A Critical Review on Li-ion battery SOC estimation using the Measurement-Based Techniques and Model-Based Techniques

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Abstract: - The quick progress of smart grids and new energy electric vehicles has led to a growing demand for batteries. The battery management system (BMS) is an important component of the battery-operated energy storage device. In this paper, we systematically analyze and investigate the State Of Charge (SOC) estimation methods. This work provides a comprehensive examined of the most frequently battery state of charge estimation techniques utilized in BMSs. The current paper, through the review of available research, presents almost Measurement-Based and Model-Based approaches in the BMS. Additionally, in the hope of providing some inspiration to the development and design of the next-generation BMSs, the various challenges and prospects of the study on future battery management are revealed.

Key-Words: - Battery Management System (BMS), Electric Vehicle (EV), Equivalent Circuit Model (ECM), Lithium-Ion Battery, Open Circuit Voltage (OCV), Measurement-Based Techniques, Model-Based Techniques, State Of Charge estimation.

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1 Introduction

Energy storage technology is a crucial technology key for new energy electric vehicles and smart grid development, [1]. With the rapid growth of the new energy electric vehicle, the lithium-ion battery has become the fastest-growing energy storage solution among chemical and physical energy storage solutions, [2]. The frequent fire accidents of electric vehicles in recent years, on one hand, put electric vehicles into the hot search of public opinion, on the other side, raise the high requirements and challenges for battery management technology, [3].

Accurately estimating the State of Charge (SOC) of lithium-ion batteries is significant for the proper operation of Battery Management Systems (BMS), [4]. Reliable estimation of the SOC also helps to optimize system performance, ensure efficient energy management, and extend the operational life of the battery, [5]. Variations in battery characteristics due to ageing, temperature fluctuations, and non-linear behavior make SOC estimation particularly complex, [6]. Thus, the development of advanced techniques for accurate SOC estimation is crucial for improving the reliability and efficiency of BMSs, contributing to safer and more efficient use of lithium-ion batteries in various applications, [7].

Among the various methods developed to estimate the SOC of lithium-ion batteries, two main families can be distinguished: Measurement-Based Techniques and Model-Based Techniques, [8]. Measurement-based methods, such as coulomb counting or voltammetry techniques, are generally simple to implement and computationally inexpensive [9], but they are sensitive to cumulative errors, sensor drift, and do not take into account complex battery dynamics, [10]. Conversely, model-based approaches, like Kalman filters [11], neural networks [12], or non-linear observers [13], provide a more accurate estimate by incorporating the dynamic and thermal behaviors of the battery [14]. However, the latter requires fine modeling of the system, a calibration effort, and higher computing power, [15]. Thus, the choice between these two approaches depends on the trade-off between implementation complexity, desired accuracy, and system usage conditions (Table 1).

In this critical review, we seek to present a comprehensive comparative overview of the SOC estimation techniques based on lithium-ion batteries, focusing on the advantages and drawbacks of measurement-based and model-based approaches, [7]. This study attempts to determine the most powerful methods which are most applicable to a variety of BMS designs, factoring in practical limitations like non-linearity, ageing, temperature and online requirements, [20].

Table 1. Comparison of Measurement-Based and Model-Based SOC Estimation Approaches

Criteria	Measurement-Based Approach	Model-Based Approach	
Principle	Rely on direct measurements (voltage, current, etc.)	Rely on mathematical modeling of battery behavior	[16], [17]
Complexity	Low	Medium to High	[16], [18]
Accuracy	Medium, affected by drift and noise	High if the model is properly tuned	[16], [19]
Typical applications	Simple BMS, low-criticality systems	Electric vehicles, drones, energy storage systems	[17], [19]

Table 2. List of abbreviations

BMS	Battery Management System
LIB	Lithium-ion Battery
EV	Electric Vehicle
SOC	State Of Charge
SOH	State of Health
SMO	Sliding Mode Observer
OCV	Open Circuit Voltage
PNGV	Partnership for a New Generation of Vehicles
SPM	Single Particle Model
LO	Leuenberger Observer
PIO	Proportional-Integral Observer
HIO	H-infinity (H∞) Observer
P2D	Pseudo-Two-Dimensional model
EKF	Extended Kalman Filter
UKF	Unscented Kalman Filter
EIS	Electrochemical Impedance Spectroscopy
EM	Empirical Model

