A Systematic Review of Electrochemical Model-based Lithium-ion Battery State Estimation in Battery Management Systems

Feng Guo [a,b,*], Luis D. Couto [a,b], Grietus Mulder[a,b], Khiem Trad [a,b], Guangdi Hu [c], Odile Capron [a,b], Keivan Haghverdi [a,b]

[a] VITO, Boeretang 200, 2400 Mol, Belgium
[b] EnergyVille, Thor Park 8310, 3600 Genk, Belgium
[c] School of Naval Architecture and Ocean Engineering, Guangzhou Maritime University, 510725 Guangzhou, China
* Corresponding author: Feng Guo, feng.guo@vito.be

Abstract

This study presents a systematic review of electrochemical model-based battery state estimation methods. A search was conducted in Web of Science, Scopus, and IEEE Explore databases, resulting in the selection of 102 relevant research articles. These articles were carefully analyzed to summarize research trends, model selection, and estimation methods. Research trends cover publication years, journals, keywords. In terms of model selection, the review examines scalability, programming languages & software, battery materials, the choice of models, model simplification techniques, and parameter identification processes. The estimation methods are assessed based on the specific battery states and the algorithms employed for state estimation. The results indicate that while research in this area has been growing, it primarily focuses on individual cells, with limited attention paid to battery modules and packs. There is a noticeable lack of standardization in model simplification and parameter identification processes. Most studies concentrate on a single state estimation, with state of charge being mostly investigated, followed by state of health and state of temperature. Future research should address state estimation for modules and packs, parameter identification, model simplification, joint multi-state estimation, and better utilization of internal battery information for improving battery performance and safety.

Keywords: Electrochemical models, Lithium-ion batteries, Battery state estimation, Battery management systems, State of charge, Systematic review

Abbreviations

AEM	Average-electrode model
BMS	Battery management systems
CKF	Cubature Kalman filter
DFN	Doyle-Fuller-Newman
ECMs	Equivalent circuit models
EKF	Extended Kalman filter
ESPM	Extended Single Particle Model
FDM	Finite difference method
FEM	Finite element method
FVM	Finite volume method
GA	Genetic algorithm
KF	Kalman filter
LCO	Lithium Cobalt Oxide
LFP	Lithium Iron Phosphate
LMO	Lithium Manganese Oxide
MCMB	Mesocarbon Microbeads

MHE	Moving horizon estimation
MPM	Many-Particle Model
NCA	Lithium Nickel Cobalt Aluminum Oxide
NMC	Lithium Nickel Manganese Cobalt Oxide
P2D	Pseudo-Two-Dimensional
PDE	Partial differential equations
PF	Particle filter
PI	Proportional-integral
PID	Proportional-integral-derivative
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PSO	Particle swarm optimization
RQ	Research questions
SEIKF	Singular evolutive interpolated Kalman filter
SMO-ERL	Sliding-mode observers with an exponential reaching law
SMO-URL	Sliding-mode observers with a uniform reaching law
SOB	State Of Balance
SOC	State Of Charge
SOE	State Of Energy
SOF	State Of Function
SOH	State Of Health
SOP	State Of Power
SOT	State Of Temperature
SOX	State Of X
SPM	Single Particle Model
SPMe	Single Particle Model with Electrolyte
UKF	Unscented Kalman filter

1 Introduction

As the notion of carbon neutrality increasingly gains traction as a developmental objective among nations worldwide, clean energy and energy storage technologies have witnessed remarkable progress in recent years [1]. Lithium-ion batteries have emerged as a fundamental energy storage solution across various applications, encompassing electric vehicles, portable electronics, and grid energy storage. Owing to their high energy density, long cycle life, and comparatively minimal self-discharge rates, they represent the preferred option for numerous applications [2]. To preserve optimal performance, safety, and longevity, battery management systems (BMS) are utilized to supervise and regulate battery operations. Consequently, the advancement of secure and dependable BMS has become a focal point of research, and the establishment of such systems is of paramount importance [3, 4].

A main component of BMS involves estimating various battery states, including State Of Charge (SOC), State Of Energy (SOE), State Of Health (SOH), State Of Power (SOP), State Of Temperature (SOT), State Of Balance (SOB), State Of Function (SOF), among others. These battery states can be collectively referred to as State of X (SOX) [4]. The SOC reflects the remaining capacity of the battery and is the most central state for battery management and control [4]. SOE is similar to SOC, except that it is defined in terms of residual energy [4]. The SOH reflects the health state of the battery. Regarding SOH, there are two definitions, one based on the decay of battery capacity, and one based on the increase of internal resistance [4]. The SOT of a battery is a crucial factor that significantly influences its safety. Battery temperature can typically be categorized into three types: battery surface temperature, battery core temperature, and battery bulk temperature. Battery core temperature is usually the maximum temperature inside the battery, and battery bulk temperature refers to the average temperature inside the battery [4]. SOP is an important state that affects the safety and performance of a battery, and SOP reflects how much maximum power a battery can output at a given moment [5]. The SOB is an emerging concept in battery research, focusing on the assessment and regulation of uniformity within a battery system [6]. SOF is an indicator used to determine whether a battery system can meet the requirements of a specific application [4]. Accurately determining these states is crucial for ensuring battery safety and optimizing both battery life and performance. The aforementioned battery states are often not directly measurable and necessitate estimation based on battery voltage, current, temperature, and additional information gathered through sensors and historical operating data. Lithium-ion batteries function as chemical energy storage systems. Their internal reaction mechanisms are inherently complex and nonlinear. This complexity makes the accurate description and estimation of various battery states particularly challenging [7].

Battery state estimation techniques primarily encompass direct measurement methods [8], machine learning methods [9], and model-based methods [10-13]. The direct measurement method like Coulomb counting has the advantage of simple logic and does not require a large amount of computation, but often results in large errors due to initial values and measurement noise. Machine learning approaches adeptly address nonlinear problems and are well-suited for battery state estimation applications. Nevertheless, machine learning techniques function as black boxes, precluding an understanding of the internal logic, and this makes it very difficult to perform fault diagnosis. At the same time, bottlenecks in computation capacity and data storage limit the application of machine learning methods. Model-based approaches typically exhibit commendable estimation accuracy and robustness when applied in the BMS. However, the accuracy of model-based techniques heavily relies on the accuracy of the battery model [11]. Designing a model-based battery state estimation method based on a highly accurate battery model could yield superior estimation accuracy and enhance BMS performance.

The most common model-based methods used to estimate battery states in BMS rely on equivalent circuit models (ECMs). These models are characterized by their minimal computational complexity and therefore can be accommodated by BMS processors [14]. However, ECMs are phenomenological models, hence they cannot provide an accurate estimation of certain battery states, such as SOH, owing to an insufficient understanding of the influence on future behaviors, aging, and safety levels. Consequently, this can lead to the design of overly conservative estimation algorithms, which cannot fully exploit the existing potential of the battery. Additionally, the electrochemical model offers a greater advantage over the ECMs by providing more detailed information about the battery internals. This is more beneficial for enhancing BMS performance and ensuring battery safety. Physics-based models rooted in fundamental electrochemical principles offer notable advantages. One prominent example is the Pseudo-Two-Dimensional (P2D) model, also referred to as the Doyle-Fuller-Newman (DFN) model or Newman model [15]. It describes the battery dynamics with a set of coupled partial differential equations (PDE). Employing the electrochemical battery model facilitates a more comprehensive understanding of the battery's internal information. Nonetheless, employing electrochemical models for the development of battery management systems encounters a multitude of obstacles, including the necessity for simplification of electrochemical models owing to the computational capacity constraints of current BMS processor. Furthermore, designing battery state estimation algorithms based on intricate electrochemical models presents a formidable challenge. Consequently, conducting a review of the research advancements in this domain is of paramount importance.

The flowchart of battery state estimation based on electrochemical models is presented in Fig. 1. The process commences with the modeling, which includes modeling for a single cell or a battery pack, the specific battery materials, the choice of software or programming language, and the selection of the precise electrochemical model. The second step entails model simplification, specifically involving the simplification of the electrochemical model and the identification of model parameters. The third step comprises the state estimation using the electrochemical model, including the choice of states to estimate and the selection of the specific estimation method. Finally, the validation.

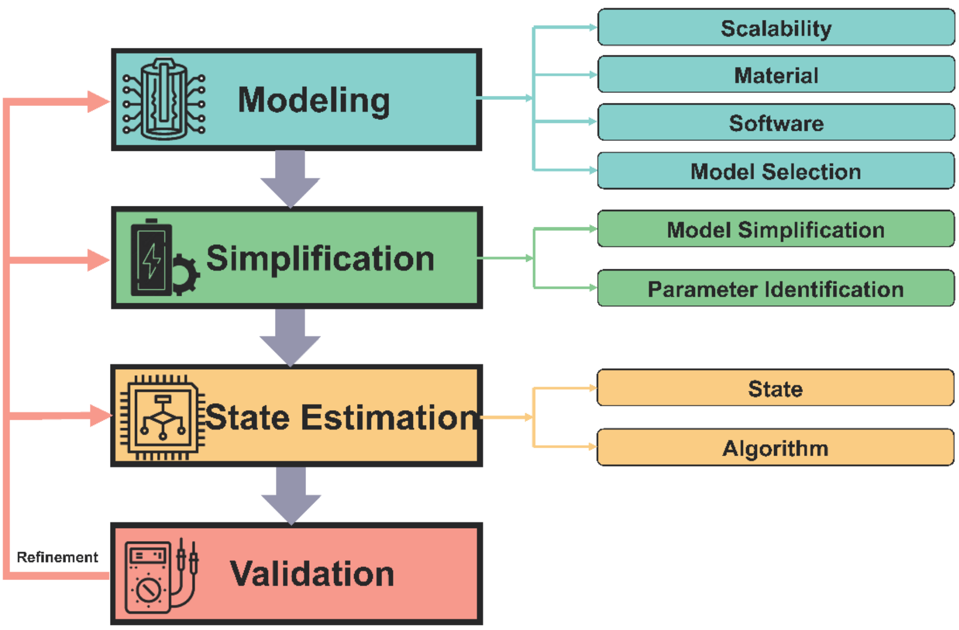

Fig. 1. Battery state estimation based on electrochemical models.

Currently, there are a number of published literature reviews in this field. Park et al. [16] conducted an extensive analysis of contemporary approaches to battery state estimation methods through a literature review. Nevertheless, a significant proportion of the articles examined primarily focus on the ECMs methodology. Comprehensive reviews of battery modeling and state estimation approaches are presented by Wang et al. [4] and Hu et al. [17], although their assessments only cursorily address the electrochemical model and fail to offer an in-depth exploration of battery state estimation based in the electrochemical model. Although Planella et al. [18] provide a detailed outline of the electrochemical battery models, their investigation does not include battery state estimation techniques. As a result, a systematic review centering on state estimation based on electrochemical models remains absent.

The systematic literature review is a novel approach to review literature [19]. Traditional literature reviews tend to be limited by the author's understanding and bias in retrieving papers.

Unlike traditional literature review methods, it provides a systematic method for literature retrieval and writing process. This approach significantly reduces research biases. Additionally, it ensures the presentation of results is both comprehensive and transparent. In this paper, we followed the process in Fig. 1 to present a systematic literature review that encapsulates battery state estimation methods based on electrochemical models, equipping researchers with valuable references and insights for future studies. The specific research questions (RQ) to be addressed are as follows:

RQ1: What were the research trends?

RQ2: What electrochemical battery models were used for battery state estimation?

RQ3: Which battery state was selected for estimation and what algorithms were used?

2 Method

This section will refer to the PRISMA method [19] for systematic literature reviews. It specifically includes: literature search strategy, literature selection criteria, and data extraction process.

2.1 Literature search strategy

This study searched a total of three high-quality databases, namely: Web of Science, Scopus and IEEE Explore. The following Boolean logic were searched: (“battery” OR “batteries”) AND (“electrochemical” OR “physic*”) AND (“state estimation” OR “state of charge” OR SOC OR “state of energy” OR SOE OR “state of health” OR SOH OR “state of power” OR SOP OR “state of temperature” OR SOT OR “state of balance” OR SOB OR “state of function” OR SOF). The search keywords are divided into three main levels: battery, electrochemical model, and battery state. The search keywords are searched in the title, keywords and abstract of the article. To reduce the work of screening papers in next steps, during the search process, filters are applied to select only journal articles, English-language articles, and to exclude literature reviews for a more focused and efficient search. The retrieval time range is up to December 31, 2023.

2.2 Selection criteria

The papers were screened using the PRISMA method. The specific process is shown in Fig. 2. In the first step, the papers were searched in the three databases using the method introduced in Section 2.1, and a total of 6597 articles (Web of Science:2715, Scopus:2819, IEEE Explore:1063) were retrieved. The first step was performed to de-duplicate the papers, leaving 3455 articles remaining. The second part is to screen the articles according to their titles and abstracts, and a total of 2375 articles are screened out in this step. The third step is to check whether the full text of the article is available. This step is all available in full text, so no articles are excluded. The fourth step is to read the full text of the article and make a detailed screening according to the screening criteria, which are shown in Table 1. It is worth noting that, although the search filters were set to exclude review articles and non-English articles, some such articles were still retrieved. This is due to errors in the database system's labeling. After the fourth step of screening, all articles that meet the requirements can be ultimately obtained. Finally, 102 articles [20-121] were selected to meet the requirements (see Appendix 1).

