A comprehensive review,” *J Energy Storage*, vol. 44, p. 103273, Dec. 2021, doi: 10.1016/J.EST.2021.103273.

[28] “What Is BMS? - News.” Accessed: Sep. 30, 2024. [Online]. Available: https://www.fangpusun.com/news/what-is-bms-76816591.html

[29] M. K. Tran *et al.*, “A comprehensive equivalent circuit model for lithium-ion batteries, incorporating the effects of state of health, state of charge, and temperature on model parameters,” *J Energy Storage*, vol. 43, p. 103252, Nov. 2021, doi: 10.1016/J.EST.2021.103252.

[30] D. Mu, J. Jiang, and C. Zhang, “Online Semiparametric Identification of Lithium-Ion Batteries Using the Wavelet-Based Partially Linear Battery Model,” *Energies 2013, Vol. 6, Pages 2583-2604*, vol. 6, no. 5, pp. 2583–2604, May 2013, doi: 10.3390/EN6052583.

[31] M. Doyle, T. F. Fuller, and J. Newman, “Modeling of Galvanostatic Charge and Discharge of the Lithium/Polymer/Insertion Cell,” *J Electrochem Soc*, vol. 140, no. 6, pp. 1526–1533, Jun. 1993, doi: 10.1149/1.2221597/XML.

[32] L. Liu, J. Zhu, and L. Zheng, “An Effective Method for Estimating State of Charge of Lithium-Ion Batteries Based on an Electrochemical Model and Nernst Equation,” *IEEE Access*, vol. 8, pp. 211738–211749, 2020, doi: 10.1109/ACCESS.2020.3039783.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

[33] K. Li, K. J. Tseng, F. Wei, and B. H. Soong, "A Practical Lithium-ion Battery Model Based on the Butler-Volmer Equation," *2018 International Power Electronics Conference, IPEC-Niigata - ECCE Asia 2018*, pp. 1592–1597, Oct. 2018, doi: 10.23919/IPEC.2018.8507765.
[34] R. Drummond and S. R. Duncan, "Observer design for the Doyle–Fuller–Newman Li-ion battery model without electrolyte dynamics," *J Energy Storage*, vol. 23, pp. 250–257, Jun. 2019, doi: 10.1016/J.EST.2019.02.012.
[35] M. Petit, E. Calas, and J. Bernard, "A simplified electrochemical model for modelling Li-ion batteries comprising blend and bidispersed electrodes for high power applications," *J Power Sources*, vol. 479, p. 228766, Dec. 2020, doi: 10.1016/J.JPOWSOUR.2020.228766.
[36] C. Li, N. Cui, C. Wang, and C. Zhang, "Reduced-order electrochemical model for lithium-ion battery with domain decomposition and polynomial approximation methods," *Energy*, vol. 221, p. 119662, Apr. 2021, doi: 10.1016/J.ENERGY.2020.119662.
[37] M. H. Sulaiman and Z. Mustaffa, "State of charge estimation for electric vehicles using random forest," *Green Energy and Intelligent Transportation*, vol. 3, no. 5, p. 100177, Oct. 2024, doi: 10.1016/J.GEITS.2024.100177.
[38] P. Eleftheriadis, S. Giazitzis, S. Leva, and E. Ogliari, "Data-Driven Methods for the State of Charge Estimation of Lithium-Ion Batteries: An Overview," *Forecasting 2023, Vol. 5, Pages 576-599*, vol. 5, no. 3, pp. 576–599, Sep. 2023, doi: 10.3390/FORECAST5030032.
[39] G. Luo, J. Meng, X. Ji, X. Cai, and F. Gao, "A data driven model for accurate SOC estimation in EVs," *Proceedings of the IEEE International Conference on Industrial Technology*, pp. 352–357, Apr. 2017, doi: 10.1109/ICIT.2017.7913256.
[40] P. A. Satyan and R. G. Sutar, "A Survey on Data-Driven Methods for State of Charge Estimation of Battery," *Proceedings of the International Conference on Electronics and Sustainable Communication Systems, ICESC 2020*, pp. 996–1004, Jul. 2020, doi: 10.1109/ICESC48915.2020.9155926.
[41] M. Korkmaz, "SoC estimation of lithium-ion batteries based on machine learning techniques: A filtered approach," *J Energy Storage*, vol. 72, p. 108268, Nov. 2023, doi: 10.1016/J.EST.2023.108268.
[42] Y. Dong, K. Chen, G. Zhang, and R. Li, "Joint Estimation of State of Charge and State of Health of Lithium-Ion Batteries Based on Stacking Machine Learning Algorithm," *World Electric Vehicle Journal 2024, Vol. 15, Page 75*, vol. 15, no. 3, p. 75, Feb. 2024, doi: 10.3390/WEVJ15030075.
[43] M. Ismail, R. Dlyma, A. Elrakaybi, R. Ahmed, and S. Habibi, "Battery state of charge estimation using an Artificial Neural Network," *2017 IEEE Transportation and*

Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

Electrification Conference and Expo, ITEC 2017, pp. 342–349, Jul. 2017, doi: 10.1109/ITEC.2017.7993295.