In this investigation, the state of charge estimation hotspots in battery management has been discussed. Moreover, the outlooks of the study on state of charge estimation are proposed. The remainder of this work is organized in the following: Section 2 reviews the fundamentals of SOC estimation. Section 3 provides the Measurement-Based Techniques. Section 4 presents Model-Based Techniques. Comparative analysis and discussion are dedicated to section 5, and finally, Section 6 concludes this study. The main abbreviations used throughout the paper are summarized in Table 2.

2 Fundamentals of SOC Estimation

The SOC is a key factor in lithium-ion battery management that denotes the battery's remaining capacity as a fraction of its full capacity, [21]. The SOC at some time t Is mathematically described by the expression, [22]:

$$SOC = \frac{C_P}{C_m} \times 100\% \qquad (1)$$

where C_P is the residual capacity that can be used to run the electronics equipment. C_m is represented as the maximum cell capacity that is physically available and typically defined by the electrochemical properties of a battery.

The battery Non-linear behavior, dependence of the behavior on controlling conditions, and the impact of ageing, due to degradation, all contribute to the challenge of predicting the SOC of lithium-ion batteries accurately, [23]. Due to the complicated electrochemical characteristics of batteries, they do not react linearly to current and voltage changes (i.e., their response is nonlinear), thus, simple models cannot allow accurate estimation of SOC over all considered conditions, [16]. In addition, SOC is strongly influenced by performing conditions including fast charging and discharging, temperature, or intensity of use, further complicating estimation in varied and dynamic environments.

Over the years, numerous approaches have been enhanced for estimating the SOC of lithium-ion batteries, which can be grouped into two main groups [21]: measurement-based and model-based techniques (Figure 1).

The former relies mainly on direct measurements such as coulomb counting, OCV method, or impedance, and have been identified by their flexibility, simplicity, and low computational cost. However, they present an increased sensitivity to measurement errors, drift, and non-ideal operating conditions, [5]. In parallel, model-based approaches incorporate a mathematical representation of battery behavior, whether empirical models or equivalent circuits [24] or even electrochemical models [25]. These methods are frequently used with estimation algorithms like the Kalman filter, the sliding mode observer [26], and H infinity [27] provide a more accurate estimate of the SOC, particularly under dynamic conditions or in the presence of ageing, [28].

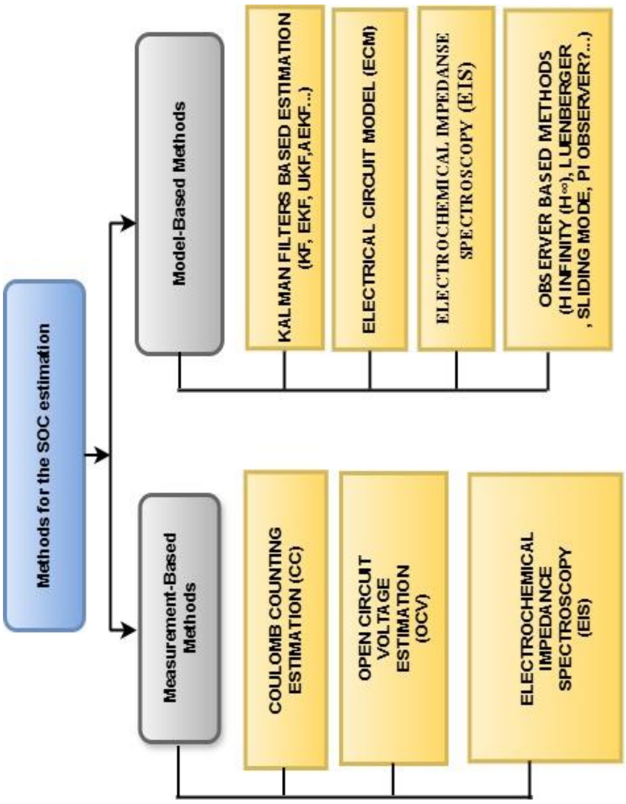

Fig. 1: Classification of the SOC estimation methods

3 Measurement-Based Techniques

Convenient and simple, measurement-based techniques measure SOC by mapping characteristic parameters (such as internal resistance, OCV, impedance spectroscopy, etc.) to SOC, [29].