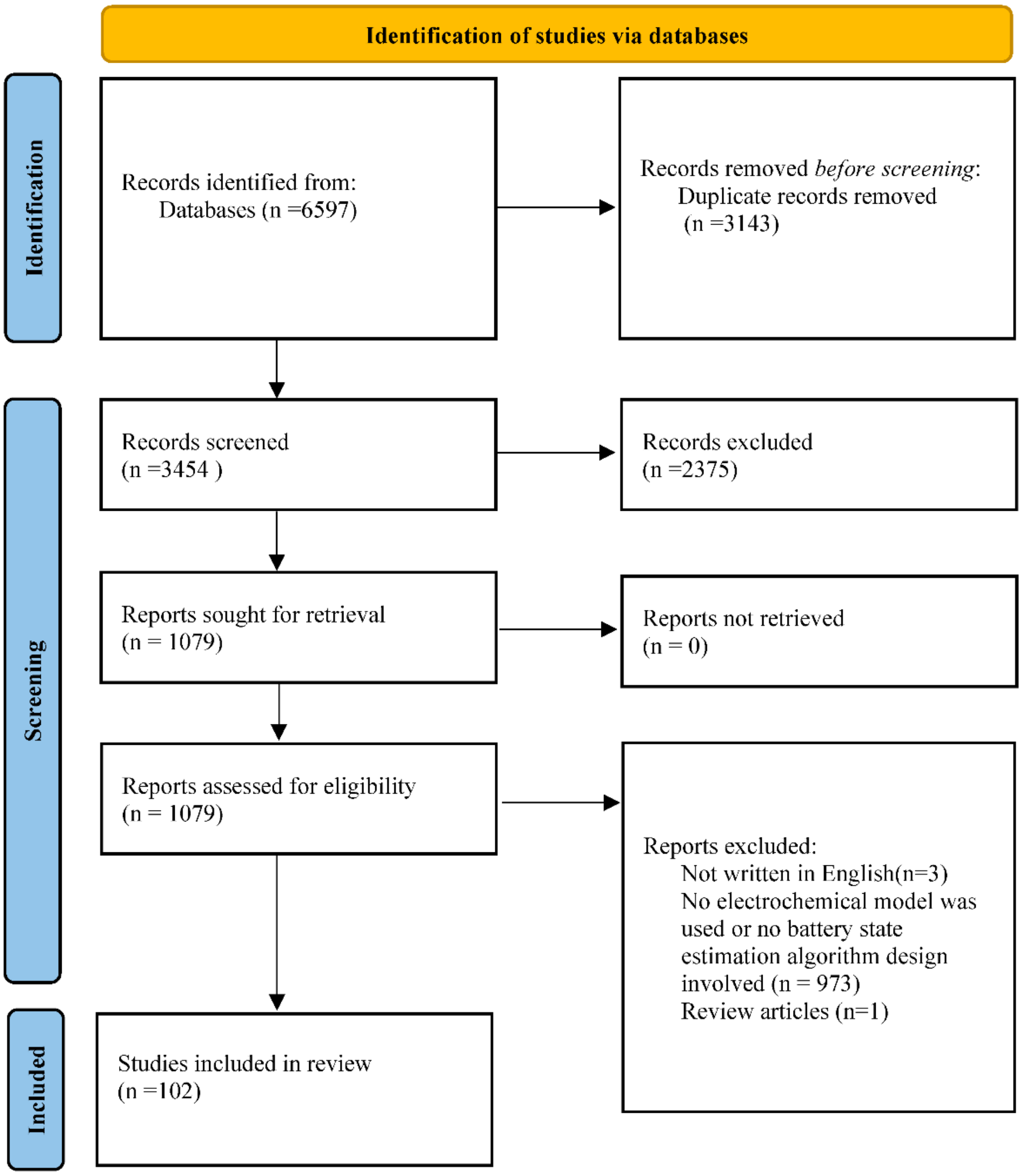

Fig. 2. Article Screening Results.

Table 1 Exclusion and Inclusion Criteria.

Inclusion Criteria	Exclusion Criteria
Lithium-ion battery	Solid-state or other types of batteries
Using P2D and its derivative battery models	Not using P2D and its derivative battery models
Battery state estimation algorithm design using electrochemical model	No electrochemical model was used, or no battery state estimation algorithm design involved
Lithium-ion battery	Other types of batteries
Journal Papers	Non-journal papers
Empirical study	Literature Review
Written in English	Written in other languages

2.3 Data extraction process

The data selection process was guided by three research questions outlined in the Introduction section. Data extraction will be carried out from Table 2, i.e.

1. Extraction centered on research trends: including trends in number of papers published annually, distribution of published papers across journals, distribution of keywords in papers.
2. Extraction focused on electrochemical models: battery formation methods, utilized programming languages and software, types of battery materials employed, electrochemical model utilized, model simplification method employed, and method used for identifying battery model parameters.
3. Extraction pertained to state estimation methods: which the battery states are estimated, and the techniques used to estimate them.

Table 2 Data extraction.

Category	Item	Description
RQ1: Research trends	Years	Number of papers published annually
	Journals	Distribution of published papers across journals
	Keywords	Distribution of keywords in papers
RQ2: Electrochemical models	Scalability	Battery formation methods for single cells, modules, or packs
	Programming Language & Software	Utilized programming languages and software
	Materials	Types of battery materials employed
	Model Selection	Electrochemical model utilized
	Model Simplification	Model simplification method employed
	Parameter Identification	Method used for identifying battery model parameters
RQ3: State estimation	State	Battery states estimated
	Algorithm	Estimation methods used

3 Results

Following the data extraction method introduced in Section 2.3, the specific results are presented in detail in this section.

3.1 RQ1: What were the research trends?

This subsection answers the first research question and delves into the research trends in electrochemical model-based battery state estimation. Specifically, it examines the publication year, the academic journals, and the specific keywords utilized within these screened articles.

3.1.1 Year

Fig. 3 illustrates the annual publication trend of research articles focusing on battery state estimation using electrochemical models. Commencing in 2006 with the paper of Santhanagopalan et al. [74] , a steady growth in the number of such studies is evident. Notably, there has been a marked upsurge in pertinent publications since 2020, signifying an escalating interest among researchers within this domain. Especially in 2023, the number of publications called a greater increase in the previous years, indicating that the battery state estimation based on electrochemical model has attracted more and more researchers' attention.

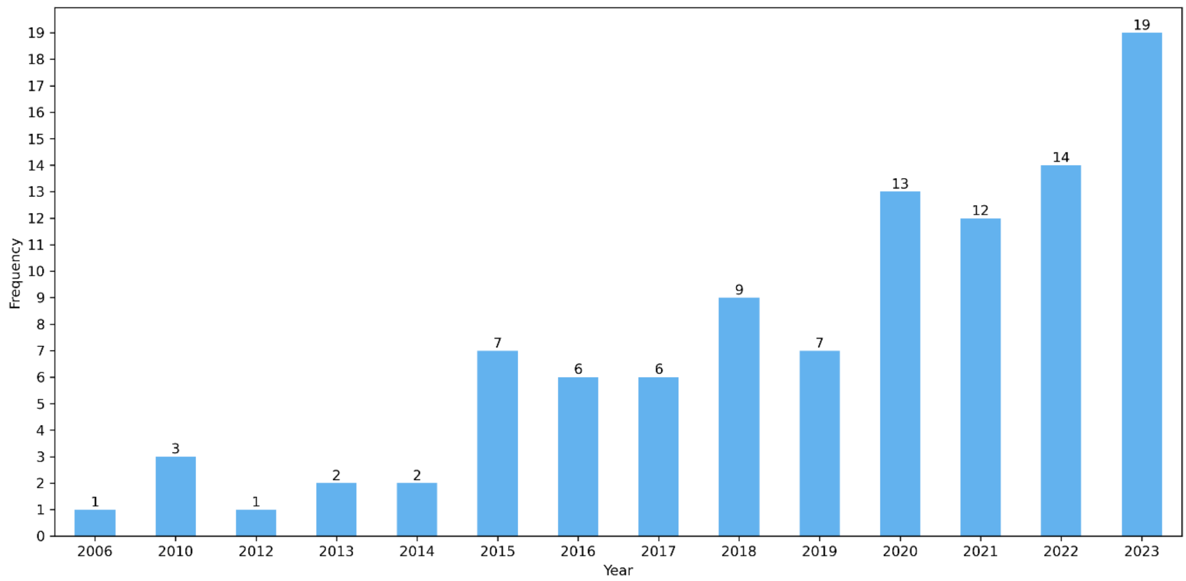

Fig. 3. Annual paper publication trends.

3.1.2 Journals

Fig. 4 demonstrates the distribution trend of published articles in this field. Journals with less than 2 publications are classified as Others. Research in this domain is predominantly featured in high-impact factor journals specializing in electrochemistry, control, and energy. This can be attributed to the interdisciplinary nature of the subject, necessitating an amalgamation of expertise in electrochemistry, control, and energy applications. The leading three journals contributing to this area of research include Journal of Power Sources (17), IEEE Transactions on Control Systems Technology (14), and Journal of Energy Storage(10).

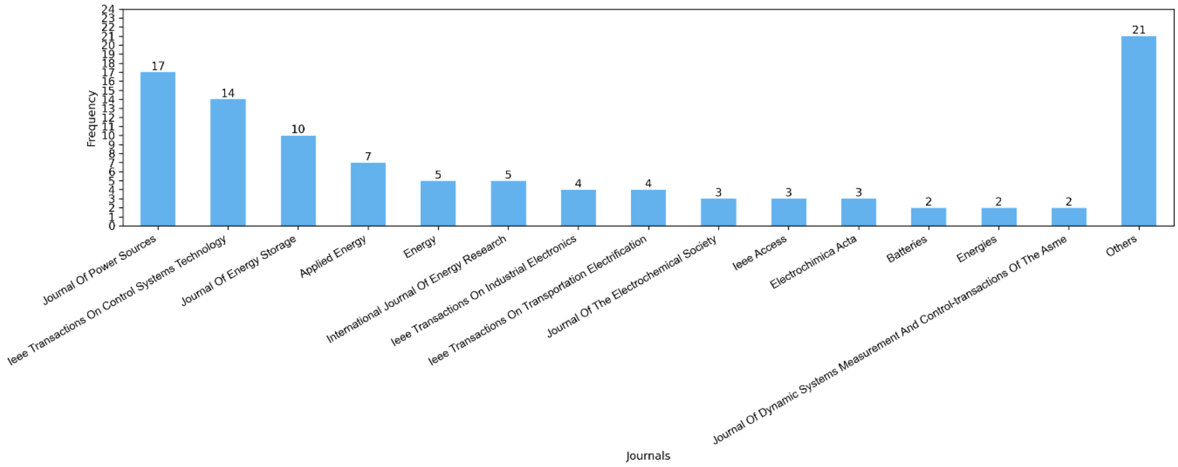

Fig. 4. Trends in journal publication.

3.1.3 Keywords

In this subsection, a keyword analysis of the 102 selected articles is conducted, noting that 8 (ID1, ID12, ID27,ID30, ID41, ID48, ID49, ID72) of these articles did not provide keywords. Therefore, a total of 94 articles that provided keywords are analyzed. A word cloud figure is employed to illustrate the frequency of the keywords. Fig.5 exhibits the results, with larger font sizes signifying higher frequencies of the corresponding keywords. This visualization offers a rapid understanding of the primary themes and concepts underpinning the research.

"Lithium-ion battery" and "Lithium-ion batteries" are the most frequently employed keywords, while "Electrochemical model" is also frequently mentioned. "State of charge", "State of charge estimation" and "SOC estimation" are the most commonly cited battery state keywords, followed by "State of health". The "Pseudo-two-dimensional model" and the "Single particle model" are the two most prevalent electrochemical models. "Extended Kalman filter" and "Kalman filter" are the most widely used methods for battery state estimation. The multiple mentions of "Battery management system" and "Battery management systems" indicate researchers' interest in the application of battery state estimation methods within battery management systems. "Parameter identification" also appears with high frequency, highlighting its importance in model-based battery state estimation. The accuracy of the battery model parameters greatly influences the final estimation results, underscoring the significance of identifying the parameters of the battery model.

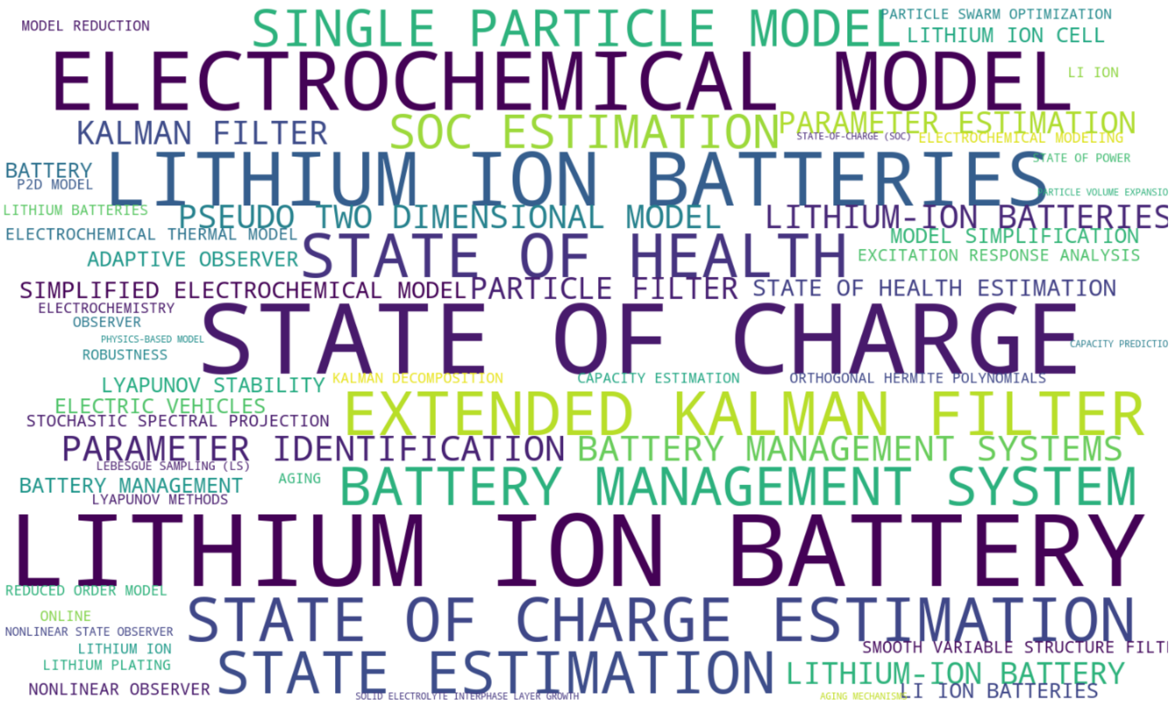

Fig. 5. Word cloud for keywords.