[44] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data 2021 8:1*, vol. 8, no. 1, pp. 1–74, Mar. 2021, doi: 10.1186/S40537-021-00444-8.

[45] X. Fan, W. Zhang, C. Zhang, A. Chen, and F. An, "SOC estimation of Li-ion battery using convolutional neural network with U-Net architecture," *Energy*, vol. 256, p. 124612, Oct. 2022, doi: 10.1016/J.ENERGY.2022.124612.

[46] J. Chen, Y. Zhang, J. Wu, W. Cheng, and Q. Zhu, "SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output," *Energy*, vol. 262, p. 125375, Jan. 2023, doi: 10.1016/J.ENERGY.2022.125375.

[47] M. A. Hannan *et al.*, "Deep learning approach towards accurate state of charge estimation for lithium-ion batteries using self-supervised transformer model," *Scientific Reports 2021 11:1*, vol. 11, no. 1, pp. 1–13, Oct. 2021, doi: 10.1038/s41598-021-98915-8.

[48] D. Jiani, L. Zhitao, W. Youyi, and W. Changyun, "A fuzzy logic-based model for Li-ion battery with SOC and temperature effect," *IEEE International Conference on Control and Automation, ICCA*, pp. 1333–1338, 2014, doi: 10.1109/ICCA.2014.6871117.

[49] D. Saji, P. S. Babu, and K. Ilango, "SoC Estimation of Lithium Ion Battery Using Combined Coulomb Counting and Fuzzy Logic Method," *2019 4th IEEE International Conference on Recent Trends on Electronics, Information, Communication and Technology, RTEICT 2019 - Proceedings*, pp. 948–952, May 2019, doi: 10.1109/RTEICT46194.2019.9016956.

[50] A. J. Salkind, C. Fennie, P. Singh, T. Atwater, and D. E. Reisner, "Determination of state-of-charge and state-of-health of batteries by fuzzy logic methodology," *J Power Sources*, vol. 80, no. 1–2, pp. 293–300, Jul. 1999, doi: 10.1016/S0378-7753(99)00079-8.

[51] J. C. Álvarez Antón, P. J. García Nieto, F. J. de Cos Juez, F. Sánchez Lasheras, M. González Vega, and M. N. Roqueñí Gutiérrez, "Battery state-of-charge estimator using the SVM technique," *Appl Math Model*, vol. 37, no. 9, pp. 6244–6253, May 2013, doi: 10.1016/J.APM.2013.01.024.

[52] J. C. Alvarez Anton, P. J. Garcia Nieto, C. Blanco Viejo, and J. A. Vilan Vilan, "Support vector machines used to estimate the battery state of charge," *IEEE Trans Power Electron*, vol. 28, no. 12, pp. 5919–5926, 2013, doi: 10.1109/TPEL.2013.2243918.

[53] 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.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

[54] G. F. Guo, L. Shui, X. L. Wu, and B. G. Cao, "SOC Estimation for Li-Ion Battery Using SVM Based on Particle Swarm Optimization," *Adv Mat Res*, vol. 1051, pp. 1004–1008, 2014, doi: 10.4028/WWW.SCIENTIFIC.NET/AMR.1051.1004.

[55] P. Spagnol, S. Rossi, and S. M. Savaresi, "Kalman Filter SoC estimation for Li-Ion batteries," *Proceedings of the IEEE International Conference on Control Applications*, pp. 587–592, 2011, doi: 10.1109/CCA.2011.6044480.

[56] P. Shrivastava, T. K. Soon, M. Y. I. Bin Idris, and S. Mekhilef, "Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries," *Renewable and Sustainable Energy Reviews*, vol. 113, p. 109233, Oct. 2019, doi: 10.1016/J.RSER.2019.06.040.

[57] L. Hu, R. Hu, Z. Ma, and W. Jiang, "State of Charge Estimation and Evaluation of Lithium Battery Using Kalman Filter Algorithms," *Materials*, vol. 15, no. 24, Dec. 2022, doi: 10.3390/MA15248744.

[58] M. Zhang, K. Wang, and Y. T. Zhou, "Online State of Charge Estimation of Lithium-Ion Cells Using Particle Filter-Based Hybrid Filtering Approach," *Complexity*, vol. 2020, no. 1, p. 8231243, Jan. 2020, doi: 10.1155/2020/8231243.