3.1 Coulomb Counting Method

The Coulomb Counting integral method, which uses current integration to estimate the state of battery of charge, is simpler than the other approaches mentioned above, [30]. Despite its simplicity, this approach seems to have some drawbacks, [31].

$$SOC(t) = SOC\ (t_0) - \int_0^t \frac{\eta}{\sigma_a} i(t)dt \qquad (2)$$

Where σ_a is rated capacity, $SOC\ (t_0)$ represents the initial state of charge, η refers to the coulombic efficiency, i denotes the battery current, and t indicates the operation time.

The open-loop calculation may result in the sensor error, potentially leading to a larger SOC error. Furthermore, variations in capacity and Coulomb efficiency rating caused by aging and temperature can compromise the precision of SOC calculations, [32]. Additionally, the look-up table method determines the initial SOC, therefore any initial error to affect the whole SOC calculation method, [30].

3.2 Estimation Technique Based on Open-Circuit Voltage (OCV)

The OCV represents the battery's terminal voltage after a prolonged rest period under no-load conditions, and it exhibits a nonlinear dependency on the State of Charge (SOC), [24]. In actuality, the OCV-SOC table and OCV are measured to determine the SOC, [29]. This method is easy to apply, yet a prolonged rest period is necessary to make sure the measured voltage approximates the actual OCV. The OCV–SOC curve is refined by incorporating parameters such as temperature variation, material properties, and aging effects, [29].

3.3 Electrochemical Impedance Spectroscopy (EIS)

Impedance and SOC are related. An impedance table is developed by extracting SOC-dependent parameters through nonlinear estimation techniques, following the application of a current signal at a fixed frequency, [30]. Additionally, Nonlinear dynamics of impedance and SOC may result from electric current, external temperature, battery aging, and various other factors, [33]. The influence of temperature, battery degradation, and current ratio on impedance must be incorporated to maintain SOC estimation precision.

A key limitation of measurement-based techniques is the requirement for the battery to rest for an extended period to stabilize its internal electrochemistry, ensuring more accurate parameter measurements, [34]. Also, to increase its reliability, the Coulomb Counting Method is commonly combined with model-based or data-driven techniques, [14]. Furthermore, the accuracy of SOC measurement heavily relies on the precision of the SOC lookup table, [35]. Consequently, this method is unsuitable for real-time, high-precision SOC estimation applications, such as in aviation, aerospace, and the military.

4 Model-Based Techniques

Model-based estimation techniques have become essential in the advanced management of lithium-ion batteries [36]. These approaches seek to mathematically represent the internal behavior of the battery to provide a more reliable and robust estimation of the SOC, especially under dynamic and non-ideal operating conditions. They are distinguished by their ability to incorporate nonlinear effects [37], temperature dependence, aging phenomena, and transient dynamics through the use of explicit models. This section presents the main categories of estimation procedures based on models.

In SOC estimation approaches based on modeling, batteries are typically described using state-space representations. To determine the battery's internal states, a variety of nonlinear estimation algorithms also adaptive filtering techniques are applied. Among the most widely used are the Leuenberger Observer [39], the H-infinity (H∞) Observer [11], the Proportional-Integral (PI) Observer [40], the Sliding Mode Observer [26], also the Kalman Filter [38].