3.2 RQ2: What electrochemical battery models were used for battery state estimation?

This subsection answers the second research question. Specifically, scalability, programming language and software, battery material, model selection, model simplification and parameter identification.

3.2.1 Scalability

Scalability, in the context of the use of battery, typically encompasses three levels [122]: cell, module, and pack. A cell is the fundamental unit, which is connected in series or parallel configurations to create a module. Subsequently, multiple modules are interconnected in series or parallel arrangements to form a comprehensive battery pack. This hierarchical structure exemplifies the scalability concept in battery formation. The statistical results on the battery state estimation for each battery formation level are shown in Table 3.

Of the 102 articles analyzed, all focused on cell-level state estimation algorithms. A mere 4 studies extended the cell-level battery state estimation to encompass both module and pack levels. Article ID 37 investigates SOC estimation for a battery pack comprising 6 single cells connected in series. Similarly, article ID 73 explores SOC estimation for a battery pack containing 4 single cells connected in series. And article ID 53 examines SOC and SOT for a battery pack with 12 single cells connected in series. ID87 uses electrochemical model to study the battery SOC and SOT estimation for the case where the cells are connected in series or in parallel. Most research focuses on cell-level because modeling and state estimation for single cell is relatively straightforward. The models are easier to construct, and simulations and experiments are simpler to conduct. In contrast, battery packs and modules consist of multiple cells connected in series or parallel, leading to more complex electrical and thermal coupling effects, which make state estimation significantly more challenging. These findings suggest that most of the current research in this domain is centered on cell-level state estimation, with minimal investigation into module-level and pack-level state estimation.

Table 3 Battery formation results.

	Number	Article ID
Cell	102	All Articles
Module or pack	4	ID37, ID53, ID73, ID87

3.2.2 Programming language and software

In this study, the usage of programming languages and software in the analyzed papers is quantified. The articles mentioned the programming language or software utilized, with the results presented in Table 4.

It is evident that MATLAB (57) is the most frequently employed software, primarily because it is highly suited for control algorithm development and facilitates the design of battery state estimation algorithms. Moreover, MATLAB offers a comprehensive library of functions that streamline battery modeling and parameter identification.

COMSOL Multiphysics (19) is the second most used software, with its battery simulation results typically serving as benchmarks or points of comparison to verify the accuracy of proposed models or battery state estimation methods. LabVIEW (2) is generally utilized in hardware-in-the-loop testing, while Fortran (2), C++ (1), and C (1) are employed for battery simulation to reduce the calculation time.

Given the complexity of electrochemical modeling, some open-source battery models can be leveraged as a foundation for battery state estimation research. Examples of such models and their associated programming languages include Slide (C++) [123], DUALFOIL (Fortran) [124], fastDFN (MATLAB) [125], LIONSIMBA (MATLAB) [126], and PyBaMM (Python) [127].

Table 4 Programming language and software

Programming language and software	Number	Article ID
MATLAB	57	ID1, ID3-ID7, ID9-ID11, ID13, ID14, ID16-19, ID21-23, ID25, ID27, ID29, ID30, ID31, ID33, ID40, ID41, ID43, ID46, ID51, ID53, ID57, ID59, ID60, ID62, ID63, ID65-71, ID73, ID74, ID83-90, ID92, ID97-100
COMSOL	19	ID7, ID11, ID22, ID23, ID25, ID28, ID31, ID39, ID43, ID44, ID53, ID56, ID59, ID66, ID68, ID71, ID85, ID90, ID99
LabVIEW	3	ID13, ID57, ID73
Fortran	2	ID12, ID71
C++	1	ID30
C	1	ID30

3.2.3 Materials

The active materials in the battery define the voltage boundaries and the shape of the cell voltage curve. Since mostly carbon based materials are used as negative electrode the battery types are named after the cathode material [128].

Of the 103 articles analyzed, 87 articles mention the battery materials used in their modeling. Currently, the most researched battery types in this field are Lithium Cobalt Oxide (LCO) (25), Lithium Iron Phosphate (LFP) (25), and Lithium Nickel Manganese Cobalt Oxide (NMC) (24). Lithium Manganese Oxide (LMO) (9) and Lithium Nickel Cobalt Aluminum Oxide (NCA) (6) are also prevalent lithium battery cathode materials. LMO-NMC signifies a combination of LMO and NMC materials. All the papers report graphite or Mesocarbon Microbeads (MCMB) as the negative electrode materials. Table 5 provides a list of the corresponding papers for each positive electrode material for reference. Since many of the parameters in electrochemical modeling are related to their materials, most of the papers in Table 5 list or cite the model parameters used and can be used as a reference for the reader.

Table 5 Positive electrode materials

Positive electrode materials	Number	Article ID
LCO	25	ID5, ID14, ID21, ID29, ID35, ID36, ID40, ID43, ID46, ID52, ID55, ID60, ID61, ID63, ID67, ID69-73, ID78, ID87, ID94, ID98, ID102
LFP	25	ID4, ID7-9, ID18, ID28, ID31, ID32, ID37, ID39, ID42, ID48, ID49, ID59, ID65, ID74, ID75, ID79, ID81,ID86, ID88, ID89, ID96, ID100, ID101
NMC	24	ID1, ID11, ID13, ID17, ID19, ID23, ID25, ID30, ID33, ID34, ID39, ID53, ID54, ID57, ID58, ID77, ID80, ID82, ID84, ID85, ID89, ID93, ID97, ID99
LMO	9	ID2, ID6, ID15, ID22, ID38, ID44, ID53, ID56, ID66
NCA	6	ID39, ID53, ID64, ID83, ID89, ID91
LMO-NMC	3	ID26, ID62, ID76

3.2.4 Model selection

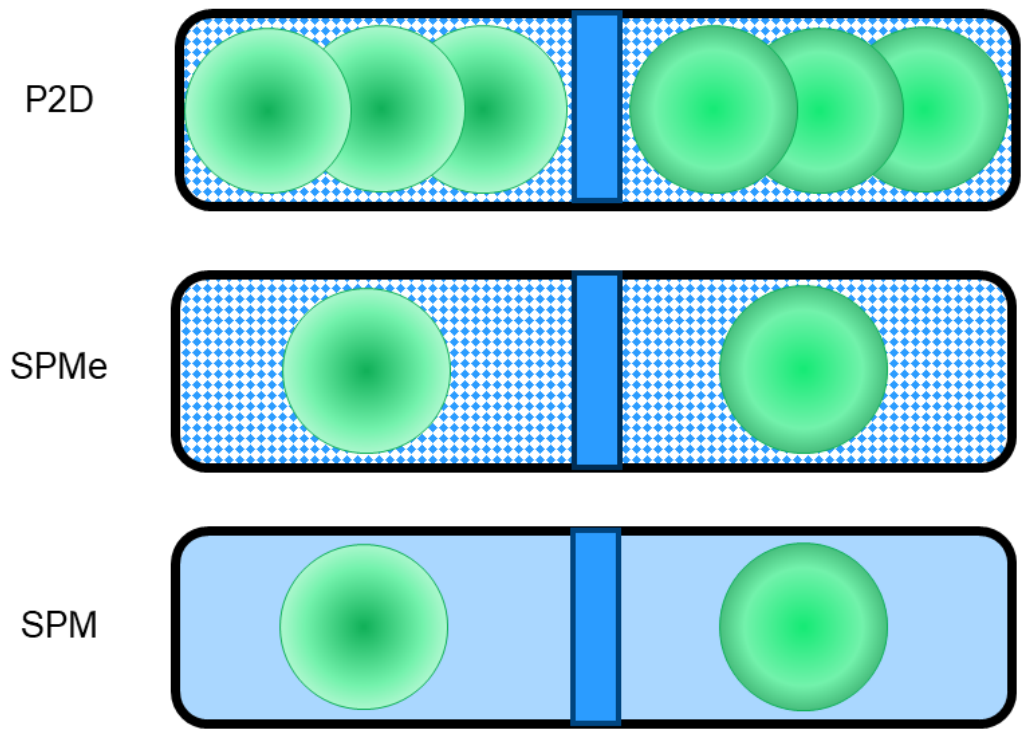

Fig. 6. Electrochemical Model.

This subsection provides an overview of the battery models employed in the screened papers. Based on our screened literature, electrochemical battery models can be broadly categorized into three main types as shown in Fig. 6. The first category is the P2D model, which serves as the foundational framework for all other electrochemical models. The P2D model provides a comprehensive description. However, when this model is simplified by reducing the multiple particles to a single representative particle, it is referred to as the Single Particle Model with electrolyte (SPMe). Further simplification occurs in the Single Particle Model (SPM), where the concentration diffusion process in the electrolyte is disregarded, and an averaged concentration value is used instead. These hierarchical models—P2D, SPMe, and SPM—reflect varying levels of complexity and approximation, offering different trade-offs between computational efficiency and accuracy depending on the specific application requirements. The results are presented in Table 6. Notably, all battery models are simplifications based on the P2D model. If that are not specifically named in the papers, are then categorized under the P2D category.

Out of the total, 47 articles utilized SPM, which offer significant simplification, enabling the design of battery state estimation algorithms with reduced computational effort. The SPM [129] is a simplified model, positing that a lithium-ion battery consists of a single representative particle for each electrode (cathode and anode), neglecting the spatial distribution of potential and concentration within the electrodes. The average-electrode model (AEM) (ID3, ID10, ID32, ID41, ID42), a type of the SPM model that replaces both lithium-ion concentration and current density with average values. Instead of a single representative particle, the AEM considers the entire electrode's average behavior. Consequently, the AEM captures the spatial distribution of lithium-ion concentration and potential within the electrodes, offering a better understanding of battery performance and efficiency. As a result of this simplification, the SPM model is less accurate during high-current charging and discharging. To address this, SPMe has been proposed.

Twenty-five papers have utilized the SPMe. It is worth noting that different studies may use varying terminologies, such as Extended Single Particle Model (ESPM) (D14, ID25, ID33, ID54, ID58, ID59, ID62, ID79, ID80, ID84, ID85). However, these models are fundamentally based on the SPM with additional physical equations to describe the electrolyte dynamics [130]. Meanwhile, ID74 proposes a battery model considering the electrical double layer effect and performs battery state estimation using this model. ID81 employed Many-Particle Model (MPM). MPM differs from SPMe in that there is not just one particle in the electrode, but multiple particles.

Thirty articles employed the P2D model as a basis for simplification when designing battery state estimation algorithms. Due to the varying simplifications used in most papers, and the lack of specific model names, they are collectively classified as P2D models. Some authors named their P2D model as 1-dimensional models. ID24 employs a model proposed by Subramanian et al. [131], simplifying it through a constant electrolyte concentration and an approximate solution to the diffusion equation. ID70 applies the model proposed by Forman et al. [132].

The aforementioned results outline the battery models used in the analyzed papers. However, these models often require further simplification before being applied to battery state estimation. The following subsection examines the model simplification methods employed in these articles.

Table 6 Battery model types

Model	Number	Article ID
SPM	47	ID1-5, ID9, ID10, ID12, ID15, ID17, ID18, ID20, ID28, ID29, ID32, ID35-38, ID40-42, ID48-ID52, ID55, ID57, ID65-68, ID70, ID72, ID73, ID76-ID78, ID82, ID87, ID88,ID94-96, ID98, ID100
SPMe	25	ID8, ID13, D14, ID21, ID22, ID25, ID26, ID30, ID33, ID44, ID54, ID56, ID58, ID59, ID62, ID74, ID79, ID80, ID81, ID84, ID85, ID91, ID93, ID101, ID102
P2D	30	ID6, ID7, ID11, ID16, ID19, ID23, ID24, ID27, ID31, ID34, ID39, ID43, ID45-47, ID53, ID60, ID61, ID63, ID64, ID69, ID71, ID75, ID83, ID86, ID89, ID90, ID92, ID97, ID99

3.2.5 Model simplification

Electrochemical models encompass numerous PDE, which present considerable complexity in solving and are unsuitable for real-time computations. Consequently, battery model simplification is typically necessary for battery state estimation. In particular, it is important to note that the accuracy of a simplified model will necessarily be reduced. Model simplification is a matter of finding a balance between model accuracy and model complexity. As illustrated in the selected articles, various methods exist for battery model simplification, namely: simplification of physical processes, finite method and function approximation, spectral method, transfer function, projection method and Artificial intelligence (AI) method. Since many of the screened articles directly use other researchers proposed models or do not mention the specific process of model simplification, this section only summarizes articles that explicitly propose model simplification methods. The results are displayed in Table 7.

Table 7 Simplification approach

Method	Number	Article ID
Finite method	27	FDM: ID3, ID9, ID10, ID15, ID16, ID17, ID20, ID27, ID30, ID35, ID38, ID41, ID46, ID49, ID51, ID52, ID54, ID60, ID65, ID77, ID81, ID95 FVM: ID71, ID97 FEM: ID50, ID90, ID99
Function approximation	37	Parabolic approximation : ID4, ID5, ID14, ID18, ID21, ID22, ID24, ID32-34, ID36, ID37, ID40, ID42, ID47, ID53, ID55, ID64, ID66-69, ID71, ID72-75, ID78, ID79, ID80, ID84, ID88, ID89, ID93, ID94, ID96, ID101
Spectral method	6	Chebyshev polynomial: ID6, ID43, ID59, ID71, ID86, ID99
Transfer function	22	Padé approximation: ID1, ID2, ID12, D13, ID19, ID25, ID26, ID29, ID44, ID45, ID52, ID56, ID57, ID70, ID76, ID85, ID91, ID92, ID100 Discrete realization algorithm: ID31, ID52 Fractional-order functions: ID82
Projection method	4	ID7, ID23, ID52, ID83
AI method	1	ID102

(1) Simplification of physical processes

Simplification of physical processes means directly ignoring some reaction processes considered as unimportant. For instance, the SPM reduces the electrode to a particle, while the AEM employs the average value to represent the lithium-ion concentration and current density. Most articles adopt methods that simplify physical processes, most frequently by converting a distribution to a constant or average value. This approach effectively streamlines the model and minimizes computational effort while maintaining model accuracy within certain boundaries like low C-rate. In ID11 and ID97, the lithium diffusion in the solid phase is simplified by equivalent circuit model. This simplifies the lithium diffusion physical processes within the cell, thus making the model simpler.