[59] S. Liu, X. Dong, X. Yu, X. Ren, J. Zhang, and R. Zhu, "A method for state of charge and state of health estimation of lithium-ion battery based on adaptive unscented Kalman filter," *Energy Reports*, vol. 8, pp. 426–436, Nov. 2022, doi: 10.1016/J.EGYR.2022.09.093.

[60] Z. Cui, W. Hu, G. Zhang, Z. Zhang, and Z. Chen, "An extended Kalman filter based SOC estimation method for Li-ion battery," *Energy Reports*, vol. 8, pp. 81–87, Aug. 2022, doi: 10.1016/J.EGYR.2022.02.116.

[61] M. Zhang, K. Wang, and Y. T. Zhou, "Online State of Charge Estimation of Lithium-Ion Cells Using Particle Filter-Based Hybrid Filtering Approach," *Complexity*, vol. 2020, no. 1, p. 8231243, Jan. 2020, doi: 10.1155/2020/8231243.

[62] X. Liu, X. Fan, L. Wang, and J. Wu, "State of Charge Estimation for Power Battery Base on Improved Particle Filter," *World Electric Vehicle Journal 2023, Vol. 14, Page 8*, vol. 14, no. 1, p. 8, Dec. 2022, doi: 10.3390/WEVJ14010008.

[63] Y. He, Z. Hong, Z. Zhang, and S. Huang, "Particle Filter Based Robust State and Parameter Estimation for Estimating SOC and Discharge Current of Lithium Batteries," *Proceedings of 2022 IEEE 11th Data Driven Control and Learning Systems Conference, DDCLS 2022*, pp. 244–249, 2022, doi: 10.1109/DDCLS55054.2022.9858503.

[64] T. Tu, J. Ding, and T. Yuan, "An improved H-infinity filter for SOC estimation of lithium-ion batteries based on fractional order model," *Chinese Control Conference, CCC*, vol. 2022-July, pp. 1390–1395, 2022, doi: 10.23919/CCC55666.2022.9902804.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

[65] Y. Chen, R. Li, Z. Sun, L. Zhao, and X. Guo, "SOC estimation of retired lithium-ion batteries for electric vehicle with improved particle filter by H-infinity filter," *Energy Reports*, vol. 9, pp. 1937–1947, Dec. 2023, doi: 10.1016/J.EGYR.2023.01.018.

[66] Y. Chen, R. Li, Z. Sun, L. Zhao, and X. Guo, "SOC estimation of retired lithium-ion batteries for electric vehicle with improved particle filter by H-infinity filter," *Energy Reports*, vol. 9, pp. 1937–1947, Dec. 2023, doi: 10.1016/J.EGYR.2023.01.018.

[67] J. Yao, J. Ding, Y. Cheng, and L. Feng, "Sliding mode-based H-infinity filter for SOC estimation of lithium-ion batteries," *Ionics (Kiel)*, vol. 27, no. 12, pp. 5147–5157, Dec. 2021, doi: 10.1007/S11581-021-04234-3/METRICS.

[68] Z. Ren and C. Du, "State of Charge Estimation for Lithium-ion Batteries using Extreme Learning Machine and Extended Kalman Filter," *IFAC-PapersOnLine*, vol. 55, no. 24, pp. 197–202, Jan. 2022, doi: 10.1016/J.IFACOL.2022.10.284.

[69] X. Lai, S. Wang, L. He, L. Zhou, and Y. Zheng, "A hybrid state-of-charge estimation method based on credible increment for electric vehicle applications with large sensor and model errors," *J Energy Storage*, vol. 27, p. 101106, Feb. 2020, doi: 10.1016/J.EST.2019.101106.

[70] F. Manzoor, H. Saleem, I. H. Naqvi, and N. A. Zaffar, "Online State of Charge Estimation Framework using Hybrid Equivalent Circuit Model and Neural Network," *IEEE Power and Energy Society General Meeting*, vol. 2023-July, 2023, doi: 10.1109/PESGM52003.2023.10252709.

[71] J. Yi, X. Zhou, J. Zhang, and Z. Li, "A Hybrid Method for SOC Estimation of Power Battery," *Journal of Control Science and Engineering*, vol. 2021, no. 1, p. 6758679, Jan. 2021, doi: 10.1155/2021/6758679.

