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Review article

Review of the Safe Operating Area (SOA) for Batteries: Evolving concepts and structured frameworks

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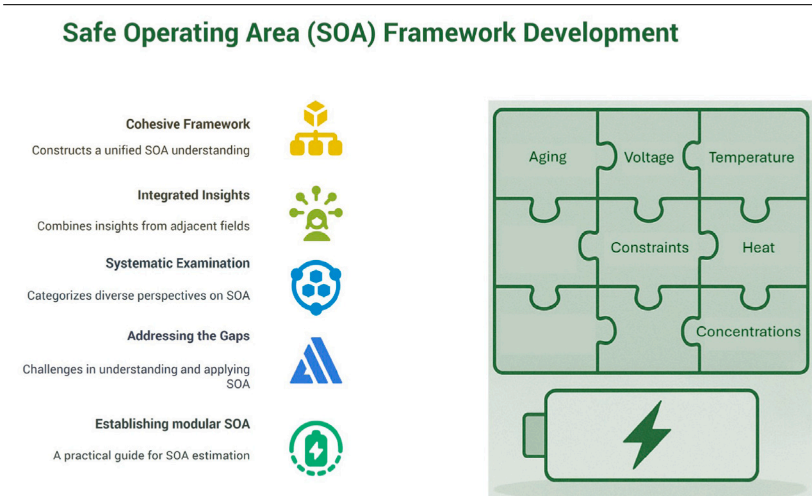
HIGHLIGHTS

- Comprehensive Review of SOA & Critical Analysis.
- Bridging SOA with Related Fields.
- Unified and Structured Framework for SOA.
- Systematic Categorization of existing SOA concepts.
- Practical Guide for Modular SOA Design.

GRAPHICAL ABSTRACT



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ABSTRACT

The Safe Operating Area (SOA) of lithium-ion (Li-ion) batteries defines the permissible range of operational conditions (e.g. temperature, voltage) within which the battery operates safely and reliably, avoiding damage, performance degradation, or critical hazards such as thermal runaway. While the SOA concept is critical for battery performance optimization and safety assurance, its evolving nature has led to inconsistent definitions and methodologies across the literature. These fragmented perspectives hinder the development of a solid understanding and practical application of SOA. This review addresses these gaps by systematically examining the diverse perspectives and methodologies surrounding SOA. It categorizes and structures related topics directly and indirectly linked to SOA while integrating insights from adjacent fields to construct a cohesive framework. By treating SOA as an evolving concept, this work assembles its "building blocks" from various disciplines, creating a comprehensive roadmap for defining and refining SOA boundaries. The proposed approach aims to guide researchers and practitioners in advancing safer, more efficient battery systems.

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1. Introduction

Lithium-ion batteries have become the preferred power source for electric energy storage due to their high energy density, long lifespan, high cell voltage, and low self-discharge rates. These advanced performance characteristics make them the leading choice for efficient and reliable energy storage across various industries. Furthermore, with the rapid growth of the electric vehicle (EV) market, lithium-ion batteries are receiving increased research attention.

Lithium-ion batteries are known for their high cost, primarily due to the expensive raw materials and manufacturing processes required to produce them. Current estimates suggest that they account for approximately 30% of the total cost of an electric vehicle [1]. While the overall trend shows a decline in battery costs per unit of capacity, as highlighted in a comprehensive study that analyzed 50 independent reports on lithium-ion battery costs across different applications and technologies [2], batteries are expected to continue representing a significant portion of energy system expenses for the foreseeable future.

The growing reliance on batteries leads to new challenges, including the environmental and economic issues associated with mining raw materials and managing toxic battery waste. As demand for batteries increases, so do concerns about their lifecycle, particularly regarding the extraction of raw materials and the disposal of hazardous waste. To address these challenges, extending battery lifespan and exploring research areas such as second-life applications are becoming increasingly important. This highlights the crucial role of optimal and advanced battery management systems (BMS), ensuring longer battery life, safer operation, and minimizing environmental impact.

A battery management system is an essential device that ensures the safe, efficient, and reliable operation of batteries across various applications. The primary function of a BMS is to continuously monitor the cells and ensure they operate within the defined or estimated safe operating area (SOA). This SOA is crucial for preventing damage and ensuring longevity, as it defines the permissible range for parameters such as current, voltage, and temperature. Depending on the system's complexity, the SOA may be dynamically estimated by the BMS or predetermined by the cell manufacturer, setting strict upper and lower limits for temperature, current, and voltage to safeguard the battery's integrity.

Beyond cell monitoring and maintaining optimal battery conditions, a BMS can also be responsible for several other tasks, including estimating the State of Charge (SOC), assessing the State of Health (SOH), and cell balancing. Collectively, these functions enhance battery performance, extend lifespan, and prevent potential issues such as overcharging, deep discharging, and thermal runaway.

At the heart of a BMS is the battery model, which plays a crucial role in determining the system's capabilities. The complexity and accuracy of the BMS largely depend on the sophistication of this model. Battery models are generally categorized into four main categories: empirical, semi-empirical, data-driven, and physics-based models [3–7].

Empirical models are developed from experimental data to predict battery behavior under various conditions without addressing the underlying physical processes. These straightforward and computationally efficient models are ideal for real-time applications. However, they require extensive data collection and testing, which can be costly. Additionally, their reliance on interpolation limits their ability to capture the dynamic nature of battery behavior. Any deviation from the data within the lookup table can lead to significant errors.

The next type of models are semi-empirical, semi-theoretical models. The most well-known model in this category is the Equivalent Circuit Model (ECM). This model represents the battery using a combination of resistors and capacitors, which simulate the battery's internal resistance, capacitance, and dynamic response to charge and discharge cycles. The equivalent circuit model is popular for its balance between simplicity and accuracy, providing valuable insights into the battery's performance while remaining computationally efficient. However, ECM model parameters often lack direct physical meaning. As a result, these models are limited in providing deep insights into the underlying mechanisms of battery behavior. Additionally, they lack strong predictive capabilities, especially when operating outside the range of conditions for which they were calibrated. Therefore, the safe operating area used by BMS systems based on empirical or ECM models tends to be straightforward and somewhat limited in capability. Despite their simplicity and lack of strong predictive capabilities, BMS systems based on ECM models remain the most widely used in the industry today, thanks to their speed and computational efficiency [8]. In real-time applications, battery systems are typically composed of multiple modules and packs, each containing numerous individual cells. Monitoring each of these cells is critical for ensuring safe operation, but as the size of the system grows, so does the complexity of monitoring. That requires proportional computational power and an increased quantity of hardware components, such as microcontrollers, which in turn increases the costs. To balance performance with cost-effectiveness, many opt for simpler models that require less memory and are more computationally efficient. This trade-off is a key reason why ECM models are widely used in BMS design.

The third category of battery models, known as physics-based models, delves into the battery's internal parameters and aims to simulate its behavior using electrochemical equations. At the top of this list for detail and accuracy is the pseudo-two-dimensional (P2D) model, also referred to as the Doyle–Fuller–Newman (DFN) model. Named after its developers, this model represents one of the most comprehensive and precise approaches available for battery simulation [9–12]. Unlike empirical or ECM models, the P2D model is grounded in electrochemical principles, with parameters that carry clear physical significance. This model allows for detailed insights into the internal processes of a battery. It can accurately track key phenomena such as concentration changes in both the solid phase and the electrolyte, and monitor the precise potentials and currents in these phases. Moreover, the P2D model can be integrated with additional models, such as thermal and aging models, to simulate the battery cell's thermal behavior and the degradation mechanisms caused by side reactions. This capability enhances the model's versatility, allowing for a more comprehensive battery performance, safety, and lifespan analysis.

The detailed P2D model is composed of a set of partial differential equations (PDEs) with algebraic constraints, defined along the x-axis, which represents the length of the battery. The active particles within the electrodes are modeled as spheres, with their behavior described along the radial coordinate r. A complete list of P2D model equations is available in Table A.1 of Appendix. The P2D model typically requires 15 to 30 parameters [13]. However, this is only an approximate estimate, as the exact number of parameters can vary depending on additional features integrated into the model, such as heat generation, aging effects, or other extensions. While this structure of PDEs with algebraic constraints and numerous parameters ensures high accuracy, it can also lead to a computationally intensive model, resulting in slower simulation times. The slow computation of P2D models is not a major issue for offline applications, such as battery cell design or offline simulations. However, in online applications, where the models need to run and make predictions in real time, this becomes a significant drawback, making them unsuitable for such use cases. That challenge has driven scientists to explore methods for accelerating the computation of the P2D model [14–17], as well as to develop reduced-order models that simplify the P2D framework while maintaining its key characteristics for faster, real-time applications. Among these, the Single Particle Model (SPM) is the most well-known [18–25]. Ali et al. [26] conducted a comparative study on the performance and accuracy of physics-based P2D models versus reduced-order models.

The final category includes data-driven and machine learning (ML) models, which depend on large datasets, making data quality and extensive empirical testing essential. These models analyze patterns within the data to estimate battery states and support various applications [27–32]. However, the complexity of battery dynamics poses significant challenges, making it difficult for ML to function effectively as a purely black-box approach. To address this, some research integrates physics-informed techniques to enhance interpretability and improve model reliability [33–36].

Today's trend in battery development is moving toward larger cells with higher maximum capacities [37,38]. This evolution makes accurate SOA estimation more crucial than ever. As these larger cells can store significantly more energy, the risks of fires or powerful explosions increase, making precise SOA estimation essential for ensuring safety and performance. Additionally, the use of larger cells reduces the total number of cells in a battery pack, paving the way for the adoption of physics-based battery models over traditional electric circuit-based models. One of the main challenges of physics-based modeling is ensuring computational efficiency for real-time applications. However, with fewer cells to monitor, the shift towards these more detailed models becomes more feasible, allowing for more precise SOA estimation and improved safety management by physics-based models.

In the next section, an overview of the historical development of SOA in the literature is provided, with the reasons behind its design being explained. Following that, current trends and evolving definitions of SOA, along with methods of estimation, are explored. The subsequent section will focus on the establishment of a safe operating area using physics-based modeling and constraints.

2. Safe operating area: Literature review & history

The safe operating area defines a range of operational conditions such as min/max voltage, current, temperature, and state of charge that ensure a lithium-ion battery's safe and reliable functioning. Staying within this envelope is critical to prevent damage, extend battery life, and minimize safety risks.