The approach of simplifying physical processes is very convenient to implement and allows for the simplification of specific parts as needed, striking a good balance between model complexity and accuracy. Unlike the methods discussed later, which focus on how to solve PDE and enhance the speed and accuracy of their solutions. Simplification of physical processes can be combined with the methods introduced later to further simplify the model.

(2) Finite method

Finite method refers to the technique of converting a continuous spatial domain into a finite set of discrete points or elements, which is crucial for solving PDE that characterize a wide range of physical and engineering phenomena. The finite difference method (FDM) and the finite volume method (FVM) are frequently employed. The finite element method (FEM) is another well-known approach. The advantage of finite method is that it can be easily applied, and it generally used as benchmark methods to solve PDE. But the accuracy of the finite method is related to how many nodes it uses for computation, the more nodes you have the more accurate results you can get, but it also means longer computation time and larger memory requirements.

For finite method, there are also methods to reduce the amount of computation while ensuring high accuracy. Simplification using the theory of largescale systems, an FDM containing 50 nodes can be simplified to contain only 5 nodes(ID3, ID10). In ID 16, a second-order Runge-Kutta method to solve an FDM with 10 node. But as the number of FDM nodes increases, the solution of Runge-Kutta method will be unstable. ID97 uses the Implicit-Explicit Method to discretize the FVM, which is typically faster and more accurate to solve compared to Implicit Euler Method.

The advantage of the finite method is that it is very easy to apply, and the number of nodes can be adjusted according to the actual needs to balance the accuracy and computational speed. It is possible to combine different discretization methods to speed up the computation. The finite method is often used as a baseline method for solving PDE.

(3) Function approximation

The function approximation method is a widely adopted approach for simplifying complex models by replacing computationally or expressively complex parts with simpler functions. The most common function approximation method used in electrochemical model is the parabolic approximation method [131]. Based on the results in Table 7, it can be seen that the number of papers employing the parabolic approximation method is the greatest. This is because it’s very easy to apply. And the calculation is very fast, which is crucial for application in BMS. At the same time this method also retains the physical meaning and can be used to directly calculate the average lithium-ion concentration and the surface lithium-ion concentration, which are two state quantities that are important for battery state estimation. However, it has the disadvantage of lower accuracy than other methods, especially at currents greater than 1C [133]. At the same time, the parabolic approximation method cannot add nodes to further improve the accuracy like finite method or spectral method. Nevertheless, if the goal is to develop battery state estimation algorithms that can be applied in a BMS, it is also a good choice due to its computational speed.

(4) Spectral method

Spectral methods are an efficient way to solve PDE and are also used to solve PDE in electrochemical models. In spectral methods, the function to be solved is expressed as a set of basic functions, with Chebyshev polynomials being the most common basis function. All retrieved papers using spectral methods employ Chebyshev polynomials as basis function. Spectral methods have been proven to generally offer higher accuracy and faster convergence rates compared to finite methods. Furthermore, accuracy can be further improved by increasing the number of nodes. However, a disadvantage is that they are complex to implement and require a strong background in mathematics, which is why only a few papers have applied this method.

(5) Transfer function

The transfer function method uses the Laplace transform, which converts a function of a real variable t (usually time) into a function of a complex variable s (complex frequency). The transform has the useful property of converting differential equations to algebraic equations and simplifying the model. When the PDE is converted to the frequency domain, it can be solved using different methods. The most commonly used solution method is the Padé approximation. There are also a very few screened papers that use discrete realization algorithm and fractional-order functions for PDE solving. The transfer function approach has the advantage of high accuracy and the choice of different orders of approximation to balance accuracy and computational speed. At the same time, choosing a lower order for the approximation may cause the model to perform poorly in the high frequency part.

(6) Projection method

The projection method is a mathematical technique used to solve PDE. This method simplifies the problem solving process by finding approximate solutions by projecting an infinite-dimensional problem into a finite-dimensional subspace. Similar to spectral methods, projection methods can also be complex to implement in programming. Consequently, fewer papers employing projection methods were identified in the screened literature.

(7) AI method

AI method can also be used to solve PDEs. In ID102, the authors introduced a novel approach termed the Physics-Informed Multiple-Input Operator Network (PI-MIONet) for solving PDEs within electrochemical models. Unlike traditional numerical methods typically employed for PDE resolution, this AI-driven model leverages the principles of physics to inform the network's learning process. The findings demonstrated that PI-MIONet is not only capable of accurately solving the PDEs inherent in electrochemical models but also offers a potentially more efficient and scalable alternative to conventional numerical techniques. This advancement underscores the growing potential of AI models in complex scientific computations, particularly in fields where traditional methods may be computationally intensive or challenging to implement.

3.2.6 Parameter identification

The accuracy of the battery model is directly affected by the correct selection of the battery model parameters. The battery model parameters also have a significant impact on the accuracy of the model-based state estimation results. The identification of the parameters of the electrochemical model is relatively complicated, and in the research papers on electrochemical model-based state estimation method, the battery parameters are generally adopted from the existing papers. However, even for the same model and type of battery, the battery parameters of each battery may be slightly different due to manufacturing and other reasons. So, to improve the accuracy of the battery state estimation algorithm, it is necessary to re-identify some parameters of the battery model. Among the 102 articles screened, 27 articles mentioned battery parameter identification, and Table 8 summarizes them.

Within the scope of these 27 articles, particle swarm optimization (PSO) is the most used methods for parameter identification. The majority of these papers focus on re-identifying a limited number of parameters in the model, while still relying on data from other publications for the remaining parameters. Notably, only ID59 and ID84 re-identify over 20 parameters. Additionally, ID93 is also a good choice to perform parameter sensitivity analysis first and then select high sensitivity are parameters for estimation.

Operating conditions employed for parameter identification generally fall into two categories: constant current charging and discharging, and dynamic operating conditions. Most articles exclusively utilize either constant current conditions or dynamic conditions. This is because it is simpler to use only one operating condition for battery parameter identification. However, ID59, ID60, and ID84 stand out by incorporating both types of conditions for battery parameter identification. Employing a more comprehensive range of conditions yields more accurate battery parameters. Conversely, relying on a single condition increases the likelihood of the algorithm identifying only a local optimum rather than a global optimum solution.

Temperature exerts a significant influence on battery model parameters. A mere 4 papers (ID1, ID4 ID77, and ID84) consider experimental battery data at multiple temperatures for parameter identification. The remaining papers consider only a single temperature. Broadly speaking, incorporating a greater variety of experimental data conditions and temperature conditions contributes to obtaining more precise battery model parameters.

Table 8 Summary of battery parameters identification method

Article ID	Approach	Identified Parameters	Experimental Data	Ambient Temperature
ID1	Adaptive particle swarm optimization	6	0.1C discharge	0°C,25 °C,45°C
ID4	least square optimization	16	-	0 °C, 15 °C, 25°C, 35°C, 55°C
ID5	PSO	12	0.2C discharge	20°C

ID16	GA	7	DST	25 °C
ID17	PSO	4	-	-
ID18	GA	-	-	-
ID20	Levenberg–Marquardt algorithm	-	CCCV (1C) charge	25 °C
ID36	PSO	-	-	-
ID38	Levenberg–Marquardt algorithm	7	-	-
ID49	least square optimization	7	-	-
ID51	least square optimization	6	-	-
ID58	GA	16	HPPC	23 °C
ID59	Ant Lion Optimizer	21	2C discharge US06 DST UDDS	25 °C
ID60	Gradient free function minimization algorithm	9	A set of four charges (1 A, 2A and 3A at constant current and 4A with pulse current demand) and four discharges (2 A, 3.5A and 5A at constant current and 6A pulse current demand)	-
ID62	Nelder-Mead	-	1C charging/discharging	-
ID74	GA	6	0.1C charging/discharging	25 °C
ID77	GA	7	0.05C, 0.33C, 0.5C, and 1C charging/discharging	5°C,15°C,25°C,35°C,45°C,55°C
ID79	Linear decreasing weight particle swarm optimization	6	From 0.1 to 2C charging/discharging	25 °C
ID84	PSO	26	US06, DST and BJDST starting from different SOC levels	0°C,25°C,45°C
ID86	PSO	11	UDDS	25 °C
ID88	PSO	3	1C, 2C, 3C charging/discharging	-
ID91	PSO	-	UDDS	-
ID93	PSO	8	-	-
ID94	PSO	11	-	Room temperature
ID96	PSO	6	1C, 2C charging/discharging	25 °C

ID99	PSO	6	0.5C, 0.7C, 0.9C, 1C, 1.5C charging/discharging	-
ID101	Multi-verse optimizer (MVO) algorithm	15	-	-

3.3 RQ3: Which battery state was selected for estimation and what algorithms were used?

This subsection shows which battery states researchers have focused on and what methods they have used to state estimation.

3.3.1 State

Fig. 7 provides an overview of the battery states estimated in the included articles. A total of 83 articles addresses the estimation of SOC, demonstrating that the majority of research concentrates on this particular aspect. The SOH ranks second, with 26 articles examining concerns related to battery aging and lifespan. Additionally, 11 articles investigate the temperature estimation (SOT) of the battery, typically focusing on both the internal core temperature and the surface temperature. A smaller subset of studies, comprising 4 articles, employs electrochemical models to estimate the SOP of the battery. Furthermore, 2 articles utilize electrochemical models to analyze SOB. In summary, the SOC and SOH are the two battery states that currently garner the most attention from researchers. SOE and SOF are not mentioned by any article. The specific results can be found in Appendix 1.

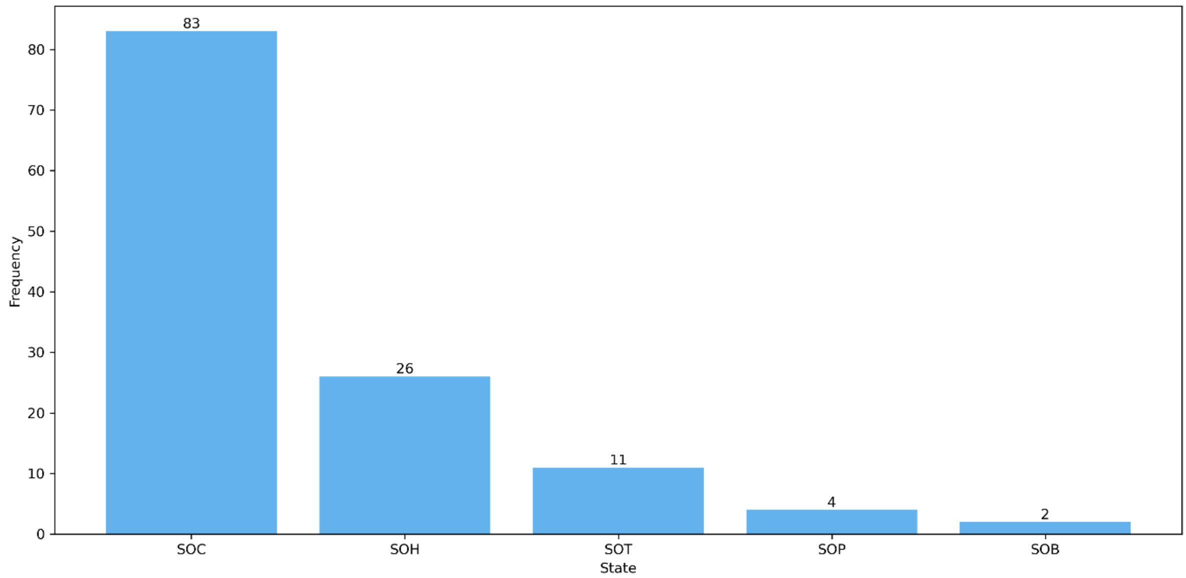

Fig. 7. Battery state statistics results.

Fig. 8 illustrates the yearly distribution of battery states, revealing that the SOC consistently remains the predominant focus across all years. In recent times, there has been a noticeable increase in the number of researchers concentrating on the SOT, SOP, and SOH. As these three states are intimately connected to battery safety, this shift in research interest underscores a growing emphasis on monitoring and ensuring the safe usage of the battery. It is worth noting that the sum of the battery states discussed above exceeds the total number of articles. The reason for this discrepancy is that many of the articles involve estimates for more than one battery state. From Appendix 1, a total of 80 articles focused on estimating a single battery state, indicating that the majority of the research is centered around one specific state, typically either the SOC or SOH. Furthermore, 20 articles estimated two battery states concurrently, with the most prevalent combinations being SOC&SOH or SOC&SOT. A mere two articles (ID10 and ID11) estimated three battery states simultaneously. ID10 estimates SOC, SOT, and SOB while ID11 estimates SOC, SOT, and SOH. Notably, no papers were found to estimate more than three battery states at once.

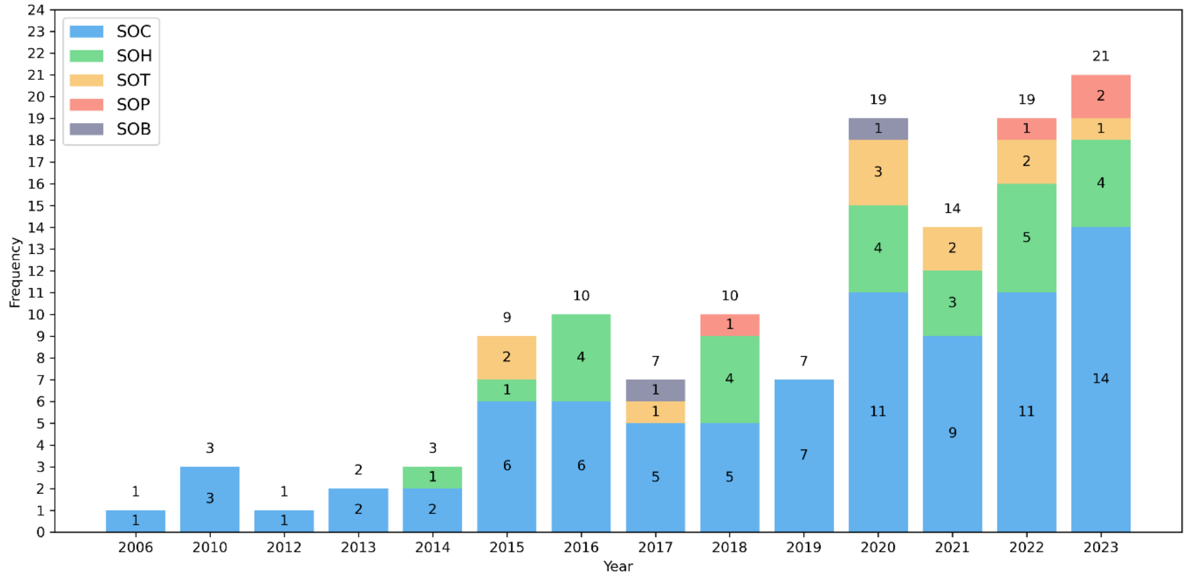

Fig. 8. Battery state results distributed by year.