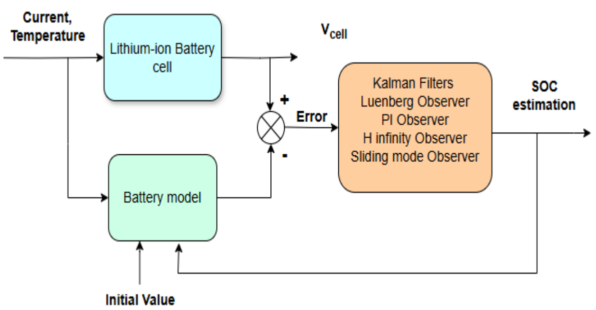

Fig. 2: Flowchart of proposed framework for the proposed model-based SOC estimation technique

Figure 2 illustrates a typical diagram of model-based State Of Charge estimation techniques, [41]. These methodologies can be regarded as hybrid approaches [42], as they integrate the coulomb counting (ampere-hour integration) method with OCV-based lookup tables. In this structure, the SOC serves as a critical link between the integration-based estimation and the OCV reference data. However, any inaccuracy in the SOC estimation derived from ampere-hour integration directly impacts the determination the OCV of the battery, which subsequently increases errors in the prediction of the terminal voltage.

4.1 Equivalent Circuit Models (ECM)

ECM are some of the best widely used on account of their balanced accuracy, complexity, and ease of implementation, [43]. They model the battery with electrical components like capacitors, resistors, and sometimes inductors. The most commonly used models can be roughly summarized as Rint, Thevenin, n-RC (with one or more RC branches), and PNGV model, [44] (Figure 3). These models are particularly suitable for embedded applications and are often combined with estimation algorithms.

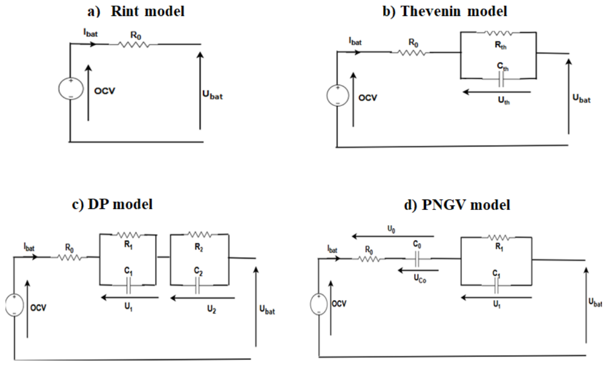

Fig. 3: The schematic of an ECM models of a LIB

4.2 Electrochemical Models (SPM, P2D)

Electrochemical modeling approaches, including the Pseudo-Two-Dimensional model (P2D) also the Single Particle Model (SPM), aim to explain the behavior of the battery using the fundamental equations of thermodynamics and electrochemical kinetics, [45]. These models provide an in-depth understanding of internal mechanisms, including charge transfer, ion transport, and diffusion within electrodes, offering high estimation accuracy (Figure 4).

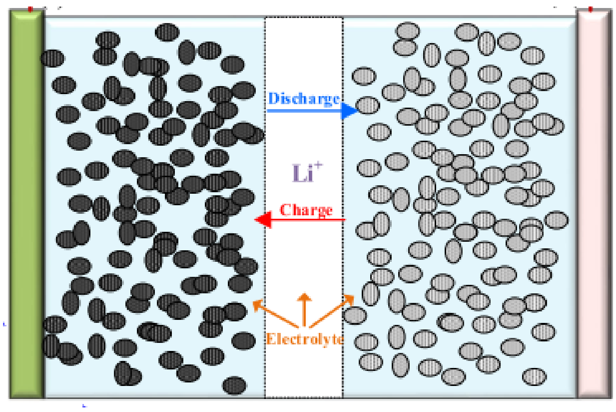

Fig. 4: Structural diagram of a lithium-ion battery's EM, [46]

However, their mathematical complexity and computational cost limit their application to offline simulations or systems with significant computational resources. Recent research focuses on simplifying these models to enhance their suitability for real-time and embedded systems.