The conditions monitored within the SOA can vary depending on the type of battery model used in the BMS. An ECM-based BMS, relying on an equivalent circuit model, primarily uses measured inputs like current, voltage, and temperature but cannot provide detailed internal physical insights about the battery. In contrast, physics-based models like the P2D model offer a deeper understanding by providing internal battery information, such as lithium-ion concentrations in the electrodes and other electrochemical variables inaccessible to ECM-based models.

2.1. A literature review

In the literature, terms such as safe operating area, Safe Operating Window (SOW), Safety Boundaries, Operational Limits, and Safety envelopes are often used interchangeably to represent similar concepts. Table 1 presents studies that reference and define SOA-related concepts and their corresponding SOA categories.

Generally, SOA is portrayed as a set of static, predefined boundary limits for key variables like temperature, voltage, SOC, and maximum allowable charge/discharge currents. Manufacturers typically establish these boundaries based on extensive testing and empirical analysis to ensure safe operation across a range of conditions [39–58].

The most basic battery management system keeps the system within these predefined safe limits by monitoring variables like voltage, temperature, and current to ensure they remain within the specified range. More advanced BMS features include controlling the SOC to avoid overcharging or over-discharging. Because SOC cannot be directly measured, these systems rely on SOC estimation methods to manage this critical parameter accurately.

Table 1
Categorization of SOA definitions in the literature.

Literature	Characteristics	References
Static empirical predefined SOA	Definitions emphasizing static SOA, based on rigid predefined constraints.	[39–58]
Probabilistic SOA & SOS	Definitions derived from a probabilistic approach.	[59–61]
Static physics-based precalculated SOA	Definition derived from physics-based principles that account for factors such as concentration limits, battery abuse, and side reactions.	[62–72]

The second group of studies approaches the concept of safe operation from a probabilistic perspective, focusing on estimating the State of Safety (SOS) based on hazard risks and probabilities [59–61]. In these studies, the risk level is quantified by calculating the product of hazard severity and hazard likelihood, where severity is often rated on a scale from 0 to 7, and likelihood ranges from 1 to 10. This probabilistic approach involves defining the SOS as a probability function that integrates multiple sub-functions, each representing specific abuse conditions such as over-voltage, high temperature, or mechanical stress. The overall SOS value is then derived by multiplying these individual distributions, which allows for a more flexible assessment of safety that reflects the likelihood of various failure modes under different conditions. In this approach, each operating condition is assigned a safety score. If the system operates in unsafe conditions for any period—an inherently hazardous scenario—this data is recorded and lowers the overall safety score for that specific cell, reflecting its prior exposure to abuse. The cumulative scoring method provides a more comprehensive picture of the cell's long-term safety status by accounting for past operational stresses. This perspective introduces a slightly more dynamic definition of SOA compared to the traditional static SOA provided by cell manufacturers. Instead of using hard thresholds as in traditional static empirical SOA definitions, the probabilistic SOS framework introduces a continuous hazard probability distribution, where the risk gradually increases as operating conditions become more extreme.

The third group, representing the most recent trend in SOA literature, emphasizes the development of a static SOA envelope derived from physics-based modeling principles. These models account for factors such as aging, side reactions, and battery abuse, offering a more detailed and precise approach to defining the SOA [62–72]. Studies in this category typically aim to optimize charging protocols while incorporating battery degradation and abuse constraints. A growing trend toward integrating these advanced SOA definitions into advanced Battery Management Systems is also emerging. Although direct studies on advanced SOA remain relatively limited, recent research established a solid foundation for these advancements. A deeper discussion of this approach will be provided in Section 3.

2.2. SOA history

One of the primary challenges with lithium-ion batteries is the potential for hazardous incidents, such as fires or explosions, during operation. Historically, preventing these catastrophic failures has been the central focus of SOA estimation and BMS development. However, due to limited advancements in battery science, computational tools, and data availability in earlier years, classical SOA approaches concentrated exclusively on macroscopic, measurable operating conditions—primarily voltage, temperature, and current. These classical SOA frameworks were designed to prevent thermal runaway, a critical failure mode in lithium-ion batteries.

Thermal runaway in a lithium-ion battery refers to a self-perpetuating cycle in which an increase in temperature triggers exothermic chemical reactions within the cell, releasing more heat.

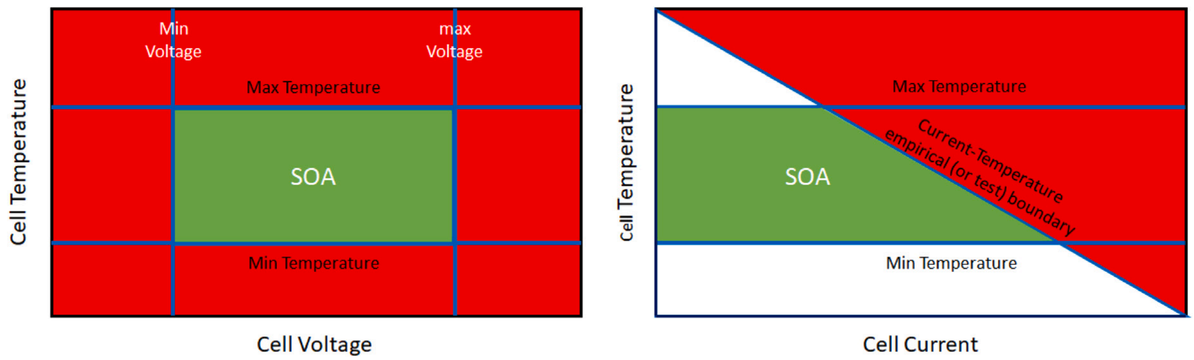

Fig. 1. Static safe operating area based on predefined constraints.
Source: Adapted from Fleischer et al. [56].

The heat accumulation can cause the internal temperature to rise rapidly, leading to the degradation of cell materials, gas release, and, in severe cases, fire or explosion. Extensive studies have documented the sequence of events leading to thermal runaway, with efforts focusing on understanding the chemical reactions, thermal dynamics, and voltage thresholds involved [73–79]. While there is broad agreement on the reactions involved in thermal runaway, the exact starting and ending points of these reactions may vary slightly across different studies.

The review by Chen et al. [54] provides a comprehensive analysis of the chemical reactions involved in thermal runaway, outlining the corresponding temperature and voltage conditions in each battery component, such as the anode, cathode, and electrolyte. From these chemical reaction criteria, a critical temperature map was developed, correlating each reaction with its corresponding thermal limit. Exceeding these thresholds initiates thermal runaway, making this map a foundational element of the classical SOA, prioritizing temperature constraints to ensure safe operation.

Key factors that can trigger fire or thermal runaway reactions in lithium-ion batteries include:

- Overcharging
- Over-current
- Internal short circuits
- External short circuit
- Exposure to internal or external heat
- External physical damage to the battery

Of the six potential causes of thermal runaway, overcharging, overcurrent, internal and external short circuits, and exposure to heat generated internally are related to the core principles of battery operation. That highlights the importance of a well-designed battery management system. By utilizing functions such as modeling and safe operating area estimation, a BMS can actively prevent thermal runaway incidents and ensure the safe operation of the battery system. Therefore, besides the battery failure temperature map, the battery system's dynamic behavior should have been included in the BMS. That logically results in simple battery models from empirical models to ECM models. The limitation of these models has driven research that emphasizes macroscopic and measurable safety indicators, including the overall battery voltage, the electric current passing through the cell, and the temperature within the cell [73,80–82].

This perspective aligns with the priorities of battery manufacturers, who aim to ensure the safe operation of their products. Manufacturers typically provide detailed guidelines for safe battery charging and discharging, including the maximum and minimum voltage, current, and temperature limits, as specified in their product data sheets [83,84]. That has led to the widespread adoption of a simple, static SOA, often represented as a rectangular boundary defined by voltage, current, and temperature constraints. These predefined limits establish a static framework for SOA, ensuring safe battery operation within set boundaries, as schematically illustrated in Fig. 1. Additionally, this approach reinforced the use of the standard Constant Current–Constant Voltage (CCCV) protocol for charging and discharging.

The conventional approach to SOA and charging protocols is cautious, setting operational limits based on testing and empirical models that rely on external, macroscopic variables such as temperature, voltage, and current [85]. To this date, most Battery Management Systems utilize empirical or ECM to monitor battery performance, ensuring it remains within these conservative limits. This conservatism arises from the limitations of these models, which, by depending on macroscopic metrics, lead to wider safety margins than necessary. Consequently, engineers often oversize battery packs as a precaution, resulting in increased costs and greater environmental impact [86]. Moreover, because conventional SOA definitions typically cannot adapt to the battery's aging process, they may appear conservative at the beginning of life. However, even these conservative estimates can eventually overstate the safe operating area, as the battery becomes more susceptible to degradation and abuse over time.

Despite these limitations, the traditional SOA still remains the predominant approach in BMS manufacturing due to its simplicity and high computational efficiency [8].

3. Safe operating area: Current trends, and evolutions

As research into battery aging mechanisms advances, it has become evident that failures in lithium-ion batteries can arise from both sudden events and gradual degradation. Sudden failures may occur under extreme conditions such as overcharging or elevated temperatures. In contrast, many failures result from the cumulative effects of slow side reactions and aging processes that progressively damage the cell over time. While early-stage aging may appear negligible, its long-term impact can be significant, potentially leading to critical failures. Consequently, there is a growing focus on understanding and mitigating the aging mechanisms and safety risks associated with side reactions in lithium-ion batteries. This updated definition of SOA also accounts for the gradual degradation pathways that may eventually lead to failure over time [86].

Several studies, including those by Smith et al. and Chaturvedi et al. have challenged the conventional perspective by questioning not only the foundational assumptions of conventional SOA but also the industry-standard CCCV charging protocol [85,86]. These efforts have inspired research focused on refining the definition of SOA for batteries through the application of physics-based models. That modern approach to SOA integrates conventional operational limits such as voltage, temperature, and current with advanced physics-based models that capture the complex dynamics and physics occurring inside the battery.