3.3.2 Algorithms

In this subsection, we provide a detailed account of the specific methods employed for battery state estimation in the reviewed literature for each battery state.

(1) SOC

In electrochemical models, the SOC is typically represented by calculating the normalized lithium-ion concentration in electrodes. This method provides a quantitative measure of the SOC by comparing the current concentration of lithium-ions to the maximum possible concentration, thus indicating the battery's charge level. The SOC is a critical parameter for assessing the performance and efficiency of the battery, and it is determined using the following equation:

$$SOC = \frac{C_{Li} - C_{Li,min}}{C_{Li,max} - C_{Li,min}} \tag{1}$$

where C_{Li} represents the average lithium-ion concentration in the electrode, $C_{Li,min}$ is the minimum lithium-ion concentration, and $C_{Li,max}$ is the maximum lithium-ion concentration. This equation normalizes the concentration between 0% and 100%, providing a standardized measure of the battery's charge state. Typically, the SOC of the anode is used to represent the overall SOC of the battery. In some cases, the average SOC of both the anode and cathode is employed to provide a more comprehensive indication of the battery's SOC. Therefore, SOC estimation algorithms based on electrochemical models primarily focus on estimating the average lithium-ion concentration (C_{Li}) in both the anode and cathode. This estimated average lithium-ion concentrations are then used to calculate the overall SOC of the battery by Eq. (1).

There are three primary categories of SOC estimation methods based on electrochemical models: model calculation method, filter, observer and AI method. The specific SOC estimation techniques implemented in each paper are summarized in Table 9.

1) Model calculation method: The model calculation method does not involve designing filters or observers for SOC estimation. Instead, it directly utilizes electrochemical models for computation, typically calculating the lithium-ion concentration and subsequently deriving the battery's SOC. The advantage of this method is that it is straightforward, but it cannot handle the influence of measurement noise and unknown initial conditions, which makes it difficult to guarantee high accuracy in practical applications in BMS. To overcoming the effects of initial value errors, ID73 and ID89 use the OCV method in the initial phase of the algorithm to compute the correct initial value, and then use this correct initial value to initialize the battery model. This solves the problem of the initial value, but it also cannot deal with the interference caused by measurement noise.

2) Filters: The second primary category for SOC estimation encompasses various types of filters. The primary purpose of a filter is to estimate the state of a system in the presence of noise. It not only relies on the current measurements but also integrates previous state estimates and the system's dynamic model. A filter effectively reduces the impact of measurement noise, thereby providing a more accurate state estimation.

The Kalman filter (KF) is the most commonly used filter. The original KF requires that the dynamic and measurement processes be linear. However, electrochemical models are often nonlinear, making it necessary to adapt the KF to handle nonlinear systems. As a result, variations of the KF that can accommodate nonlinearity are commonly employed in the design of filters based on electrochemical models. The most widely used variations include the Extended Kalman Filter (EKF), the Unscented Kalman Filter (UKF), and the Cubature Kalman Filter (CKF). Among these, the EKF is the most frequently employed option, often serving as the benchmark algorithm for comparison purposes. Several studies (ID10, ID26, ID27, ID32, ID41, ID42, ID43, ID45, ID47, ID52, ID55, ID60, ID67, ID68, ID71, ID72, ID74, ID79, ID81and ID98) have utilized the EKF. Numerous filter variations based on the EKF have also been implemented, such as the dual EKF in ID19 and ID100, adaptive EKF in ID33, ID37 and ID67, Lebesgue-sampling-based EKF in ID36 and ID94, EKF combined with smoothing variable structure filter in ID3. The UKF has been applied in ID18, ID23, ID31, ID47, ID64, ID72, ID75, and ID102, while adaptive UKF filter is used in ID25, dual UKF in ID46, adaptive square-root sigma-point KF in ID13. Sigma-point KF and UKF are the same filter with different name. There are also other KF-based variations that have been used for SOC estimation, such as: singular evolutive interpolated Kalman filter (SEIKF) in ID11, cubature Kalman filter (CKF) in ID84, adaptive CKF in ID80, and square-root CKF in ID59. The EKF linearizes the system model by performing a first-order Taylor expansion of the nonlinear system. Specifically, EKF uses the Jacobian matrix to approximate the nonlinear functions of the system with linear ones. The advantage of EKF is its relatively low computational complexity. However, its drawback is that it can lead to significant estimation errors in highly nonlinear systems. The UKF utilizes the Unscented Transformation to directly propagate the mean and covariance, capturing the key characteristics of the distribution by selecting a set of "sigma points" in the state space, without requiring linearization. Therefore, UKF typically provides better estimation accuracy than EKF, although at the cost of increased computational complexity. The CKF generally performs better when dealing with high-dimensional systems, making it particularly well-suited for situations where there are many states to estimate.

Another prominent filter type is the particle filter (PF), which has been employed in ID26, ID34, ID64, ID86, and ID93. The advantage of the PF is its ability to directly handle nonlinear systems; however, its computational complexity is higher than that of the KF. Some studies have also explored other filters for SOC estimation, such as moving-window filtering in ID7, State-dependent-Riccati-equation filter in ID9, and smooth variable structure filter in ID65.

3) Observers: The observers are another common method for SOC estimation. The observer is designed to estimate the internal state of a system by measuring its output. Compared to filters, observers generally have lower computational complexity, as they primarily rely on the system model for feedback adjustments and do not need to handle large amounts of noise and uncertainty.

Nonlinear observers are utilized in ID22, ID29, ID50, ID51 and ID87, ID91, ID95, while ID5 employs a nonlinear observer with terminal voltage feedback injection. ID40 uses a feedback observer. Nonlinear adaptive observers are employed in ID17, ID49, and ID70. ID24 features an output error injection observer, whereas ID12 and ID78 incorporate backstepping PDE state observers. ID20 and ID56 utilize proportional-integral (PI) observers, and ID44 opts for a proportional-integral-derivative (PID) observer. Luenberger observers are employed in ID69, with ID66 integrating a Luenberger observer combined with a Recursive Least Squares method. ID21 makes use of moving horizon estimation (MHE), and both ID32 and ID42 employ sliding-mode observers with a uniform reaching law (SMO-URL) as well as sliding-mode observers with an exponential reaching law (SMO-ERL). Lastly, ID28 incorporates observers with the backstepping method and H-infinity observers.

4) AI method: AI methods have also been employed for SOC estimation based on electrochemical models. In ID18, a neural network was added to the SPM model to correct its errors, and a UKF was designed based on this hybrid model to perform SOC estimation. A combination of GA and electrochemical model is used in ID92 for battery SOC estimation. In ID99, the internal state information from the electrochemical model is used as input to train a neural network model for estimating SOC. In ID102, a neural network was used to solve the PDEs in the electrochemical model, and a UKF was designed based on this hybrid model to estimate the battery's SOC. The studies mentioned above indicate that AI methods show potential in state estimation based on electrochemical models.

Table 9 SOC estimation method in corresponding paper results

Method	Article ID
Model Calculation	ID1, ID4, ID14, ID15, ID35, ID53, ID58, ID63, ID64, ID73, ID83, ID89,
Filters	ID3, ID7, ID9-11, ID13, ID18, ID19, ID23, ID25-27, ID30-33, ID36, ID37, ID41-43, ID45-47, ID52, ID55, ID59, ID60, ID64-68, ID71, ID72, ID74, ID75, ID79-81, ID84, ID86, ID93, ID94, ID98, ID100, ID102
Observers	ID5, ID12, ID17, ID20-22, ID24, ID28, ID29, ID32, ID40, ID42, ID44, ID49-51, ID56, ID66, ID69, ID70, ID78, ID87, ID91, ID95
Machine learning	ID18, ID92, ID99, ID102

(2) SOH

The electrochemical model can describe the physical process of battery aging well, which will be beneficial for SOH estimation. The SOH estimation methods used in the screened articles can also be classified into 4 categories, and the specific results are presented in Table 10.

1) Model calculation method: ID1 employs Gaussian process regression in conjunction with an SPM to calculate the remaining battery capacity. ID2, ID8, ID88, and ID96 develop an SPM-based battery aging model, which is then used to calculate the battery capacity loss. Empirical data was used to establish the relationship between battery capacity and the number of cycles in ID16. This was achieved by applying a third-order polynomial equation. ID35 implements a back-propagation neural network to estimate battery capacity and subsequently integrates the updated capacity into an SPM to compute the capacity-based SOH and the internal resistance-based SOH. The final SOH is determined as the minimum of these two values. Finally, ID39, ID61 and ID90 develop a battery aging model based on the P2D model. Most papers model battery aging and then directly apply the model's calculations to the aging process. This is equivalent to an open-loop estimation of SOH.

2) Filters: ID11 estimates the SOH utilizing the SEIKF. ID19 applies DEKF for SOH estimation. ID26 employs the Kalman smoother, PF, and EKF to estimate SOH. ID34, ID57, and ID62 utilize the PF for SOH estimation purposes. ID47 implements both the EKF UKF for estimating SOH. Lastly, ID52 and ID76 employ the EKF to estimate the SOH of the battery. ID101 uses PF to estimate SOH.

3) Observers: ID12 employs a backstepping PDE state estimator for SOC estimation, and the SOH-related battery model parameters are estimated using the least squares method in conjunction with the SOC state estimation results.ID20 utilizes a PI observer to estimate the battery capacity and resistance. ID21 implements a MHE technique for SOH estimation. ID40 applies an adaptive observer-based SOH estimator by estimating the maximum lithium-ion concentration of anode. ID54 uses an adaptive interconnected observer that adjusts itself based on the relationship between the system's components for better capacity estimation. Lastly, ID82 incorporates an iterative model-based observer to estimate the internal resistance and capacity fade , which iteratively refines the estimation process to improve the accuracy of the SOH estimation.

4) Machine learning: ID35 uses neural networks to estimate capacity and then update the battery model.

Table 10 SOH estimation method in corresponding paper results

Method	Article ID

Model Calculation	ID1, ID2, ID8, ID16, ID35, ID39, ID61, ID88, ID90, ID96
Filters	ID11, ID19, ID26, ID34, ID47, ID52, ID57, ID62, ID76, ID101
Observers	ID12, ID20, ID21, ID40, ID54, ID82
Machine learning	ID35

(3) SOT

As illustrated in Table 11, a total of 11 articles focusses on estimating the SOT. ID10 develops a thermal model, which calculates both core and surface temperatures. ID53 utilizes a lumped temperature model to estimate the temperature. ID11 employs SEIKF to determine the bulk temperature. ID18 applies UKF to estimate the battery core temperature, while ID43 uses EKF to estimate the bulk temperature. ID46 leverages dual UKF to estimate the bulk, surface, and core temperatures. ID59 implements square-root CKF for temperature estimation, and ID28 uses an H-infinity temperature observer to estimate the surface temperature. ID49 applies an adaptive observer for bulk temperature estimation, and ID78 utilizes a backstepping state observer to estimate the bulk temperature. ID87 uses a nonlinear observer to estimate the surface temperature.

The battery surface temperature can typically be measured using cost-effective temperature sensors, which renders the need for estimating the battery surface temperature less crucial. According to the findings in ID46, in certain situations, the battery core temperature can be as much as 45 °C higher than the surface temperature. Relying solely on bulk temperature estimation makes it challenging to prevent thermal runaway in the battery. Therefore, it is essential to estimate the core temperature of the battery to ensure better safety management.

Table 11 SOT estimation method in corresponding paper results

Method	Article ID
Model Calculation	ID10, ID53
Filter	ID11, ID18, ID43, ID46, ID59
Observer	ID28, ID49, ID78, ID87

(4) SOP and SOB

A total of 4 articles (ID38, ID77, ID85, ID97) deal with the estimation of SOP, and there are fewer studies on SOP estimation based on electrochemical models. ID38 has calculated the SOP based on the lithium-ion concentration in the SPM, rather than using the commonly used terminal voltage and current. ID77 uses the grey wolf optimizer method for SOP estimation of batteries based on SPM. ID85 uses Gaussian process regression method to simplify the model and improve computational speed. Moreover, it proposes the concept of safe operation area (SOA), using the Electrode surface concentration, electrolyte concentration, slide-reaction overpotential and terminal voltage as indicators to set a safe operating range, and uses this as a constraint for the estimation of SOP. ID97 uses nonlinear model predictive control method for SOP estimation.

ID10 employs an active equalization control strategy based on the SPM to compute the battery's SOB. Meanwhile, ID48 adopts a multivariable SOC/capacity balancing strategy, utilizing the ESPM as a foundation for calculating the battery's SOB.

4 Discussion

The discussion section delves into the current issues and future research directions faced by electrochemical model-based, as well as the limitations of this study.