[72] C. U. Udeogu, "A Novel SOC Estimation for Hybrid Energy Pack using Deep Learning," Dec. 2022, Accessed: Sep. 30, 2024. [Online]. Available: https://arxiv.org/abs/2212.12607v1

[73] X. Renxin, H. Yanwen, Z. Wei, and C. Zhaohui, "A novel approach to estimate the state of charge for lithium-ion battery under different temperatures incorporating open circuit voltage online identification," *J Energy Storage*, vol. 67, p. 107509, Sep. 2023, doi: 10.1016/J.EST.2023.107509.

[74] J. Yun, Y. Choi, J. Lee, S. Choi, and C. Shin, "State-of-Charge Estimation Method for Lithium-Ion Batteries Using Extended Kalman Filter With Adaptive Battery Parameters," *IEEE Access*, vol. 11, pp. 90901–90915, 2023, doi: 10.1109/ACCESS.2023.3305950.

[75] P. Takyi-Aninakwa, S. Wang, H. Zhang, X. Yang, and C. Fernandez, "An optimized long short-term memory-weighted fading extended Kalman filtering model with wide temperature adaptation for the state of charge estimation of lithium-ion batteries," *Appl Energy*, vol. 326, p. 120043, Nov. 2022, doi: 10.1016/J.APENERGY.2022.120043.

Power System Technology
ISSN:1000-3673
Received: 06-06-2024 Revised: 15-07-2024 Accepted: 28-08-2024

[76] E. P. Sangeetha, N. Subashini, T. K. Santhosh, A. L. S., and D. Uma, "Validation of EKF based SoC estimation using vehicle dynamic modelling for range prediction," *Electric Power Systems Research*, vol. 226, p. 109905, Jan. 2024, doi: 10.1016/J.EPSR.2023.109905.

[77] F. Ciortea, C. Rusu, M. Nemes, and C. Gatea, "Extended kalman filter for state-of-charge estimation in electric vehicles battery packs," *Proceedings - 2017 International Conference on Optimization of Electrical and Electronic Equipment, OPTIM 2017 and 2017 Intl Aegean Conference on Electrical Machines and Power Electronics, ACEMP 2017*, pp. 611–616, Jul. 2017, doi: 10.1109/OPTIM.2017.7975036.

[78] H. Pang, L. Guo, L. Wu, J. Jin, F. Zhang, and K. Liu, "A novel extended Kalman filter-based battery internal and surface temperature estimation based on an improved electro-thermal model," *J Energy Storage*, vol. 41, p. 102854, Sep. 2021, doi: 10.1016/J.EST.2021.102854.

[79] Y. ; Zeng *et al.*, "State of Charge Estimation for Lithium-Ion Battery Based on Unscented Kalman Filter and Long Short-Term Memory Neural Network," *Batteries 2023, Vol. 9, Page 358*, vol. 9, no. 7, p. 358, Jul. 2023, doi: 10.3390/BATTERIES9070358.

[80] S. Peng, A. Zhang, D. Liu, M. Cheng, J. Kan, and M. Pecht, "State-of-Charge Estimation of Lithium-Ion Batteries Based on Dual-Coefficient Tracking Improved Square-Root Unscented Kalman Filter," *Batteries 2023, Vol. 9, Page 392*, vol. 9, no. 8, p. 392, Jul. 2023, doi: 10.3390/BATTERIES9080392.

[81] V. Biazi, A. C. Moreira, J. L. Pinto, M. Nascimento, and C. Marques, "A particle filter-based virtual sensor for estimating the state of charge and internal temperature of lithium-ion batteries: Implementation in a simulated study case," *J Energy Storage*, vol. 61, p. 106814, May 2023, doi: 10.1016/J.EST.2023.106814.

[82] H. M. Fahmy, R. A. Swief, H. M. Hasanien, M. Alharbi, J. L. Maldonado, and F. Jurado, "Hybrid State of Charge Estimation of Lithium-Ion Battery Using the Coulomb Counting Method and an Adaptive Unscented Kalman Filter," *Energies 2023, Vol. 16, Page 5558*, vol. 16, no. 14, p. 5558, Jul. 2023, doi: 10.3390/EN16145558.

[83] M. Zheng and X. Luo, "Joint estimation of State of Charge (SOC) and State of Health (SOH) for lithium ion batteries using Support Vector Machine (SVM), Convolutional Neural Network (CNN) and Long Sort Term Memory Network (LSTM) models," *Int J Electrochem Sci*, vol. 19, no. 9, p. 100747, Sep. 2024, doi: 10.1016/J.IJOES.2024.100747.

[84] M. A. A. Khan, H. A. Khalid, R. Balan, and B. Bakkaloglu, "A novel State of Charge and State of Health estimation technique for Lithium-ion cells using machine learning based Pseudo-Random Binary Sequence method," *J Energy Storage*, vol. 55, p. 105472, Nov. 2022, doi: 10.1016/J.EST.2022.105472.