The introduction of physics-based models brought a significant enhancement to the SOA framework, enabling the incorporation of

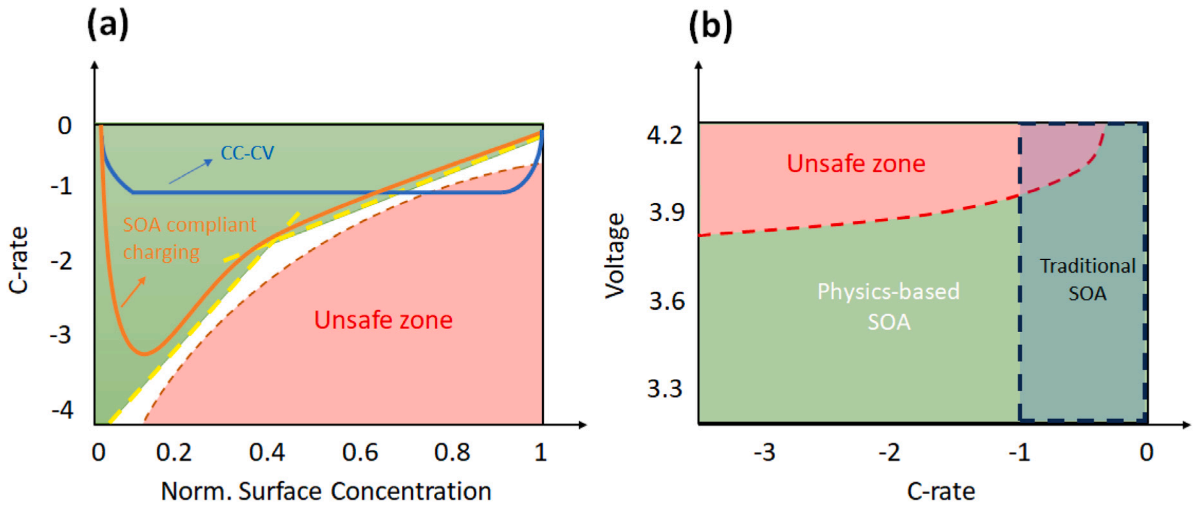

Fig. 2. The SOA defined using linearized lithium plating constraints to prevent lithium plating. (a) Static safe zone calculated by P2D model. The CC–CV protocol can go outside of the safe zone vs. the SOA-compliant charging protocol that stays in the SOA envelop (b) The comparison between the physics-based SOA (green area) and the conventional SOA (black dashed rectangle) based on the max/min current and voltage value. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Adapted from Couto et al. [62].

side reactions and aging mechanisms, particularly those driven by battery stress or abuse. By accounting for these additional variables, researchers aim to improve battery reliability, extend operational lifespans, and mitigate risks associated with misuse or failure [62–72].

For instance, Couto et al. [62] challenged conventional SOA assessments that rely on conservative limits for current and voltage as suggested by cell manufacturers or simpler empirical models. Their study revealed that these conservative limits are not only overly cautious but may not ensure battery safety. Instead, they demonstrated that alternative charging and discharging regimes could be both faster and safer. In Fig. 2, it is illustrated that adhering strictly to conservative charging and discharging limits can lead to lithium plating, which damages the battery. Specifically, the study showed that, despite manufacturer recommendations against higher C-rates, the battery can be charged at higher rates without any stress or abuse during the initial stages of charging. However, as the SOC increases, the C-rate should be reduced to avoid violating lithium plating constraints, as calculated by the P2D model. Following a strict “max-C-rate” policy will inevitably lead the battery into the lithium plating region. In Fig. 2(a), it is shown that maintaining a constant C-rate of 2 initially appears safe but eventually leads to lithium plating as the battery continues to charge. Alternatively, the figure demonstrates that the battery can be charged at higher C-rates while remaining completely safe, provided the C-rate is gradually reduced to adhere to lithium plating constraints as the state of charge (SOC) increases.

These studies demonstrate that the SOA region can be expanded, allowing batteries to operate under conditions that were previously considered unsafe, leading to improved efficiency. This expansion also makes features such as fast charging more feasible. However, it has also been shown that even within the more conservative SOA, which is smaller, there are still areas that remain unsafe. This is because the conventional SOA does not account for aging mechanisms that degrade the battery over time. This leads to a schematic comparison between the conventional SOA and the physics-based SOA, as shown in Fig. 3.

With the review of SOA history, current trends, and its evolution now complete, the following section will offer a deeper exploration of the various methods and domains related to SOA. It will provide a more in-depth examination of the various methods and domains associated with SOA, offering a comprehensive overview of approaches for defining the SOA envelope and its constraints.

4. Establishing the boundaries of the safe operating area

With this broader understanding of the safe operating area, attention must now be directed toward detailing the specific boundaries and constraints that define the SOA envelope. Various methods and strategies used to establish these limits will be examined, followed by an analysis of approaches for accurately estimating the SOA envelope.

Several topics in the literature and previous research are closely related to the concept of the safe operating area, although they do not directly address it. In this review, these related studies have been categorized and grouped to provide a comprehensive understanding of the relevant research landscape:

- State of Power (SOP)
- Aging
  - SEI (Solid Electrolyte Interphase)
  - Lithium plating
  - Particle cracking
- Optimal charging and fast charging

The critical question of how to estimate a safe operating area centers around defining the boundaries of the SOA envelope. Several approaches for establishing these constraints are closely tied to the research topics associated with SOA. Each of these topics will now be explored in greater detail.

4.1. State of Power (SOP)

One approach to establishing a hard constraint for defining one of the limiting edges of the SOA envelope involves the State of Power (SOP) concept. The SOP represents the power available to the battery at a given moment, which must be accurately estimated. This concept is closely tied to the battery’s current state.

When the SOP of a battery cell is known at a specific time, it provides a limit to the power that can be safely drawn from the battery. For instance, the user cannot demand more power in an electric vehicle than what is available based on the SOP estimation. This enables the formation of a dynamic constraint that adjusts according to the battery’s states. Consequently, the voltage and current limits can be determined based on the relationship $P = I \cdot V$, ensuring safe and reliable operation.

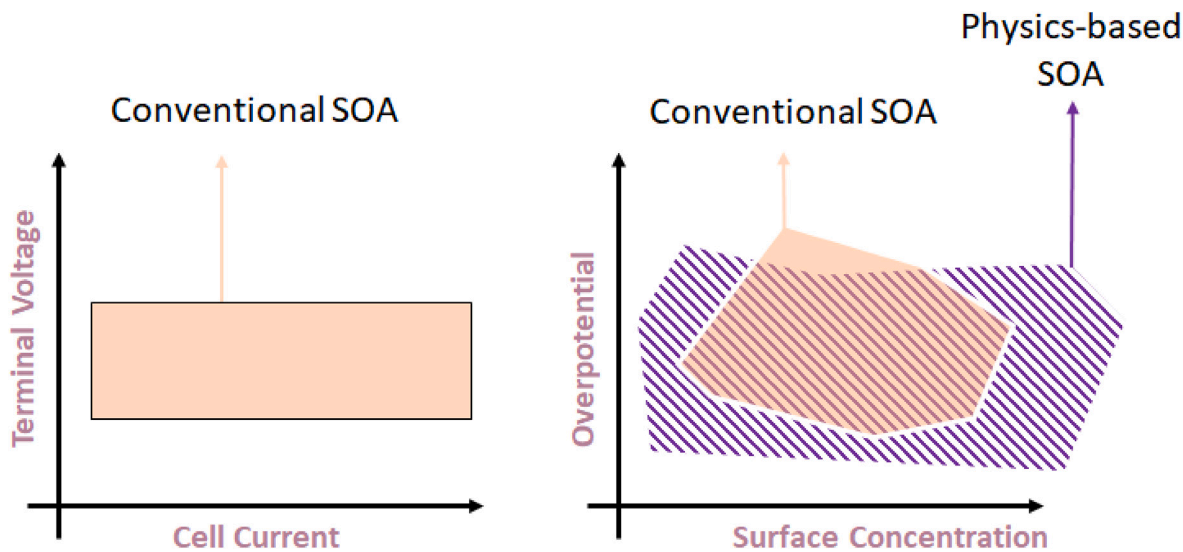

Fig. 3. Schematic illustration comparing conventional and physics-based SOAs. The physics-based SOA has the potential to be larger than the conventional SOA, allowing for more efficient operation. Additionally, certain regions deemed safe within the conventional SOA are identified as unsafe when analyzed using the physics-based SOA framework.

The literature primarily identifies three main categories of SOP estimation:

- Characteristic map-based methods
- Model-based methods
    - Empirical models
    - Physics-based models
- Machine learning methods

4.1.1. *Characteristic map-based SOP*

In the characteristic map-based approach, an offline multidimensional power capability map is derived from extensive testing and stored within the battery management system. This map captures the static relationships between the SOP, and various battery states such as temperature, voltage, and state of charge. As a result, significant memory needs to be allocated for this purpose [87,88].

Moreover, the effectiveness of this method is limited by the inherent complexity and nonlinear nature of lithium-ion batteries. Battery performance is highly dependent on operating conditions, which can change dynamically. Consequently, a pre-stored offline characteristic map may not accurately represent the battery's real-time power capability. It fails to account for variations in environmental factors, aging effects, and transient behaviors that influence power availability [89]. Another disadvantage arises from the adaptation technique. The characteristic map method aims to estimate the maximum available power, but the system rarely reaches the maximum power limit in real-world operation. These rare instances are the only opportunities to compare the estimated values with actual performance, limiting the ability to refine the model and leading to inaccuracies in the adaptation process [55].

4.1.2. *ECM and empirical models for SOP estimation*

The estimation of the SOP has been thoroughly investigated using equivalent circuit models to ensure the maximum current under constraints imposed by cell parameters such as voltage and SOC [90–93]. The study by Xiong et al. [94] developed and validated a peak power estimation method for $LiMn_2O_4$ lithium-ion cells using a Hardware-in-the-Loop (HIL) test system. The approach integrates an Electrochemical Polarization (EP) model with real-time parameter identification via the Recursive Least Square (RLS) algorithm, delivering reliable power estimates across varying SOC levels, even under sudden load changes. In a subsequent study, Xiong et al. [95] demonstrated that combining an Electrochemical Polarization (EP) model with an Adaptive Extended Kalman Filter (AEKF) significantly enhances lithium-ion battery state estimation and dynamic performance. The approach incorporates a hybrid power pulse test and a multi-step joint estimation method for SOC and peak power, delivering accurate and robust predictions of SOP. The approach by Waag et al. [96] addresses the current-dependent behavior of battery resistance and incorporates nonlinearities in battery modeling using an empirical model. Their study demonstrates improvements in power estimation, particularly for aged batteries and under low-temperature conditions. A similar study by Wang et al. [97] investigated the use of a diffusion-based effect modeled as nonlinear resistance within the equivalent circuit model to estimate the maximum charge and discharge power. Finally, a dual Kalman filter technique has been developed to enable real-time predictions of peak power across various temperature ranges and aging conditions, showcasing accuracy and adaptability [93].