4.1 Issues and Future research

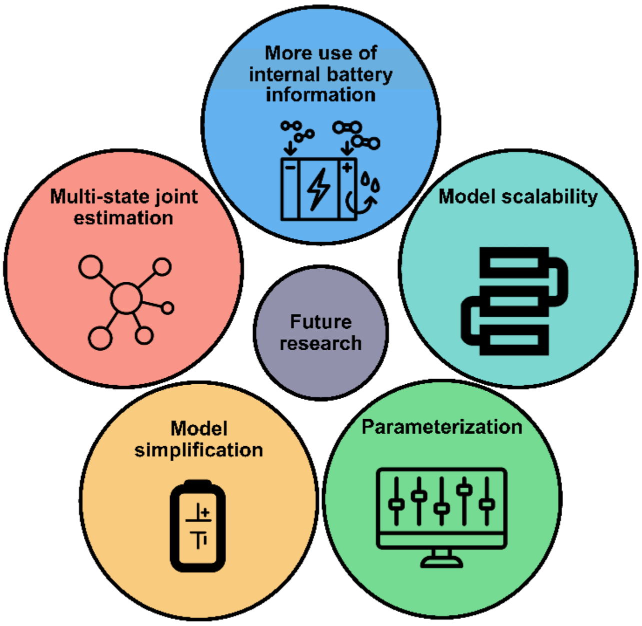

Fig.9. Future Research.

Based on the results of Section 3, the current challenges and future research directions for battery state estimation based on electrochemical models are presented in Fig. 9, which specifically include: model scalability, parameterization, model simplification, multi-state joint estimation, and more use of internal battery information.

4.1.1 Model Scalability

As can be seen from the results of Section 3.2.1, most existing studies focus primarily on individual cell. However, in practical applications, individual cells are often connected in series and parallel to form battery modules or packs. Due to manufacturing processes, achieving perfect consistency among new single cells is difficult. As cells are used, inconsistencies between them tend to increase for various reasons, such as discrepancies in manufacturing, uneven temperature distribution within battery modules and packs, and other factors.

This disparity indicates that treating the entire pack as a singular large battery cell may compromise battery safety assurance. Similarly, the state of a battery pack cannot be unequivocally deduced by merely amalgamating the states of its constituent cells. The rationale behind this lies in the understanding that the overall performance of a battery module or pack may not be contingent upon the summative performance of all individual cells. However, adopting an electrochemical model-based estimation for each cell unit poses its own set of challenges, particularly regarding data storage and computational capacity of processors. So, the state estimation of batteries after aggregation is also very worthy of research. We can choose to estimate only a few battery cells in the most critical positions, thereby reducing the computational load on the BMS processor. This approach also provides guidance for the SOA. Consequently, it is suggested that forthcoming research should accentuate the state estimation for battery modules and packs based on electrochemical models. ID87 studies the state estimation of battery cells in series and parallel configurations based on an SPM model, which can provide a reference for subsequent research.

4.1.2 Parameterization

Parameter identification for electrochemical models is very challenging due to the fact that the measurement of many parameters requires high precision equipment, and some parameters can’t be measured directly. Furthermore, electrochemical models tend to be over-parameterized, meaning that two distinct sets of parameters may yield similar outputs. This complicates parameter estimation and raises the research threshold for studies based on electrochemical models. A notable issue is that many researchers do not provide complete battery parameters and test data in their publications.

In the future, further public disclosure of electrochemical model parameters and corresponding test data would be advantageous, as it could lower the research barrier for electrochemical models. This would not only benefit researchers working on battery state estimation and control based on electrochemical models but also facilitate cross-sectional comparisons of various methods. Additionally, there is currently a lack of comparative research on parameter identification methods, such as comparing the accuracy, computational speed, and stability of different methods. For instance, when performing parameter identification on batteries intended for secondary use, where each battery exhibits varying degrees of aging, it becomes necessary to identify parameters for each individual cell. If this process must be applied to 1000 cells and the chosen method is time-consuming, the total duration can become excessively lengthy. Therefore, it is crucial to identify a parameter identification method that not only ensures accuracy and stability but also operates with high computational efficiency.

As observed in Section 3.2.6, there is a lack of standardized processes for parameter identification methods in battery models, with different researchers employing diverse methods, operating conditions, and temperatures. Parameter identification for electrochemical models often necessitates a comprehensive understanding of the model's operating mechanism, as well as sensitivity analysis, parameter grouping, and optimal experimental designs [134]. It would be worthwhile to propose a simple and practical battery parameters identification process. This will effectively lower the threshold for the use of electrochemical models.

4.1.3 Model simplification

Based on the findings presented in Section 3.2.5 and Section 3.2.6, it is evident that numerous battery models and associated simplification methods have been developed with the goal of battery state estimation. Statistically, the adoption of SPM-based models is by far the most prevalent. However, when it comes to further simplification of these models, researchers have employed diverse approaches, and there is a notable lack of cross-sectional comparisons. In particular, the lack of discussions regarding which simplification methods are suitable for designing battery state estimation algorithms. It must also be clear what limitations the simplifications imply like steady state (dis)charging, low C-rate or narrow temperature band. If the application is targeting a BMS, then a comparison of model computation speeds is also critical. The results of ID53 indicate that an electrochemical model can be implemented in the BMS and offers higher accuracy than the ECM while only adding an acceptable amount of operating time. Given these circumstances, the investigation of model simplification for battery state estimation is an essential area for future research. A more comprehensive understanding of the most effective simplification methods will enable the development of improved battery state estimation algorithms, facilitating the application of electrochemical models in BMS. Additionally, according to the study in ID102, using AI methods for the simplification of electrochemical models, or developing hybrid models that combine AI with electrochemical models, are also promising research directions.

4.1.4 Multi-state joint estimation

As indicated by the findings in Section 3.3.1, current research primarily focuses on the estimation of individual battery states, with researchers designing specific estimation algorithms for each single state. However, in practical applications, different states are often interconnected, such as the estimation of SOP, which requires information on SOC. Compared with single-state estimation, multi-state joint estimation methods are more advantageous in optimizing the efficiency and accuracy of the overall algorithm.

Using an electrochemical model can get detailed internal battery information. This facilitates the direct computation of some states based on their physical definitions. For instance, ID38 derived the formula for SOP directly from its physical definition, which is specifically used for SOP calculations. This direct approach is not feasible with equivalent circuit models.

Furthermore, while equivalent circuit models often require different estimation algorithms for different state estimates, an electrochemical model enables the design of a unified battery state estimation algorithm. This singular method can estimate internal battery parameters, which are then used to compute various related battery states. This efficiency simplifies the overall process, enhancing the functionality and accuracy of the BMS.

Looking forward, it is essential to conduct research on joint estimation of multiple states based on electrochemical models and investigate the interaction mechanisms between different states. This will fully utilize the advantages of electrochemical models.

4.1.5 More use of internal battery information

The electrochemical model provides more in-depth information about the internal workings of a battery compared to the ECMs. This additional insight enables researchers to better monitor the battery, optimize its performance, and ensure its safety. Not only does the electrochemical model enhance the accuracy of battery state estimation, but it also plays a crucial role in safeguarding the battery as well. Relying solely on the equivalent circuit model makes it challenging to meet battery safety requirements, resulting in conservative designs for current BMS that do not fully exploit the battery's potential.

As demonstrated in the results from Section 3.3, the majority of researchers still concentrate primarily on battery SOC estimation. This approach fails to fully capitalize on the benefits offered by electrochemical models. In ID85, the internal information calculated from the electrochemical model is used to design the SOA. ID38 calculates SOP directly with internal battery information. They are all good example of utilizing the battery internal information. For instance, ID46 estimates the battery core temperature using an electrochemical model, effectively preventing thermal runaway. This method is superior to those that rely on measuring the battery's surface temperature or calculating the average temperature. Future research should explore battery safety design based on electrochemical models.

4.2 Limitations

Due to the scope of this literature review being primarily focused on battery state estimation based on electrochemical models, it may not comprehensively cover studies related to battery modeling, model simplification, and parameter identification. Consequently, readers interested in these areas may find it necessary to consult additional literature reviews or research papers within those specific fields.

5 Conclusion

The widespread use of lithium-ion batteries has led to an increasing demand for enhancing battery efficiency and ensuring safety. Designing battery state estimation methods based on electrochemical models can optimize battery performance and safety. In this study, a systematic review of existing electrochemical model-based battery state estimation research was conducted. A total of 102 research articles were selected, and their research trends, electrochemical model selection, and battery state estimation methods were systematically summarized. The results indicate that research in this area has been growing in recent years. The results demonstrate the good results and the great potential of electrochemical model-based battery state estimation achieved so far. At the same time, the gaps in the current research are also raised. The majority of research has focused on individual cells, with less attention paid to battery modules and packs. There is a lack of standardization in model simplification methods and model parameter identification processes. Most studies have been conducted only for single state estimation, with SOC being the most commonly studied, followed by SOH and SOT, and very few studies have been conducted for SOP and SOB. Future research in this field should focus on state estimation for modules and packs, parameter identification and model simplification for state estimation, joint multi-state estimation, and utilizing more internal battery information for state estimation. In conclusion, this paper demonstrates comprehensive progress in electrochemical modeling-based battery state estimation. Existing problems and future research directions are also evaluated and discussed, which will provide a comprehensive reference for readers interested in this field.

CRediT authorship contribution statement

Feng Guo: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Roles/Writing - original draft. **Luis Couto Mendonca:** Conceptualization; Writing - review & editing. **Grietus Mulder:** Conceptualization; Writing - review

& editing. **Khiem Trad:** Supervision; Writing - review & editing. **Guangdi Hu:** Writing - review & editing. **Odile Capron:** Writing - review & editing. **Keivan Haghverdi:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Acknowledgements

This work was supported by the Dutch Ministry of Economic Affairs and Climate Policy and the Ministry of the Interior and Kingdom Relations [grant number MOOI32027]. We would like to express our gratitude to Frank Stals and Raf Ponnette for their support in this work.

Appendix

Table A Details of the reviewed studies

ID	References	State	Model	Materials
ID1	[20]	SOC, SOH	SPM	NMC
ID2	[21]	SOH	SPM	LMO
ID3	[22]	SOC	SPM	
ID4	[23]	SOC	SPM	LFP
ID5	[24]	SOC	SPM	LCO
ID6	[25]	SOC	P2D	LMO
ID7	[26]	SOC	P2D	LFP
ID8	[27]	SOH	SPMe	LFP
ID9	[28]	SOC	SPM	LFP
ID10	[29]	SOC, SOT, SOB	SPM	
ID11	[30]	SOC, SOH, SOT	P2D	NMC
ID12	[31]	SOC, SOH	SPM	
ID13	[32]	SOC	SPMe	NMC
ID14	[33]	SOC	SPMe	LCO
ID15	[34]	SOC	SPM	LMO
ID16	[35]	SOH	P2D	
ID17	[36]	SOC	SPM	NMC
ID18	[37]	SOC, SOT	SPM	LFP
ID19	[38]	SOC, SOH	P2D	NMC
ID20	[39]	SOC, SOH	SPM	
ID21	[40]	SOC, SOH	SPMe	LCO
ID22	[41]	SOC	SPMe	LMO
ID23	[42]	SOC	P2D	NMC
ID24	[43]	SOC	P2D	
ID25	[44]	SOC	SPMe	NMC
ID26	[45]	SOC, SOH	SPMe	LMO-NMC
ID27	[46]	SOC	P2D	
ID28	[47]	SOC, SOT	SPM	LFP
ID29	[48]	SOC	SPM	LCO
ID30	[49]	SOC	SPMe	NMC
ID31	[50]	SOC	P2D	LFP
ID32	[51]	SOC	SPM	LFP

ID33	[52]	SOC	SPMe	NMC
ID34	[53]	SOC, SOH	P2D	NMC
ID35	[54]	SOC, SOH	SPM	LCO
ID36	[55]	SOC	SPM	LCO
ID37	[56]	SOC	SPM	LFP
ID38	[57]	SOP	SPM	LMO
ID39	[58]	SOH	P2D	LFP,NMC,NCA
ID40	[59]	SOC, SOH	SPM	LCO
ID41	[60]	SOC	SPM	
ID42	[61]	SOC	SPM	LFP
ID43	[62]	SOC, SOT	P2D	LCO
ID44	[63]	SOC	SPMe	LMO
ID45	[64]	SOC	P2D	
ID46	[65]	SOC, SOT	P2D	LCO
ID47	[66]	SOC, SOH	P2D	
ID48	[67]	SOB	SPM	LFP
ID49	[68]	SOC, SOT	SPM	LFP
ID50	[69]	SOC	SPM	
ID51	[70]	SOC	SPM	
ID52	[71]	SOC, SOH	SPM	LCO
ID53	[72]	SOC, SOT	P2D	LMO,NMC,NCA
ID54	[73]	SOH	SPMe	NMC
ID55	[74]	SOC	SPM	LCO
ID56	[75]	SOC	SPMe	LMO
ID57	[76]	SOH	SPM	NMC
ID58	[77]	SOC	SPMe	NMC
ID59	[78]	SOC, SOT	SPMe	LFP
ID60	[79]	SOC	P2D	LCO
ID61	[80]	SOH	P2D	LCO
ID62	[81]	SOH	SPMe	LMO-NMC
ID63	[82]	SOC	P2D	LCO
ID64	[83]	SOC	P2D	NCA
ID65	[84]	SOC	SPM	LFP
ID66	[85]	SOC	SPM	LMO
ID67	[86]	SOC	SPM	LCO
ID68	[87]	SOC	SPM	
ID69	[88]	SOC	P2D	LCO
ID70	[89]	SOC	SPM	LCO
ID71	[90]	SOC	P2D	LCO
ID72	[91]	SOC	SPM	LCO
ID73	[92]	SOC	SPM	LCO
ID74	[93]	SOC	SPMe	LFP
ID75	[94]	SOC	P2D	LFP
ID76	[95]	SOH	SPM	LMO-NMC
ID77	[96]	SOP	SPM	NMC
ID78	[97]	SOC, SOT	SPM	LCO
ID79	[98]	SOC	SPMe	LFP
ID80	[99]	SOC	SPMe	NMC
ID81	[100]	SOC	SPMe	LFP
ID82	[101]	SOH	SPM	NMC
ID83	[102]	SOC	P2D	NCA
ID84	[103]	SOC	SPMe	NMC
ID85	[104]	SOP	SPMe	NMC

ID86	[105]	SOC	P2D	LFP
ID87	[106]	SOC,SOT	SPM	LCO
ID88	[107]	SOH	SPM	LFP
ID89	[108]	SOC	P2D	LFP,NMC,NCA
ID90	[109]	SOH	P2D	
ID91	[110]	SOC	SPMe	NCA
ID92	[111]	SOC	P2D	
ID93	[112]	SOC	SPMe	NMC
ID94	[113]	SOC	SPM	LCO
ID95	[114]	SOC	SPM	
ID96	[115]	SOH	SPM	LFP
ID97	[116]	SOP	P2D	NMC
ID98	[117]	SOC	SPM	LCO
ID99	[118]	SOC	P2D	NMC
ID100	[119]	SOC	SPM	NMC
ID101	[120]	SOH	SPMe	LFP
ID102	[121]	SOC	SPMe	LCO

References

[1]Nyamathulla S, & Dhanamjayulu C. A review of battery energy storage systems and advanced battery management system for different applications: Challenges and recommendations. J Energy Storage 2024; 86, 111179.