4.3 Kalman Filters (EKF, UKF, AKF)

Kalman filters are among the most powerful tools for SOC estimation within a probabilistic framework. The Extended Kalman Filter (EKF) is widely applied in conjunction with ECMs to handle nonlinearities by linearizing the system around the operating point. The Unscented Kalman Filter (UKF), on the other hand, uses sigma-point filtering to achieve better accuracy without requiring linearization. Lastly, Adaptive Kalman Filters dynamically adjust their parameters to track system variations, such as battery aging or abrupt load changes, thereby improving estimation robustness.

4.4 Observer-based Method

State observers are powerful tools used to estimate internal state variables of a system based on externally measurable inputs and outputs. [39], the concept of the state observer enables state feedback control in systems where direct measurement of internal states is either impractical or impossible. This innovation has significantly broadened the scope of modern control systems by offering a practical pathway for real-time state estimation. Over the years, Observer-based estimation techniques including the LO, SMO, PIO, and HIO have become increasingly popular in battery management applications, particularly aimed at estimating lithium-ion batteries' State of Health (SOH) as well as State of Charge (SOC). These methods provide an effective equilibrium of robustness, clarity, also estimation reliability in different operating environments.

5 Comparative Analysis and Analysis

Estimating the State of Charge (SOC) remains a significant challenge in the management of lithium-ion batteries. Given the wide variety of techniques suggested in the research, A systematic comparison is essential to guide both scientists also industry experts in determining the best-suited method for their particular use cases. The main characteristics of the SOC estimation approaches discussed in the previous sections are summarized in Table 3 (Appendix).

The main difficulty in SOC estimation for LIBs is achieving high accuracy and robustness in the algorithm with minimal computational demands, allowing integration into low-cost BMS platforms. For embedded applications, ECM-based models coupled with EKF or UKF are the most widely adopted, due to their effective balance between algorithmic accuracy and computational demand, [47]. The aim is to identify an efficient SOC estimation algorithm that achieves a balance between precision and computational cost.

Usually, the SOC error is generated from a variety of publications, such as current also voltage, an inaccurate battery model, initial SOC, and inaccurate parameter selection during optimization, [49]. Therefore, it is necessary to develop a technique with low SOC error sources. Finally, the effects of battery ageing, which cause a gradual decrease in capacity, an increase in internal impedance, and changes in electrochemical reactions, affect the accuracy of SOC estimation techniques, [50].

To overcome these challenges, advanced modeling and estimation methods need to be developed to take account of this non-linearity, aging effects. Therefore, there is a growing interest in AI-based estimation techniques (such as neural network algorithms and deep learning) to enhance real-time estimation and robustness under complex operating conditions.

6 Conclusion

This paper provides a comprehensive review of the current literature on State of Charge (SOC) estimation for batteries, with particular attention to applications in electric vehicles (EVs). Both measurement-based and model-based SOC estimation techniques are examined and synthesized. The discussion includes various approaches to SOC estimation considering aspects such as remaining capacity and battery lifespan. Furthermore, recommendations for future research directions to enhance the accuracy and practicality of SOC estimation for lithium-ion batteries (LIBs) are proposed. It is noted that significant errors in battery modeling and measurement instrumentation can critically affect SOC estimation accuracy. Lastly, the paper addresses the existing challenges and future perspectives in SOC estimation research, emphasizing that the insights and standards highlighted may guide the advancement and deployment of effective Battery Management Systems (BMS).

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authorS wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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APPENDIX

Table 3. Comparative analysis of SOC estimation techniques

Technique	Accuracy	Complexity	Computational Cost	References
Coulomb Counting	Low	Very Low	Very Low	[30]
OCV-Based Estimation	Medium	Low	Low	[24]
ECM + EKF	High	Medium	Medium	[38], [47]
SPM (Single Particle Model)	Very High	Very High	Very High	[48]
Adaptive Kalman Filter	High	High	Medium	[38]
Luenberger Observer	Medium	Medium	Low	[39]
Sliding Mode Observer	High	Medium–High	Medium	[26]

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- Itto El-kabassi: Conceptualisation, methodology, software, validation and writing.
- Abdelamalek Ouannou: Methodology and software.
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