A review paper by Waag et al. [55] compares different variations of the empirical models and their performance on SOP estimation based on the empirical battery models. This review emphasizes the need to adapt models to the battery's aging status, the current-dependent behavior of battery impedance, and the differences observed among multicell packs. In a more recent review study, Guo et al. [98] comprehensively examined SOP estimation methods, emphasizing those based on equivalent circuit models. Guo noted that while the 1-RC model is effective for SOP estimation, its accuracy declines across broad frequency ranges, impacting long-term predictions. Fractional order models offer improved frequency response but are computationally demanding, whereas model fusion techniques may present a balanced alternative.

The use of empirical models for predicting the SOP has been well investigated. These models are typically easy to implement and require minimal computational resources, which has made them the standard in many applications. However, there is a growing trend towards physics-based modeling, which delivers significantly improved accuracy and is becoming more feasible for real-time applications. While the industry is gradually shifting towards physics-based models, the transition is slow. Nevertheless, these models hold significant promise due to their superior accuracy and reliability, making them a valuable investment for future applications despite their current prevalence in academic research and varying levels of technological readiness.

4.1.3. Physics-based models and SOP

Another category of studies on State of Power prediction leverages electrochemical models. Unlike equivalent circuit models, which focus on macroscopic observed variables like cell terminal voltage and current, electrochemical models provide a more detailed representation of the internal processes within batteries. While ECM models may result in conservative power predictions due to their limited link with battery internal dynamics, electrochemical models bind available power to factors such as lithium concentration within electrode particles, leading to more accurate forecasts. During discharging, for instance, the ability of lithium ions to migrate from the surface of the negative electrode particles into the electrolyte is essential for generating power. The surface serves as the interface where lithium ions transition into the electrolyte. As lithium ions exit the surface, they need to be replenished by lithium from deeper within the particles. This replenishment relies on lithium diffusion from the particle's core to the surface, a process constrained by the diffusion coefficient within the solid material. The speed at which lithium reaches the surface ultimately determines the battery's available power over time. In spherical coordinates, Fick's second law for diffusion in a spherical particle can be expressed as:

$$\frac{\partial C}{\partial t} = \frac{1}{r^2}\frac{\partial}{\partial r}\left(Dr^2\frac{\partial C}{\partial r}\right), \tag{1}$$

where C is the concentration of lithium ions within the particle, t is time, r is the radial distance from the center of the particle and D is the diffusion coefficient. A complete list of P2D model equations is available in Table A.1 in Appendix.

Numerous studies in the literature utilize physics-based modeling for power prediction [70–72,89,99–104]. Lee et al. [100] proposed using the solid-phase lithium concentration at the particle surface as a constraint to manage battery power limits. They developed a proportional–integral controller to maintain the surface concentration within specified utilization limits. Li et al. [101] demonstrated that surface lithium concentration is an effective predictor of a battery's power capability, also incorporating temperature and aging effects to refine power capability predictions. Zheng et al. [102] focused on instantaneous power by deriving a formula based on Gibbs free energy and the battery's internal resistance, ultimately establishing an equation that links instantaneous power to the surface lithium concentration. Li et al. [72] accelerated the power estimation via Gaussian process regression. Li et al. [103] developed a method to predict power in thicker electrodes using P2D models, specifically addressing cases where the assumption of uniform current density is no longer valid. Smith et al. [70] have used a linearized reduced order P2D model to calculate the maximum safe current that respects the lithium plating constraints to avoid this side reaction. Perez et al. [71] implemented a reference governor to adjust the commanded current by introducing a parameter $\beta \in [0,1]$. When any constraints were breached, the value of β was decreased, whereas it was increased when all constraints were met. Sun et al. [89] proposed an SPM model incorporating temperature-dependent parameters such as diffusion coefficients and internal resistance. The model utilizes physical lithium-ion concentration limits to govern the SOP, while the Grey Wolf Optimizer (GWO) algorithm determines peak charge and discharge capabilities across different time horizons.

Similar to Sun et al. [89], several studies employ various optimization algorithms for power prediction. Zou et al. [104] compared four algorithms—bisection, genetic algorithm (GA), particle swarm optimization (PSO), and Grey Wolf Optimizer (GWO) to predict peak power capabilities in lithium-ion batteries using an electrochemical model. The study estimated peak power based on surface lithium-ion concentration limits by utilizing an SPM model with lithium-ion concentrations in solid particles. Each algorithm was evaluated on accuracy, convergence rate, computational speed, and complexity. The results indicated that the GWO method excelled in convergence rate and computational efficiency while maintaining high accuracy.

4.1.4. Machine learning and SOP

In a data-driven approach, the battery is modeled as a black box, disregarding its internal reaction mechanisms and specific characteristics. This method considers the SOP as the model's output, while inputs include voltage, temperature, and SOC. Xiong et al. [105] applied a data-driven approach using recursive least squares and adaptive extended Kalman filter algorithms to enable real-time joint estimation and updating of model parameters for voltage, SOC, and SOP. In a study by Fleischer et al. [106], a self-learning algorithm for estimating SOP was developed using an Adaptive Neuro-Fuzzy Inference System (ANFIS). This approach incorporates inputs such as current amplitude, charge accumulation, state of charge, temperature, and time-averaged voltage during a pulse to forecast the battery terminal voltage after a specified prediction window. The ANFIS training process employs a two-step hybrid learning strategy: first, a forward pass with fixed premise parameters is executed to calculate the output error, followed by a backward pass using gradient descent to adjust these parameters. Ultimately, the peak discharge and charge current/power are derived through iterative system executions, with the estimation gradually refining to reach the peak value via a bisection method.

While data-driven methods are theoretically effective at tackling nonlinear challenges, their performance heavily relies on the quality of training data and the techniques employed. They face limitations in dynamic conditions, as battery behavior is inherently dynamic, which restricts their broader application. Moreover, acquiring SOP references across diverse operating environments poses significant challenges, particularly due to the effects of temperature and battery aging. Collecting high-quality data for training machine learning models can be labor-intensive and time-consuming, especially since SOP is not directly measurable [98].

However, some studies try to address these challenges by hybrid use of data-driven techniques alongside a battery model. For example, Tang et al. [107] used a model-based Extreme Learning Machine (ELM) algorithm to forecast the batteries' future power capability, voltage, and temperature under varying SOC and temperatures. They substitute the standard activation functions found in traditional ELMs with a series of sub-models, each comprising a 1-RC model and a thermal model. These sub-models utilize randomly selected initial SOC and parameters within a reasonable range to simulate the battery's electrical and electrothermal behaviors accurately.

In the review paper by Gou et al. [108], a comprehensive compilation of studies focused on power prediction and SOP estimation is presented, covering all relevant research up to 2024.

4.2. Aging

In some interpretations of SOA, battery safety encompasses not only preventing immediate failures but also minimizing long-term degradation. This brings the concept of aging into the scope of SOA. A well-defined safe operating area should outline an operational envelope where aging effects are controlled and minimized. Therefore, an effective approach to defining an SOA for battery cells involves incorporating aging constraints to limit degradation over time. Moreover, the safety limits should evolve with the battery's state of health, reflecting its increasing vulnerability to stress and degradation as it ages.

A practical distinction can be made by clarifying whether an operating condition poses an immediate safety risk or contributes to gradual degradation. Some conditions fall within a critical zone, where violations can lead to instantaneous failure or hazardous events. In contrast, others may accelerate aging and reduce battery lifespan over time, which can eventually cause the battery to fail. The latter typically defines the recommended operating area, which is a more conservative subset of the broader SOA. From a design perspective, the SOA can be conceptualized in two layers: the outer layer encompasses critical safety constraints that must not be violated to prevent dangerous failures,

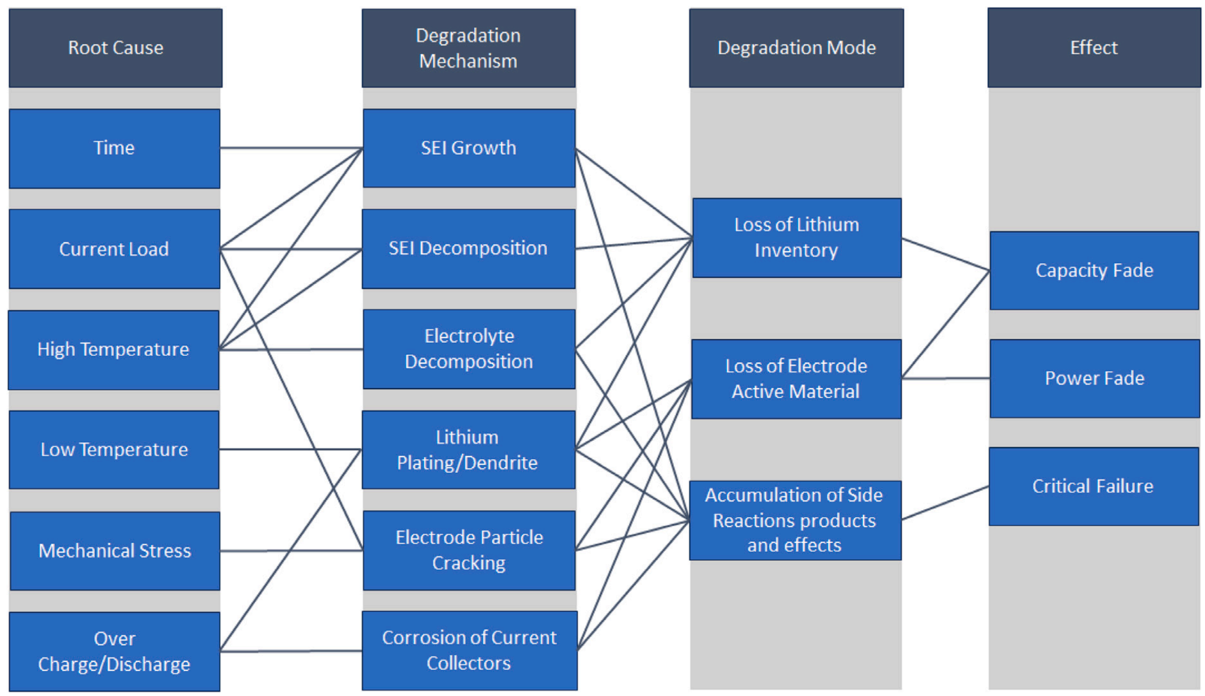

Fig. 4. Aging mechanism, the root causes and effects on a battery cell.
Source: Inspired and adapted from Birkl et al. [109].