[2] Hu X, Xu L, Lin X, Pecht M. Battery lifetime prognostics. Joule 2020;4(2):310-46.

[3] Demirci O, Taskin S, Schaltz E, et al. Review of battery state estimation methods for electric vehicles-Part I: SOC estimation. . J Energy Storage 2024, 87: 111435.

[4] Wang Y, Tian J, Sun Z, Wang L, Xu R, Li M, Chen Z. A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. Renewable Sustainable Energy Rev 2020;131:110015.

[5] Xiang S, Hu G, Huang R, et al. Lithium-ion battery online rapid state-of-power estimation under multiple constraints. Energies, 2018, 11(2): 283.

[6] Wang S, Shang L, Li Z, Deng H, Li J. Online dynamic equalization adjustment of high-power lithium-ion battery packs based on the state of balance estimation. Appl Energy. 2016;166:44-58.

[7] Li Y, Karunathilake D, Vilathgamuwa DM, Mishra Y, Farrell TW, Zou C. Model order reduction techniques for physics-based lithium-ion battery management: A survey. IEEE Ind Electron Mag 2021;16(3):36-51.

[8] Zhao L, Lin M, Chen Y. Least-squares based coulomb counting method and its application for state-of-charge (SOC) estimation in electric vehicles. Int J Energy Res 2016;40(10):1389-99.

[9] Kang L, Zhao X, Ma J. A new neural network model for the state-of-charge estimation in the battery degradation process. Appl Energy 2014;121:20-7.

[10] Plett GL. Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs: Part 3. State and parameter estimation. J Power Sources 2004;134(2):277-92.

[11] Guo F, Hu G, Xiang S, Zhou P, Hong R, Xiong N. A multi-scale parameter adaptive method for state of charge and parameter estimation of lithium-ion batteries using dual Kalman filters. Energy 2019;178:79-88.

[12] Guo F, Hu G, Hong R. A parameter adaptive method with dead zone for state of charge and parameter estimation of lithium-ion batteries. J Power Sources 2018;402:174-82.

[13] Schwunk S, Armbruster N, Straub S, Kehl J, Vetter M. Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries. J Power Sources 2013;239:705-10.

[14] Krewer U, Röder F, Harinath E, Braatz RD, Bedürftig B, Findeisen R. Dynamic models of Li-ion batteries for diagnosis and operation: a review and perspective. J Electrochem Soc 2018;165(16):A3656.

[15] Fuller TF, Doyle M, Newman J. Simulation and optimization of the dual lithium-ion insertion cell. J Electrochem Soc 1994;141(1):1.

[16] Park S, Ahn J, Kang T, Park S, Kim Y, Cho I, Kim J. Review of state-of-the-art battery state estimation technologies for battery management systems of stationary energy storage systems. J Power Electron 2020;20:1526-40.
[17] Hu X, Feng F, Liu K, Zhang L, Xie J, Liu B. State estimation for advanced battery management: Key challenges and future trends. Renewable Sustainable Energy Rev 2019;114:109334.
[18] Planella FB, Ai W, Boyce A, Ghosh A, Korotkin I, Sahu S, Sulzer V, Timms R, Tranter T, Zyskin M, Cooper S. A continuum of physics-based lithium-ion battery models reviewed. Prog Energy 2022.
[19] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. Int J Surg 2021;88:105906.
[20] Wu S, Pan W, Zhu M. A Collaborative Estimation Scheme for Lithium-Ion Battery State of Charge and State of Health Based on Electrochemical Model. J Electrochem Soc 2022;169(9):090516.
[21] Li J, Landers RG, Park J. A comprehensive single-particle-degradation model for battery state-of-health prediction. J Power Sources 2020;456:227950.
[22] Xu X, Lin Y, Wang F, Yang S, Zhou Z. A hybrid observer for SOC estimation of lithium-ion battery based on a coupled electrochemical-thermal model. Int J Green Energy 2019;16(15):1527-38.
[23] Li J, Lai Q, Wang L, Lyu C, Wang H. A method for SOC estimation based on simplified mechanistic model for LiFePO4 battery. Energy 2016;114:1266-76.
[24] Liu Y, Ma R, Pang S, Xu L, Zhao D, Wei J, Huangfu Y, Gao F. A nonlinear observer SOC estimation method based on electrochemical model for lithium-ion battery. IEEE Trans Ind Appl 2020;57(1):1094-104.
[25] Sangiri JB, Kulshreshtha T, Ghosh S, Maiti S, Chakraborty C. A novel methodology to estimate the state-of-health and remaining-useful-life of a Li-ion battery using discrete Fourier transformation. J Energy Storage 2022;46:103849.
[26] He W, Pecht M, Flynn D, Dinmohammadi F. A physics-based electrochemical model for lithium-ion battery state-of-charge estimation solved by an optimised projection-based method and moving-window filtering. Energies 2018;11(8):2120.
[27] Li J, Adewuyi K, Lotfi N, Landers RG, Park J. A single particle model with chemical/mechanical degradation physics for lithium ion battery State of Health (SOH) estimation. Appl Energy 2018;212:1178-90.
[28] Lotfi F, Ziapour S, Faraji F, Taghirad HD. A switched SDRE filter for state of charge estimation of lithium-ion batteries. Int. J. Electr Power Energy Syst 2020;117:105666.
[29] Lin Y, Xu X, Wang F, Xu Q. Active equalization control strategy of Li-ion battery based on state of charge estimation of an electrochemical-thermal coupling model. Int J Energy Res 2020;44(5):3778-89.
[30] Li Y, Wei Z, Xiong B, Vilathgamuwa DM. Adaptive ensemble-based electrochemical–thermal degradation state estimation of lithium-ion batteries. IEEE Trans Ind Electron 2021;69(7):6984-96.
[31] Moura SJ, Chaturvedi NA, Krstić M. Adaptive partial differential equation observer for battery state-of-charge/state-of-health estimation via an electrochemical model. J Dyn Syst Meas Control 2014;136(1).
[32] Bi Y, Choe SY. An adaptive sigma-point Kalman filter with state equality constraints for online state-of-charge estimation of a Li (NiMnCo) O2/Carbon battery using a reduced-order electrochemical model. Appl Energy 2020 Jan 15;258:113925.
[33] Ren L, Zhu G, Kang J, Wang JV, Luo B, Chen C, Xiang K. An algorithm for state of charge estimation based on a single-particle model. J Energy Storage 2021;39:102644.
[34] Liu L, Zhu J, Zheng L. An effective method for estimating state of charge of lithium-ion batteries based on an electrochemical model and nernst equation. IEEE Access 2020;8:211738-49.
[35] Xiong R, Li L, Li Z, Yu Q, Mu H. An electrochemical model based degradation state identification method of Lithium-ion battery for all-climate electric vehicles application. Appl energy. 2018;219:264-75.
[36] Zhang D, Dey S, Couto LD, Moura SJ. Battery adaptive observer for a single-particle model with intercalation-induced stress. IEEE Trans Control Syst Techno. 2019;28(4):1363-77.

[37] Feng F, Teng S, Liu K, Xie J, Xie Y, Liu B, Li K. Co-estimation of lithium-ion battery state of charge and state of temperature based on a hybrid electrochemical-thermal-neural-network model. J Power Sources 2020 ;455:227935.
[38] Gao Y, Liu K, Zhu C, Zhang X, Zhang D. Co-estimation of state-of-charge and state-of-health for lithium-ion batteries using an enhanced electrochemical model. IEEE Trans Ind Electron 2021;69(3):2684-96.
[39] Zheng L, Zhang L, Zhu J, Wang G, Jiang J. Co-estimation of state-of-charge, capacity and resistance for lithium-ion batteries based on a high-fidelity electrochemical model. Appl Energy. 2016;180:424-34.
[40] Hu X, Cao D, Egardt B. Condition monitoring in advanced battery management systems: Moving horizon estimation using a reduced electrochemical model. IEEE ASME Trans Mechatron 2017;23(1):167-78.
[41] Nath A, Mehta R, Gupta R, Bahga SS, Gupta A, Bhasin S. Control-Oriented Physics-Based Modeling and Observer Design for State-of-Charge Estimation of Lithium-Ion Cells for High Current Applications. IEEE Trans Control Syst Technol 2022;30(6):2466-79.
[42] Miguel E, Plett GL, Trimboli MS, Lopetegi I, Oca L, Iraola U, Bekaert E. Electrochemical model and sigma point Kalman filter based online oriented battery model. IEEE Access 2021;9:98072-90.
[43] Klein R, Chaturvedi NA, Christensen J, Ahmed J, Findeisen R, Kojic A. Electrochemical model based observer design for a lithium-ion battery. IEEE Trans Control Syst Technol 2012;21(2):289-301.
[44] Li W, Fan Y, Ringbeck F, Jöst D, Han X, Ouyang M, Sauer DU. Electrochemical model-based state estimation for lithium-ion batteries with adaptive unscented Kalman filter. J Power Sources 2020;476:228534.
[45] Bartlett A, Marcicki J, Onori S, Rizzoni G, Yang XG, Miller T. Electrochemical model-based state of charge and capacity estimation for a composite electrode lithium-ion battery. IEEE Trans Control Syst Technol 2015;24(2):384-99.
[46] Corno M, Bhatt N, Savaresi SM, Verhaegen M. Electrochemical model-based state of charge estimation for Li-ion cells. IEEE Trans Control Syst Technol 2014;23(1):117-27.
[47] Chen G, Liu Z, Su H, Zhuang W. Electrochemical-distributed thermal coupled model-based state of charge estimation for cylindrical lithium-ion batteries. Control. Eng. Pract. 2021;109:104734.
[48] Zhang D, Couto LD, Moura SJ. Electrode-level state estimation in lithium-ion batteries via Kalman decomposition. IEEE Contr Syst Lett 2020;5(5):1657-62.
[49] Allam A, Onori S. An interconnected observer for concurrent estimation of bulk and surface concentration in the cathode and anode of a lithium-ion battery. IEEE Transactions on Industrial Electronics, 2018, 65(9): 7311-7321.
[50] Gao Y, Plett GL, Fan G, Zhang X. Enhanced state-of-charge estimation of LiFePO4 batteries using an augmented physics-based model. J Power Sources. 2022;544:231889.
[51] Lin C, Tang A, Xing J. Evaluation of electrochemical models based battery state-of-charge estimation approaches for electric vehicles. Appl Energy 2017;207:394-404.
[52] Fan G, Li X, Zhang R. Global sensitivity analysis on temperature-dependent parameters of a reduced-order electrochemical model and robust state-of-charge estimation at different temperatures. Energy. 2021;223:120024
[53] Liu B, Tang X, Gao F. Joint estimation of battery state-of-charge and state-of-health based on a simplified pseudo-two-dimensional model. Electrochim Acta 2020;344:136098.
[54] Sun X, Chen Q, Zheng L, Yang J. Joint estimation of state-of-health and state-of-charge for lithium-ion battery based on electrochemical model optimized by neural network. IEEE Trans Emerg Sel Topics Power Electron 2022;4(1):168-77.
[55] Liu E, Wang X, Niu G, Lyu D, Yang T, Zhang B. Lebesgue sampling-based li-ion battery simplified first principle model for soc estimation and rdt prediction. IEEE Trans Ind Electron 2021;69(9):9524-34.
[56] Yu H, Li J, Ji Y, Pecht M. Life-cycle parameter identification method of an electrochemical model for lithium-ion battery pack. J Energy Storage. 2022;47:103591.
[57] Zheng L, Zhu J, Wang G, Lu DD, He T. Lithium-ion battery instantaneous available power prediction using surface lithium concentration of solid particles in a simplified electrochemical model. IEEE Trans Power Electron 2018;33(11):9551-60.