Table 2
Overview of degradation mechanisms with corresponding references.

Degradation mechanism	References
Particle cracking	[110–121]
Solid Electrolyte Interphase (SEI) growth and decomposition	[46,122–134]
Electrolyte decomposition	[135–143]
Corrosion of current collector	[144–148]
Lithium plating	[67,68,149–158]

while the inner layer is defined by constraints that minimize side reactions and operational stress, helping to preserve battery performance and longevity.

Fig. 4 illustrates key aging mechanisms responsible for battery degradation, highlighting their root causes and effects on battery cell performance.

In Table 2, a list of studies that address these aging mechanisms is gathered and presented alongside the corresponding research studies that explore these mechanisms. The table covers the following key degradation processes:

- *Solid Electrolyte Interphase (SEI) Growth*
  The SEI layer forms on the surface of the negative electrode during initial charging cycles in lithium-ion batteries. This layer arises from side reactions between the electrode material and electrolyte components. While initially undesirable, the SEI layer is critical in stabilizing the battery. It acts as a barrier that prevents further reactions between the active electrode material and the electrolyte, thereby reducing ongoing degradation. This semi-permeable layer allows lithium ions to pass through while blocking most other electrolyte components. However, SEI is not completely stable; as the electrode expands and contracts during charge and discharge cycles, the SEI layer can crack, exposing fresh surfaces of the electrode to the electrolyte. This results in new SEI formation, consuming lithium and electrolyte and ultimately reducing battery capacity. Therefore, maintaining a stable SEI layer is essential for battery longevity and performance. The formation of SEI layers can significantly impact ion transport, increasing internal resistance while depleting active material and electrolytes. These effects collectively reduce battery efficiency and shorten its lifespan [46,122–134].
- *SEI Cracking and Decomposition*
  The SEI layer serves as a protective barrier, shielding the active material of the electrode particles from direct contact with the electrolyte. Any decomposition, cracking or damage to this layer can increase resistance, impair lithium-ion intercalation/deintercalation, and compromise its protective function. This degradation either results in higher resistance and a decrease in cell efficiency or exposes fresh electrode surfaces to the electrolyte, prompting additional SEI formation that consumes electrolyte and active material, thereby reducing both lithium inventory and overall cell capacity [46,122,123,125,127–134].
- *Electrolyte Decomposition*
  Electrolyte decomposition is a critical issue in lithium-ion batteries, often initiated by chemical or electrochemical reactions at extreme temperatures or voltages. These reactions can generate gaseous byproducts, leading to cell swelling, increased internal pressure, and safety risks such as leakage or thermal runaway. The decomposition products can also form unwanted films on the electrode surfaces, impeding ion transport and increasing internal resistance. Over time, this process contributes to the loss of active lithium and active material degradation, accelerating capacity fading and shortening the battery's cycle life. Furthermore, the degradation of the electrolyte reduces its ionic conductivity, further impairing battery performance [135–143].
- *Particle Cracking*
  During cell charging, lithium ions intercalate into the negative electrode material, typically graphite, sometimes blended with particles like silicon. This intercalation causes the electrode particles to expand in size as they absorb lithium. During discharge, the process reverses, leading to a reduction in particle size. This constant fluctuation in particle size causes mechanical stress, leading to particle cracking. These cracks also disrupt the SEI layer that forms around each particle, exposing fresh surfaces to the electrolyte and resulting in additional SEI growth, which

reduces the lithium inventory. As cracks propagate within the electrode material, they further impair lithium-ion diffusion and compromise structural integrity, leading to notable capacity loss over time [110–121].

- *Corrosion of the Current Collector*
  In lithium-ion batteries, current collectors—typically copper for the anode and aluminum for the cathode—facilitate efficient electron transport between the external circuit and electrodes. However, these collectors are susceptible to corrosion from prolonged exposure to reactive electrolytes, acidic byproducts, and moisture, especially if the cell's hermetic seal is compromised. Under high voltage or temperature, such corrosion accelerates, forming oxides and other byproducts that degrade the collector material over time. Corrosion of the current collectors significantly impacts cell performance and safety. Increased internal resistance from corrosion products impedes electron flow, leading to capacity fading and, in severe cases, loss of electrical contact. Detached corrosion particles can contaminate other cell components, while a breach in hermiticity allows electrolyte loss or contamination. Ultimately, preventing corrosion is essential to ensure battery longevity, efficiency, and safety [144–148].
- *Lithium Plating/Dendrites*
  Lithium plating occurs when lithium ions are deposited as metallic lithium on the surface of the anode during charging, rather than intercalating into the electrode material. This phenomenon typically arises under conditions of high charging rates when overpotential drops below zero, at low temperatures, or when the electrolyte is depleted. When lithium plating occurs, it forms a layer of metallic lithium on the anode surface, reducing the amount of lithium available for intercalation. This leads to a loss of lithium inventory and contributes to capacity fade and reduced cycle life. In some cases, plated lithium can evolve into dendritic structures—needle-like growths that may penetrate the separator and pose a risk of internal short circuits [67,68,151]. However, several studies suggest that dendrite formation does not necessarily lead to short circuits or immediate safety failures, indicating a more complex and nuanced relationship between dendrites and thermal runaway [159,160]. For instance, Lu et al. [160] found no evidence of lithium dendrites penetrating the separator or reaching the cathode. Instead, they observed that dendrites predominantly grow inward, increasing cell impedance and contributing to premature capacity fade, rather than directly triggering internal short circuits. Nonetheless, lithium plating remains a critical degradation mechanism, and mitigating it requires careful optimization of charging protocols, temperature control, and electrolyte management [67,68,149–158].

4.3. Aging constraints and SOA

To define SOA boundaries based on aging mechanisms, we should consider how the underlying physics of these mechanisms and the conditions required for their occurrence can be expressed through hard constraints. These constraints are mathematical inequalities that delineate operational limits and must not be violated to prevent premature degradation.

Not all aging mechanisms lend themselves to straightforward constraints. However, in the case of lithium plating, a well-defined hard constraint can be established. Studies, including [62], have demonstrated that to prevent lithium plating, the overpotential must not drop below zero. This provides a clear and quantifiable boundary condition for safe operation.

Material decomposition, as a general aging mechanism, provides a well-defined framework for establishing constraints. The stability of battery materials, including the negative and positive electrodes, electrolytes, and SEI, is typically limited to specific voltage and temperature ranges. Operating outside these ranges leads to instability and accelerated degradation. For instance, SEI decomposition is a specific case where exceeding these limits can compromise the protective layer on the anode. Numerous studies have identified these critical thresholds for various battery chemistries. When the chemistry of a battery is well-studied, it becomes possible to define precise limits to prevent material decomposition and maintain stable operation.

SEI growth is a gradual phenomenon that occurs continuously. Various factors influence its rate, including temperature and high overpotentials inside the electrode. As shown in Fig. 4, one root cause of SEI growth is simply time, making it challenging to establish a definitive hard constraint for this mechanism.

However, alternative strategies may exist to mitigate SEI growth through hard constraints. A critical aspect of SEI growth involves mechanisms that accelerate its formation. Phenomena such as damage to the existing SEI layer—caused by cracking or decomposition—can contribute significantly to this process. For instance, particle cracking exposes fresh active material to the electrolyte, prompting the formation of new SEI layers [110,111,114]. Therefore establishing SOA could involve applying hard constraints that specifically address cracking or SEI decomposition.

Most studies modeling particle cracking focus on the mechanical stress induced by lithiation or delithiation. These stress models are typically dependent on various factors, including temperature, C-rate, diffusion coefficient, and particle size. For example, it has been shown that stress increases with both particle size and current density [112,161–163]. Other studies have analyzed the maximum stress in particles in relation to parameters such as charge rate, particle size, diffusivity, and temperature [112,161,162]. Furthermore, material properties of the electrode, such as the diffusion coefficient, elastic modulus, and lithium partial molar volume, have also been studied for their impact on stress levels [111,164]. These findings highlight the intricate relationship between material properties, operating conditions, and the likelihood of cracking in battery electrodes.

In parallel, experimental studies have investigated the critical stress thresholds at which particle cracking begins under various conditions. These thresholds provide valuable insights into the mechanical limits of electrode materials. For example, in the case of graphite, experiments have shown that cracks typically initiate at stress levels ranging from 20 to 45 MPa, with higher stress levels exacerbating the cracking and worsening mechanical degradation [165–168].

Combining insights from modeling and experimental work provides a foundation for developing algorithms to prevent cracking in battery electrodes. One notable example is the work of Takahashi et al. [110], who explored how operating conditions, particle sizes, and diffusion coefficients could be adjusted to avoid entering the critical pressure range. They found that even at extremely high C-rates, cracks do not form if the charge or discharge pulse duration is sufficiently short. Moreover, their study revealed that the current rates capable of inducing cracks during delithiation are higher than those during lithiation. This suggests that more conservative currents should be applied during lithiation to mitigate the risk of cracking.

While this section highlights only a subset of particle cracking-related studies, a more comprehensive review of the literature, summarized in Table 2, further strengthens the understanding required to model and mitigate particle cracking. By integrating insights into stress dependencies and particle crack initiation criteria, it is possible to develop advanced models or algorithms that optimize operating conditions and prevent mechanical degradation in battery electrodes. These studies highlight the potential for establishing hard constraints, such as the forbidden stress range outlined in [110], as shown in Fig. 5. By actively avoiding this range, the battery can remain within the SOA envelope. Fig. 5 illustrates two different discharge profiles, both stopped before reaching the point where further discharge would lead to the forbidden zone, where cracking is likely to occur with continued cycling.

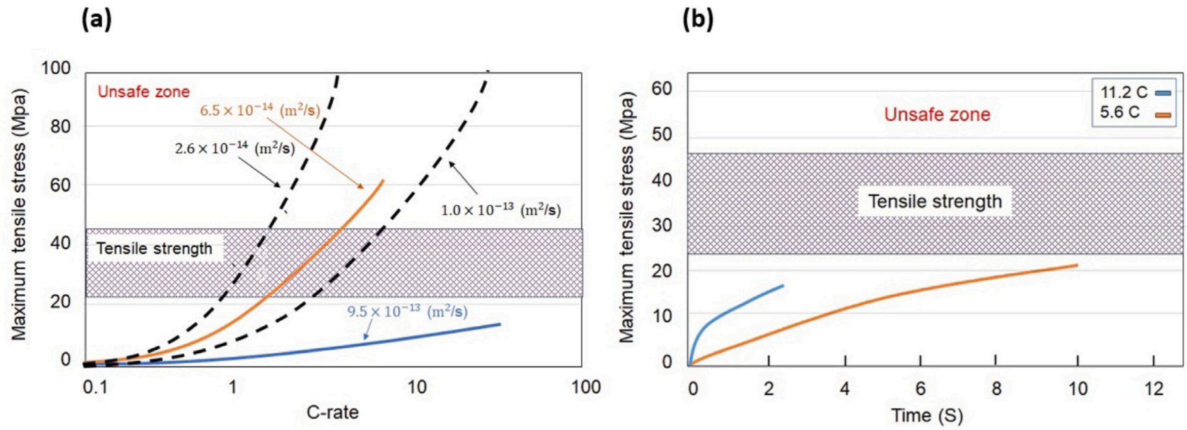

Fig. 5. Impact of C-rate and diffusion coefficient on battery cell particle cracking. (a) With higher diffusion coefficients, the charge profile enters the unsafe zone more gradually, whereas with lower diffusion coefficients, it reaches the unsafe zone much faster. (b) Maximum tensile stress profiles at the particle surface during pulse delithiation at 5.6 C for 2 s and 11.2 C for 10 s. The shaded region represents the range of reported tensile strengths for graphite, within which particles may crack.
Source: Adapted from Takahashi et al. [110].

4.4. Optimal charging

Another closely related area to the concept of SOA is the study of optimal charging and healthy fast charging [69,169–175]. These studies focus on determining the optimal charging path for batteries, often utilizing advanced optimization algorithms to minimize charging time while meeting critical constraints. These constraints typically include maintaining the battery's SOH and mitigating aging effects, ensuring a fast yet safe charging process avoiding damage, and preserving long-term performance. The outcome is usually a pre-calculated charging protocol that allows for fast charging within defined safety limits.

While optimal charging studies share similarities with SOA, there are notable differences between them. The first difference arises from the fact that charging and discharging processes pose fundamentally different challenges, particularly in specific applications. Charging is often an automated process, where a pre-defined or pre-calculated charging path can be followed. For instance, when a drone or laptop is plugged in, the device's software can fully control the charging process, determining how to charge the device optimally. In contrast, discharging behavior is more dependent on user actions. For example, a drone user's behavior—accelerating at one moment and slowing down the next—directly influences the battery's power output and discharge profile. Unlike charging, where predefined protocols are feasible, discharging requires flexibility. This is where SOA research diverges: an SOA envelope provides a framework that grants users the freedom to operate within certain boundaries while restricting operations that could harm the battery (e.g., entering "forbidden zones"). This challenge persists even with real-time optimization methods like Model Predictive Control (MPC). During discharge, control over user behavior is inherently limited. While MPC can adapt to changing conditions within predefined constraints, it cannot override the variability introduced by user-driven demands. Thus, while optimal charging studies focus on generating specific charging strategies, SOA encompasses a broader perspective that addresses both charging and discharging. However, Insights from optimal charging studies can be instrumental in developing SOA envelopes. For example, the optimal charging path derived from these studies could serve as a ceiling constraint for current in the SOA framework, ensuring safety and efficiency across both processes.

4.5. From components to completion: Developing the SOA

With all the necessary puzzle pieces now identified, the next step is establishing the SOA. The literature has not comprehensively addressed this critical aspect. While individual constraints have been studied in isolation, they have not been integrated into a unified framework. Such integration is essential to evaluating whether the constraints align or conflict with each other, as conflicting constraints may require trade-offs or optimization to determine an acceptable solution. On the positive side, certain constraints may become redundant due to being overshadowed by others, resulting in a more simplified SOA estimation. Ultimately, this process will result in a multidimensional SOA envelope constructed based on the defined safety constraints.

To date, most studies that incorporate multiple constraints simultaneously have considered factors such as temperature, voltage, state of charge (SOC), current, and a single degradation mechanism—typically lithium plating as shown in Tables 1 and 2. However, a more advanced and comprehensive SOA, particularly one rooted in physics-based modeling, requires including a broader range of constraints and their interactions. Establishing such an SOA involves either constructing a unified framework that accounts for all relevant constraints or identifying the optimal combination of these "puzzle pieces" to achieve a balanced and practical solution. This step represents a critical direction for future research on developing robust, physics-informed SOA models.

5. Static vs. Dynamic SOA envelope

In the current literature, mostly static definitions of the safe operating area have been explored, even when the models are not limited to equivalent circuit models but also include physics-based approaches. A static SOA implies that operational limits are predefined or precalculated, without dynamically adapting to factors such as time or the battery's state.

In contrast, the concept of a dynamic SOA, which has not yet been thoroughly examined, could significantly advance BMS research. Unlike its static counterpart, a dynamic SOA adapts in real-time based on the battery's state and operating history. For example, a dynamic SOA can adjust and reevaluate the limits to account for the effects of aging.

Another key distinction between static and dynamic SOA lies in their consideration of the battery's operational history. In a static SOA, the path taken to reach a given state is not accounted for. For instance, a system that has undergone rapid discharging and is significantly stressed would be treated the same as one that has been discharged slowly and is less stressed. At any moment, the static SOA envelope remains identical for both scenarios since it is not dependent on the battery's state, as illustrated in Fig. 6.a.

Conversely, a dynamic SOA adapts based on the battery's operational history and state. For example, if a limit is derived from the prediction of available power, then extreme discharging at high C-rates would deplete lithium concentration in particle layers, reducing

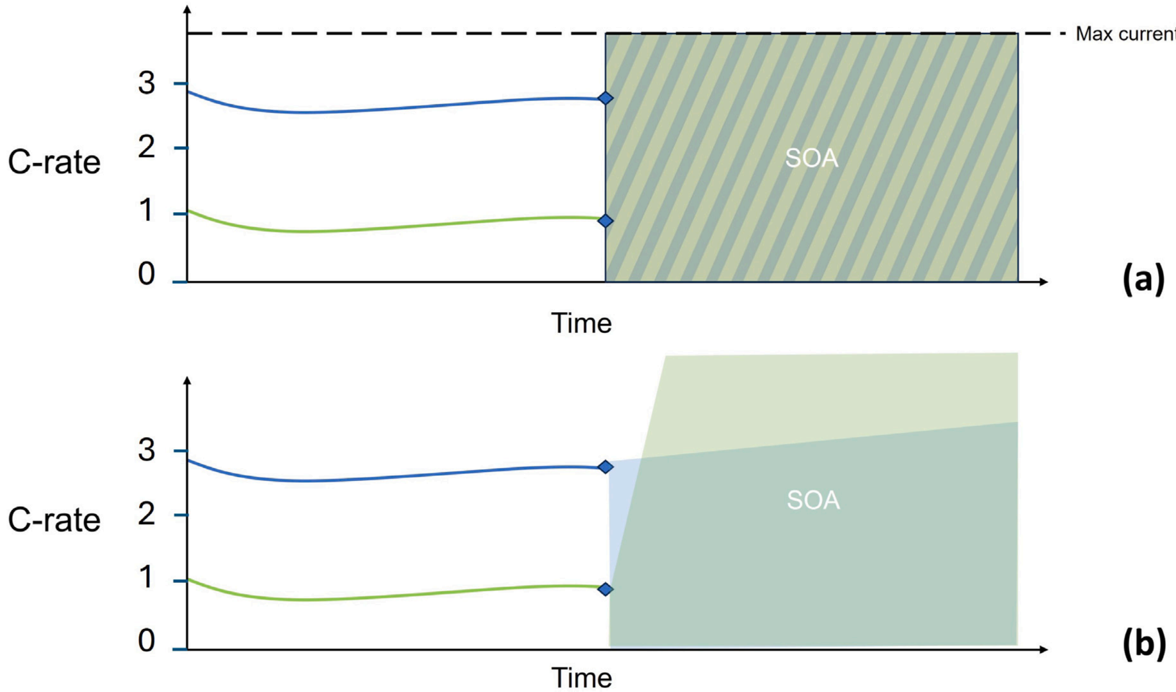

Fig. 6. Illustration of static versus dynamic SOA concepts for the upcoming time frame. The blue line represents discharge at a high C-rate, while the green line represents discharge at a lower C-rate. (a) In the ECM-based static SOA framework, the SOA prediction is identical for both scenarios, as operational history and battery state are not considered. (b) In the dynamic SOA framework, the predicted SOA adapts to the operational history, with the two scenarios resulting in different SOA envelopes due to variations in battery state caused by differing operating conditions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the battery's ability to deliver lithium ions. Consequently, the SOA envelope for this scenario would differ from that of a system discharged more gently, as shown in Fig. 6.b.

This dynamic approach highlights the need for real-time monitoring and modeling to refine SOA predictions, offering more precise and adaptable safety margins for batteries in diverse conditions. A static SOA implies that operational limits are predefined or precalculated, without dynamically adapting to factors such as time or the battery's state. In contrast, the concept of a dynamic SOA, which has not yet been thoroughly examined, could significantly advance BMS research. Unlike its static counterpart, a dynamic SOA adapts in real-time based on the battery's state and operating history. For example, a dynamic SOA can adjust and reevaluate the limits to account for the effects of aging. This will be further discussed in the next section.

In Fig. 7, a schematic representation of a static SOA is illustrated in three dimensions for better understanding. This 3D depiction includes C-rate and temperature as dimensions over time, providing a comprehensive visualization of the static SOA framework.