[58] Crawford AJ, Choi D, Balducci PJ, Subramanian VR, Viswanathan VV. Lithium-ion battery physics and statistics-based state of health model. J Power Sources 202;501:230032.
[59] Cen Z, Kubiak P. Lithium-ion battery SOC/SOH adaptive estimation via simplified single particle model. Int J Energy Res 2020;44(15):12444-59.
[60] Di Domenico D, Stefanopoulou A, Fiengo G. Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter. J Dyn Syst Meas Control 2010;132(6).
[61] Tang A, Yao L, Gong P, Jiang Y. Lithium-ion battery state-of-charge estimation of an order-reduced physics-based model in electric vehicles considering erroneous initialization. Int J Energy Res 2022;46(3):3529-38.
[62] Bizeray AM, Zhao S, Duncan SR, Howey DA. Lithium-ion battery thermal-electrochemical model-based state estimation using orthogonal collocation and a modified extended Kalman filter. J Power Sources. 2015;296:400-12.
[63] Wu L, Pang H, Geng Y, Liu X, Liu J, Liu K. Low-complexity state of charge and anode potential prediction for lithium-ion batteries using a simplified electrochemical model-based observer under variable load condition. Int J Energy Res 2022;46(9):11834-48.
[64] Smith KA, Rahn CD, Wang CY. Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries. IEEE Trans Control Syst Technol 2009;18(3):654-63.
[65] Marelli S, Corno M. Model-based estimation of lithium concentrations and temperature in batteries using soft-constrained dual unscented Kalman filtering. IEEE Trans Control Syst Technol 2020;29(2):926-33.
[66] Zou C, Manzie C, Nešić D, Kallapur AG. Multi-time-scale observer design for state-of-charge and state-of-health of a lithium-ion battery. J Power Sources. 2016;335:121-30.
[67] Docimo DJ, Fathy HK. Multivariable state feedback control as a foundation for lithium-ion battery pack charge and capacity balancing. J Electrochem Soc 2016;164(2):A61.
[68] Dey S, Ayalew B, Pisu P. Nonlinear adaptive observer for a lithium-ion battery cell based on coupled electrochemical–thermal model. J Dyn Syst Meas Control 2015;137(11):111005.
[69] Blondel P, Postoyan R, Raël S, Benjamin S, Desprez P. Nonlinear circle-criterion observer design for an electrochemical battery model. IEEE Trans Control Syst Technol 2018;27(2):889-97.
[70] Dey S, Ayalew B, Pisu P. Nonlinear robust observers for state-of-charge estimation of lithium-ion cells based on a reduced electrochemical model. IEEE Trans Control Syst Technol 2015;23(5):1935-42.
[71] Gu R, Malysz P, Yang H, Emadi A. On the suitability of electrochemical-based modeling for lithium-ion batteries. IEEE Trans. Transp. Electrification 2016;2(4):417-31.
[72] Verma MK, Basu S, Patil RS, Hariharan KS, Adiga SP, Kolake SM, Oh D, Song T, Sung Y. On-board state estimation in electrical vehicles: Achieving accuracy and computational efficiency through an electrochemical model. IEEE Trans Veh Technol 2020;69(3):2563-75.
[73] Allam A, Onori S. Online capacity estimation for lithium-ion battery cells via an electrochemical model-based adaptive interconnected observer. IEEE Trans Control Syst Technol 2020;29(4):1636-51.
[74] Santhanagopalan S, White RE. Online estimation of the state of charge of a lithium ion cell. J Power Sources. 2006;161(2):1346-55.
[75] Wu L, Liu K, Pang H, Jin J. Online SOC estimation based on simplified electrochemical model for lithium-ion batteries considering current bias. Energies 2021;14(17):5265.
[76] Bi Y, Yin Y, Choe SY. Online state of health and aging parameter estimation using a physics-based life model with a particle filter. J Power Sources 2020;476:228655.
[77] Pang H, Mou L, Guo L, Zhang F. Parameter identification and systematic validation of an enhanced single-particle model with aging degradation physics for Li-ion batteries. Electrochim. Acta 2019;307:474-87.
[78] Ding Q, Wang Y, Chen Z. Parameter identification of reduced-order electrochemical model simplified by spectral methods and state estimation based on square-root cubature Kalman filter. J Energy Storage 2022;46:103828.
[79] Speltino C, Stefanopoulou AG, Fiengo G. Parametrisation and estimation of surrogate critical surface concentration in lithium-ion batteries. Int J Veh Des 2013;61(1-4):128-56.

[80] Ashwin TR, Barai A, Uddin K, Somerville L, McGordon A, Marco J. Prediction of battery storage ageing and solid electrolyte interphase property estimation using an electrochemical model. J Power Sources. 2018;385:141-7.
[81] Sadabadi KK, Jin X, Rizzoni G. Prediction of remaining useful life for a composite electrode lithium ion battery cell using an electrochemical model to estimate the state of health. J Power Sources. 2021;481:228861.
[82] Chandra Shekar A, Anwar S. Real-time state-of-charge estimation via particle swarm optimization on a lithium-ion electrochemical cell model. Batteries. 2019;5(1):4.
[83] Tagade P, Hariharan KS, Gambhire P, Kolake SM, Song T, Oh D, Yeo T, Doo S. Recursive Bayesian filtering framework for lithium-ion cell state estimation. J Power Sources. 2016;306:274-88.
[84] Ahmed R, El Sayed M, Arasaratnam I, Tjong J, Habibi S. Reduced-order electrochemical model parameters identification and state of charge estimation for healthy and aged Li-ion batteries—Part II: Aged battery model and state of charge estimation. IEEE Trans Emerg Sel Topics Power Electron 2014;2(3):678-90.
[85] Lotfi N, Landers RG, Li J, Park J. Reduced-order electrochemical model-based SOC observer with output model uncertainty estimation. IEEE Trans Control Syst Technol 2016;25(4):1217-30.
[86] Liu E, Wang X, Niu G, et al. Uncertainty management in lebesgue-sampling-based li-ion battery SFP model for SOC estimation and RDT prediction. IEEE/ASME Transactions on Mechatronics 2022; 28(2): 611-620.
[87] Han X, Ouyang M, Lu L, Li J. Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle. Part I: Diffusion simplification and single particle model. J Power Sources. 2015;278:802-13.
[88] Han X, Ouyang M, Lu L, Li J. Simplification of physics-based electrochemical model for lithium ion battery on electric vehicle. Part II: Pseudo-two-dimensional model simplification and state of charge estimation. J Power Sources. 2015;278:814-25.
[89] Ma Y, Li X, Li G, Hu Y, Bai Q. SOC oriented electrochemical-thermal coupled modeling for lithium-ion battery. IEEE Access. 2019;7:156136-49.
[90] Sturm J, Ennifar H, Erhard SV, Rheinfeld A, Kosch S, Jossen A. State estimation of lithium-ion cells using a physicochemical model based extended Kalman filter. Appl Energy 2018;223:103-23.
[91] Rahimian SK, Rayman S, White RE. State of charge and loss of active material estimation of a lithium ion cell under low earth orbit condition using Kalman filtering approaches. J Electrochem Soc. 2012;159(6):A860.
[92] Li J, Wang L, Lyu C, Pecht M. State of charge estimation based on a simplified electrochemical model for a single LiCoO2 battery and battery pack. Energy 2017;133:572-83.
[93] Li H, Zhang W, Yang X, Jiang H, Wang Y, Yang T, Chen L, Shen H. State of charge estimation for lithium-ion battery using an electrochemical model based on electrical double layer effect. Electrochim Acta 2019;326:134966.
[94] Santhanagopalan S, White RE. State of charge estimation using an unscented filter for high power lithium ion cells. Int J Energy Res 2010;34(2):152-63.
[95] Bartlett A, Marcicki J, Rhodes K, Rizzoni G. State of health estimation in composite electrode lithium-ion cells. J Power Sources. 2015;284:642-9.
[96] Sun X, Xu N, Chen Q, Yang J, Zhu J, Xu J, Zheng L. State of Power Capability Prediction of Lithium-Ion Battery from the Perspective of Electrochemical Mechanisms Considering Temperature Effect. IEEE Trans. Transp. Electrification 2022.
[97] Tang SX, Camacho-Solorio L, Wang Y, Krstic M. State-of-charge estimation from a thermal–electrochemical model of lithium-ion batteries. Automatica 2017;83:206-19.
[98] Chaochun Y, Bingjian W, Houzhong Z, Chen L, Huanhuan L. State-of-charge estimation of lithium-ion battery based on a novel reduced order electrochemical model. Int J Electrochem Sci 2018;13:1131-46.
[99] Li X, Huang Z, Tian J, Tian Y. State-of-charge estimation tolerant of battery aging based on a physics-based model and an adaptive cubature Kalman filter. Energy 2021;220:119767.
[100] Afshar S, Morris K, Khajepour A. State-of-charge estimation using an EKF-based adaptive observer. IEEE Trans Control Syst Technol 2018;27(5):1907-23.

[101] Hosseininasab S, Lin C, Pischinger S, Stapelbroek M, Vagnoni G. State-of-health estimation of lithium-ion batteries for electrified vehicles using a reduced-order electrochemical model. J Energy Storage. 2022;52:104684.
[102] Tagade P, Hariharan KS, Kolake SM, Song T, Oh D. Stochastic spectral projection of electrochemical thermal model for lithium-ion cell state estimation. J Power Sources. 2017;343:520-35.
[103] Fan G. Systematic parameter identification of a control-oriented electrochemical battery model and its application for state of charge estimation at various operating conditions. J Power Sources. 2020;470:228153.
[104] Li W, Fan Y, Ringbeck F, Jöst D, Sauer DU. Unlocking electrochemical model-based online power prediction for lithium-ion batteries via Gaussian process regression. Appl Energy. 2022;306:118114.
[105] Wang Y, Zhang X, Liu K, et al. System identification and state estimation of a reduced-order electrochemical model for lithium-ion batteries. eTransportation. 2023;18:100295.
[106] Couto LD, Schons SM, Coutinho D, et al. A descriptor system approach for the nonlinear state estimation of Li-ion battery series/parallel arrangements. IEEE Trans Control Syst Technol. 2022;31(2):825-40.
[107] Shao J, Li J, Yuan W, et al. A novel method of discharge capacity prediction based on simplified electrochemical model-aging mechanism for lithium-ion batteries. J Energy Storage. 2023;61:106788.
[108] Gu Y, Wang J, Chen Y, et al. A simplified electro-chemical lithium-ion battery model applicable for in situ monitoring and online control. Energy. 2023;264:126192.
[109] Tian A, Yang C, Gao Y, et al. Aging effect–aware finite element model and parameter identification method of lithium-ion battery. J Electrochem Energy Convers Storage. 2023;20(3):031005.
[110] Zhang D, Park S, Couto LD, et al. Beyond battery state of charge estimation: Observer for electrode-level state and cyclable lithium with electrolyte dynamics. IEEE Trans Transp Electrification. 2022.
[111] Yang R, Li Z, Chen Z, et al. Fast state-of-charge estimation for lithium-ion batteries using a simplified electrochemical model without initial state restrictions. IEEE Trans Transp Electrification. 2023.
[112] Wang J, Meng J, Peng Q, et al. Lithium-ion battery state-of-charge estimation using electrochemical model with sensitive parameters adjustment. Batteries. 2023;9(3):180.
[113] Liu E, Niu G, Lyu D, et al. Low-cost adaptive LS-DEKF for SOC estimation and RDT prediction with SFP model. IEEE Trans Instrum Meas. 2023.
[114] Planté E, Postoyan R, Raël S, et al. Multiple active material lithium-ion batteries: Finite-dimensional modeling and constrained state estimation. IEEE Trans Control Syst Technol. 2023;31(3):1106-21.
[115] Fang D, Wu W, Li J, et al. Performance simulation method and state of health estimation for lithium-ion batteries based on aging-effect coupling model. Green Energy Intell Transp. 2023;2(3):100082.
[116] Li Y, Wei Z, Xie C, et al. Physics-based model predictive control for power capability estimation of lithium-ion batteries. IEEE Trans Ind Inform. 2023.
[117] Zhang Z, Shao J, Li J, et al. SOC estimation methods for lithium-ion batteries without current monitoring. Batteries. 2023;9(9):442.
[118] Yeregui J, Oca L, Lopetegi I, et al. State of charge estimation combining physics-based and artificial intelligence models for Lithium-ion batteries. J Energy Storage. 2023;73:108883.
[119] Hosseininasab S, Momtaheni N, Pischinger S, et al. State-of-charge estimation of Lithium-ion batteries using an adaptive dual unscented Kalman filter based on a reduced-order model. J Energy Storage. 2023;73:109011.
[120] Xu R, Wang Y, Chen Z. A migration-based method for non-invasive revelation of microscopic degradation mechanisms and health prognosis of lithium-ion batteries. J Energy Storage, 2022; 55: 105769.
[121] Zheng Q, Yin X, Zhang D. State-space modeling for electrochemical performance of Li-ion batteries with physics-informed deep operator networks. J Energy Storage, 2023; 73: 109244.

[122] VITO, Fraunhofer, Viegand Maagøe. Ecodesign and Energy Labelling of rechargeable electrochemical batteries with internal storage under FWC ENER/C3/2015-619-Lot 1 TASK 1 Report Scope (Definitions, Standards and Legislation) For Ecodesign and Energy. 2019 URL:https://ecodesignbatteries.eu/sites/ecodesignbatteries.eu/files/attachments/ED_Battery_Task%201_V29_final.pdf
[123] Reniers JM, Mulder G, Howey DA. Review and performance comparison of mechanical-chemical degradation models for lithium-ion batteries. J Electrochem Soc 2019;166(14):A3189-200.
[124] Newman J. Fortran programs for the simulation of electrochemical systems: Dualfoil5. 2. f , 2014 . URL http://www.cchem.berkeley.edu/jsngrp/.
[125] Moura S. FastDFN: Fast Doyle-Fuller-Newman (DFN) electrochemical-thermal battery model simulator. GitHub, San Francisco. 2018. URL https://github.com/scott-moura/fastDFN
[126] Torchio M, Magni L, Gopaluni RB, Braatz RD, Raimondo DM. Lionsimba: a matlab framework based on a finite volume model suitable for li-ion battery design, simulation, and control. J Electrochem Soc 2016;163(7):A1192.
[127] Sulzer V, Marquis SG, Timms R, Robinson M, Chapman SJ. Python battery mathematical modelling (PyBaMM). J Open Res Softw 2021;9(1).
[128] Mulder G, Omar N, Pauwels S, Meeus M, Leemans F, Verbrugge B, De Nijs W, Van den Bossche P, Six D, Van Mierlo J. Comparison of commercial battery cells in relation to material properties. Electrochimica Acta 2013; 87:473-88.
[129] Haran BS, Popov BN, White RE. Determination of the hydrogen diffusion coefficient in metal hydrides by impedance spectroscopy. J Power Sources. 1998;75(1):56-63.
[130] Marquis SG, Sulzer V, Timms R, Please CP, Chapman SJ. An asymptotic derivation of a single particle model with electrolyte. Journal of The Electrochemical Society. 2019 Nov 8;166(15):A3693.
[131] Subramanian VR, Diwakar VD, Tapriyal D. Efficient macro-micro scale coupled modeling of batteries. J Electrochem Soc 2005;152(10):A2002.
[132] Forman JC, Bashash S, Stein JL, Fathy HK. Reduction of an electrochemistry-based li-ion battery model via quasi-linearization and pade approximation. J Electrochem Soc 2010;158(2):A93.
[133] Subramanian VR, Boovaragavan V, Diwakar VD. Toward real-time simulation of physics based lithium-ion battery models. Electrochem Solid-State Lett. 2007;10(11):A255
[134] Miguel E, Plett GL, Trimboli MS, Oca L, Iraola U, Bekaert E. Review of computational parameter estimation methods for electrochemical models. J Energy Storage 2021;44:103388.