6. Control, state estimation and SOA

To effectively implement a safe operating area within a Battery Management System, several key elements must be integrated. These include SOA estimation, state estimation, and control, which together ensure safe and optimized battery performance:

- **SOA Estimation**
- **State Estimation**
- **Control Algorithm**

First, an algorithm capable of estimating the SOA envelope is essential to define the operational boundaries of the system as discussed in the previous sections. Once these boundaries are established, a state estimation feature is needed to pinpoint the battery's current location relative to the SOA envelope in the multidimensional space where the SOA was established. Specifically, this involves determining whether the battery's current state lies within the safe operating limits or has already exceeded them. This evaluation is carried out using a state estimation algorithm. A comprehensive systematic review of state estimation methods of over 100 studies up to 2024 is presented and analyzed in the study by Guo et al. [108]. Finally, after assessing the battery's state, a control algorithm must be implemented to regulate the charge and discharge processes, ensuring the battery operates within the SOA envelope.

In simpler systems, the control algorithm can sometimes be omitted. In such cases, when the state estimator detects that the system is operating outside the SOA, the system is immediately shut down—for example, suspending charge or discharge until the state returns within the SOA boundaries. However, this approach has significant limitations. A control algorithm adds much-needed flexibility and reliability, particularly in applications like electric vehicles, where abruptly shutting down the system is not feasible during operation. For such scenarios, the control algorithm becomes essential, ensuring continuous and safe operation by respecting the SOA constraints. The importance of this component varies depending on the system's complexity and application requirements.

Although state estimation and control algorithms are closely linked to the SOA concept, their detailed discussion is beyond the scope of this review. They are briefly mentioned here to provide a broader perspective and illustrate their connection to the SOA framework.

7. Discussion

The safe operating area framework for lithium-ion batteries is critical for ensuring safety, performance, and longevity. However, the fragmented nature of existing research and methodologies highlights the need for a unified, structured approach to SOA design.

While widely used, static SOA frameworks often fail to account for operational history, cumulative stress, and cumulative damage to the battery cell. In contrast, dynamic SOA frameworks, particularly those incorporating physics-based models, offer a more adaptive and accurate

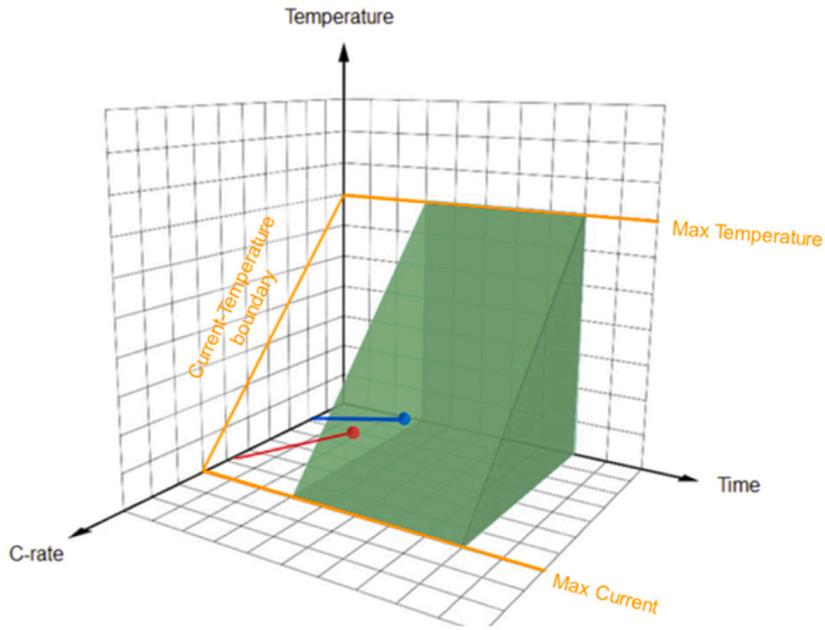

Fig. 7. Schematic representation of an ECM-based static SOA in three dimensions. The figure illustrates the relationship between C-rate, temperature, and time, showcasing the predefined and unchanging limits of the static SOA framework across these parameters. The predicted SOA envelope remains identical for both discharge scenarios. The blue and red lines represent current profiles, red high C-rate and blue low C-rate, similar to those shown in Fig. 6. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

representation of battery behavior. Future research should focus on bridging the gap between static and dynamic SOA, leveraging real-time data and predictive modeling to enhance safety and performance. Integrating these approaches makes it possible to create a more robust framework that adapts to real-world operating conditions.

Physics-based models, such as the P2D model, are crucial in SOA development. These models provide detailed insights into internal battery phenomena, enabling the incorporation of aging mechanisms and side reactions. They also allow for the establishment of hard constraints, such as preventing particle cracking or lithium plating, which are critical for long-term battery health. However, the computational complexity of these models remains a significant challenge. Advancements in model order reduction and real-time simulation techniques are necessary to make these models more practical for real-world applications.

Balancing safety and performance is another key challenge in SOA design. Traditional SOA frameworks often adopt overly conservative limits to ensure safety against hazards such as fire or explosion. However, these limits fail to account for the nuanced aging mechanisms and dynamic processes occurring within the battery, potentially causing damage in certain regions of operation. Furthermore, such conservative approaches unnecessarily constrain battery performance, especially during the initial stages of charging, where higher C-rates could be safely applied without adverse effects, thereby limiting operational efficiency. While significant progress has been made in optimal charging studies, which provide valuable insights into balancing fast charging and safety, their scope is often narrow. These studies typically focus on a limited set of constraints and lack a unified, consistent framework that integrates all safety-related considerations. Furthermore, their applicability to discharging scenarios remains underexplored, leaving a critical gap in the overall understanding of battery behavior under diverse operating conditions. Moving forward, there is an urgent need to develop modular SOA frameworks that systematically combine multiple safety constraints, such as thermal limits, voltage boundaries, power limits, and aging constraints, into a cohesive structure. Such frameworks would not only ensure operational integrity but also enable more efficient utilization of battery capacity, striking an optimal balance between safety and performance.

For future direction in SOA research, a collaborative, multidisciplinary approach is essential for developing a comprehensive SOA framework. Emphasis should be placed on real-time, short-term and long-term dynamic SOA, which considers the operational history and cumulative damage. Integration with battery management systems (BMS) and advancements in predictive algorithms will be crucial for practical implementation. By addressing these challenges and focusing on these future directions, the development of a unified SOA framework can significantly improve the safety, performance, and longevity of lithium-ion batteries.

8. Conclusion

This study comprehensively reviews the history, evolution, and trends in the safe operating area concept. It critically examines the traditional perspective of SOA, which relies on static, predefined limits, highlighting its strengths and weaknesses. Beyond the traditional framework, emerging SOA concepts often motivated by physics-based modeling are gaining attention, yet they remain fragmented, inconsistent, and unorganized across the literature. Even among studies explicitly referencing SOA or similar concepts, there has been no prior effort to systematically organize these ideas. Furthermore, many studies indirectly connected to the SOA concept lack clear links to this framework.

This work consolidates the diverse perspectives and contributions related to SOA into a unified, structured framework. By integrating both directly and indirectly related studies, it provides a foundation for a more cohesive understanding of SOA. The proposed framework emphasizes the importance of designing SOA based on multidimensional criteria, encompassing various safety constraints ranging from aging mechanisms such as plating or particle cracking to the state of power limitations. Many of these studies were conducted in isolation only caring about their topic but this study integrated them and made a link to the SOA concept. That approach clarifies the current state of the field and identifies key directions for advancing the development of robust and comprehensive SOA designs.

Table A.1
P2D model equations with double layer.

Model	Expression	Boundary conditions
Fick's second law	$\frac{\partial c_{1,m}}{\partial t} = \frac{1}{r_m^2}\frac{\partial}{\partial r_m}\left(D_{1,m}\, r_m^2 \frac{\partial c_{1,m}}{\partial r_m}\right)$	$\left.\frac{\partial c_{1,m}}{\partial r_m}\right\|_{r_m=0} = 0$ $-D_{1,m}\left.\frac{\partial c_{1,m}}{\partial r_m}\right\|_{r_m=R_m} = J_m$
Electrode kinetics	$J_m = J_{0,m}\left[\frac{c_{1,m}^{s}}{\bar{c}_{1,m}} exp\left(\frac{\alpha_m F}{RT}\eta_m^{ct}\right) - \frac{c_{1,m}^{max} - c_{1,m}^{s}}{c_{1,m}^{max} - \bar{c}_{1,m}}\,\frac{c_2}{\bar{c}_2}\, exp\left(-\frac{(1-\alpha_m)F}{RT}\eta_m^{ct}\right)\right]$	
Exchange current	$J_{0,m} = F\, k_m \left(c_{1,m}^{max} - \bar{c}_{1,m}\right)^{\alpha_m} (c_2)^{\alpha_m} \left(\bar{c}_{1,m}\right)^{\alpha_m}$	
Electronic current / potential in solid	$i_{tot} - i_{2,m} = i_{1,m} = -\sigma_m^{\mathbf{eff}}\frac{\partial \varphi_{1,m}}{\partial x}$	
Ionic current	$\frac{\partial i_{2,m}}{\partial x} - a_m C_m \frac{\partial(\varphi_{1,m} - \varphi_{2,m})}{\partial t} = a_m F J_m$	$i_{2,s} = i_{tot}$ $i_{2,n}\|_{x=0} = i_{2,p}\|_{x=L} = 0$
Potential in liquid phase	$i_{2,m} = -\kappa_m^{\mathbf{eff}}\frac{\partial \varphi_{2,m}}{\partial x} + \frac{\kappa_k^{\mathbf{eff}} RT}{F}(1 - 2t_+)\cdot \nabla \ln c_2$	$\varphi_{2,n}\|_{x=0} = 0$
Mass balance liquid phase	$\frac{\partial c_2}{\partial t} = \frac{\partial}{\partial x}\left(D_{2,m}^{\mathbf{eff}}\frac{\partial c_2}{\partial x}\right) + (1 - t_+)\left(a_m J_m + \frac{a_m C_m}{F}\frac{\partial(\varphi_{1,m} - \varphi_{2,m})}{\partial t}\right)$	$\left.\frac{\partial c_2}{\partial x}\right\|_{x=L} = 0$ $\left.\frac{\partial c_2}{\partial x}\right\|_{x=0} = 0$
Fick's second law	$\frac{\partial c_2}{\partial t} = \frac{\partial}{\partial x}\left(D_{2,s}^{\mathbf{eff}}\frac{\partial c_2}{\partial x}\right)$	
Charge conservation	$i_{tot} = i_{1,m} + i_{2,m}$	
Ohmic resistance	$\eta_p^R = \rho_p i_{tot}$, $\eta_n^R = -\rho_n i_{tot}$	
Overpotential	$\eta_m^{ct} = \varphi_{1,m} - \varphi_{2,m} - U_m\left(c_{1,m}^{s}, T\right)$	
Battery voltage	$V_{bat} = \varphi_{1,p}\|_{x=L} - \varphi_{1,n}\|_{x=0} - \eta_p^R + \eta_n^R$	
Inductance	$Z_{\mathcal{L},m} = j\omega\mathcal{L}_m$	

This study categorizes SOA concepts into distinct groups, including static predefined empirical SOA, probabilistic SOA, and static physics-based precalculated SOA. Furthermore, it examines the differences between dynamic and static SOA, offering a detailed analysis of their characteristics, advantages, and implications for safety and performance. This categorization provides a more transparent structure to the field, enhancing understanding of the available tools, the existing body of knowledge in the literature, and the potential foundations for future advancements. By organizing diverse SOA concepts into a coherent framework, this approach not only clarifies the current state of the field but also facilitates deeper insights and identifies opportunities to build upon this knowledge for future developments.

In conclusion, this study not only reviews the literature and organizes the field of SOA but also serves as a theoretical step-by-step guide for developing a modular SOA framework. This framework comprises various safety constraints that can be combined like puzzle pieces, tailored to the specific application of a battery system. By selecting and assembling the relevant constraints consistently and coherently, this approach ensures flexibility and adaptability while maintaining the integrity of the overall design.

CRediT authorship contribution statement

Keivan Haghverdi: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Dmitri L. Danilov:** Writing – review & editing, Supervision, Conceptualization. **Grietus Mulder:** Writing – review & editing, Supervision, Conceptualization. **Luis D. Couto:** Writing – review & editing, Conceptualization. **Feng Guo:** Writing – review & editing, Conceptualization. **Rüdiger-A. Eichel:** Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dmitri L. Danilov reports financial support was provided by ProMoBis BMBF project (Grant No. 03ETE046C.). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. P2D model equations

See Table A.1.

Data availability

No data was used for the research described in the article.

References

[1] D. Castelvecchi, Electric cars and batteries: how will the world produce enough? Nature 596 (7872) (2021) 336–339.
[2] L. Mauler, F. Duffner, W.G. Zeier, J. Leker, Battery cost forecasting: a review of methods and results with an outlook to 2050, Energy Environ. Sci. 14 (9) (2021) 4712–4739.
[3] A. Fotouhi, D.J. Auger, K. Propp, S. Longo, M. Wild, A review on electric vehicle battery modelling: From lithium-ion toward lithium–sulphur, Renew. Sustain. Energy Rev. 56 (2016) 1008–1021.
[4] S. Santhanagopalan, Q. Zhang, K. Kumaresan, R.E. White, Parameter estimation and life modeling of lithium-ion cells, J. Electrochem. Soc. 155 (4) (2008) A345.
[5] A. Bocca, A. Macii, E. Macii, M. Poncino, Composable battery model templates based on manufacturers' data, IEEE Des. Test 35 (3) (2017) 66–72.
[6] J. Meng, G. Luo, M. Ricco, M. Swierczynski, D.-I. Stroe, R. Teodorescu, Overview of lithium-ion battery modeling methods for state-of-charge estimation in electrical vehicles, Appl. Sci. 8 (5) (2018) 659.
[7] C.T. da Silva, B.M.d.A. Dias, R.E. Araújo, E.L. Pellini, A.A.M. Laganá, Battery model identification approach for electric forklift application, Energies 14 (19) (2021) 6221.
[8] G.L. Plett, Battery Management Systems, Volume I: Battery Modeling, Artech House, 2015.
[9] M. Doyle, T.F. Fuller, J. Newman, Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell, J. Electrochem. Soc. 140 (6) (1993) 1526.
[10] J.S. Newman, C.W. Tobias, Theoretical analysis of current distribution in porous electrodes, J. Electrochem. Soc. 109 (12) (1962) 1183.
[11] J. Newman, W. Tiedemann, Porous-electrode theory with battery applications, AIChE J. 21 (1) (1975) 25–41.
[12] T.F. Fuller, M. Doyle, J. Newman, Simulation and optimization of the dual lithium ion insertion cell, J. Electrochem. Soc. 141 (1) (1994) 1.
[13] R. Drummond, S.R. Duncan, Structural identifiability of a pseudo-2D Li-ion battery electrochemical model, IFAC- Pap. 53 (2) (2020) 12452–12458.
[14] S. Han, Y. Tang, S.K. Rahimian, A numerically efficient method of solving the full-order pseudo-2-dimensional (P2D) Li-ion cell model, J. Power Sources 490 (2021) 229571.
[15] Q. Chen, X.S. Chen, Z. Li, A fast numerical method with non-iterative source term for pseudo-two-dimension lithium-ion battery model, J. Power Sources 577 (2023) 233258.
[16] K. Haghverdi, D.L. Danilov, G. Mulder, L.D. Couto, R.-A. Eichel, On the joint dynamics of potentials and currents in porous electrodes: Model reduction, J. Power Sources Adv. 26 (2024) 100138.
[17] J. Piruzjam, G. Liu, L. Rubacek, M. Frey, T. Carraro, On the analytical solution of single particle models and semi-analytical solution of P2D model for lithium-ion batteries, Electrochim. Acta 492 (2024) 144259.
[18] D. Di Domenico, A. Stefanopoulou, G. Fiengo, Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter, 2010.
[19] S. Santhanagopalan, R.E. White, Online estimation of the state of charge of a lithium ion cell, J. Power Sources 161 (2) (2006) 1346–1355.
[20] S.J. Moura, N.A. Chaturvedi, M. Krstić, Adaptive partial differential equation observer for battery state-of-charge/state-of-health estimation via an electrochemical model, J. Dyn. Syst. Meas. Control. 136 (1) (2014) 011015.
[21] S. Dey, B. Ayalew, Nonlinear observer designs for state-of-charge estimation of lithium-ion batteries, in: 2014 American Control Conference, IEEE, 2014, pp. 248–253.
[22] G. Ning, B.N. Popov, Cycle life modeling of lithium-ion batteries, J. Electrochem. Soc. 151 (10) (2004) A1584.
[23] S. Atlung, K. West, T. Jacobsen, Dynamic aspects of solid solution cathodes for electrochemical power sources, J. Electrochem. Soc. 126 (8) (1979) 1311.
[24] M. Guo, X. Jin, R.E. White, An adaptive reduced-order-modeling approach for simulating real-time performances of li-ion battery systems, J. Electrochem. Soc. 164 (14) (2017) A3602.
[25] C. Li, N. Cui, C. Wang, C. Zhang, Reduced-order electrochemical model for lithium-ion battery with domain decomposition and polynomial approximation methods, Energy 221 (2021) 119662.
[26] H.A.A. Ali, L.H. Raijmakers, K. Chayambuka, D.L. Danilov, P.H. Notten, R.-A. Eichel, A comparison between physics-based Li-ion battery models, Electrochim. Acta 493 (2024) 144360.
[27] M. Chen, G. Ma, W. Liu, N. Zeng, X. Luo, An overview of data-driven battery health estimation technology for battery management system, Neurocomputing 532 (2023) 152–169.
[28] M. Kurucan, M. Özbaltan, Z. Yetgin, A. Alkaya, Applications of artificial neural network based battery management systems: A literature review, Renew. Sustain. Energy Rev. 192 (2024) 114262.
[29] S. Harippriya, E.E. Vigneswaran, S. Jayanthy, Battery management system to estimate battery aging using deep learning and machine learning algorithms, in: Journal of Physics: Conference Series, Vol. 2325, IOP Publishing, 2022, 012004.
[30] J.K. Thomas, H.R. Crasta, K. Kausthubha, C. Gowda, A. Rao, Battery monitoring system using machine learning, J. Energy Storage 40 (2021) 102741.
[31] T. Raoofi, M. Yildiz, Comprehensive review of battery state estimation strategies using machine learning for battery management systems of aircraft propulsion batteries, J. Energy Storage 59 (2023) 106486.
[32] D. Shi, J. Zhao, C. Eze, Z. Wang, J. Wang, Y. Lian, A.F. Burke, Cloud-based artificial intelligence framework for battery management system, Energies 16 (11) (2023) 4403.
[33] R.G. Nascimento, M. Corbetta, C.S. Kulkarni, F.A. Viana, Hybrid physics-informed neural networks for lithium-ion battery modeling and prognosis, J. Power Sources 513 (2021) 230526.
[34] J. Tian, R. Xiong, J. Lu, C. Chen, W. Shen, Battery state-of-charge estimation amid dynamic usage with physics-informed deep learning, Energy Storage Mater. 50 (2022) 718–729.
[35] Y. Merla, B. Wu, V. Yufit, R.F. Martinez-Botas, G.J. Offer, An easy-to-parameterise physics-informed battery model and its application towards lithium-ion battery cell design, diagnosis, and degradation, J. Power Sources 384 (2018) 66–79.
[36] R.G. Nascimento, F.A. Viana, M. Corbetta, C.S. Kulkarni, A framework for Li-ion battery prognosis based on hybrid Bayesian physics-informed neural networks, Sci. Rep. 13 (1) (2023) 13856.
[37] S. Link, C. Neef, T. Wicke, Trends in automotive battery cell design: a statistical analysis of empirical data, Batteries 9 (2023) 261.
[38] A. Väyrynen, J. Salminen, Lithium ion battery production, J. Chem. Thermodyn. 46 (2012) 80–85.
[39] S. Park, J. Ahn, T. Kang, S. Park, Y. Kim, I. Cho, J. Kim, Review of state-of-the-art battery state estimation technologies for battery management systems of stationary energy storage systems, J. Power Electron. 20 (2020) 1526–1540.
[40] L. Lu, X. Han, J. Li, J. Hua, M. Ouyang, A review on the key issues for lithium-ion battery management in electric vehicles, J. Power Sources 226 (2013) 272–288.
[41] R.K. Kamboj, M. Singh, A. Singh, A. Bala, Estimation of Safe Operating Area for EV battery, 2024.
[42] K. See, G. Wang, Y. Zhang, Y. Wang, L. Meng, X. Gu, N. Zhang, K. Lim, L. Zhao, B. Xie, Critical review and functional safety of a battery management system for large-scale lithium-ion battery pack technologies, Int. J. Coal Sci. Technol. 9 (1) (2022) 36.
[43] M. Held, R. Brönnimann, Safe cell, safe battery? Battery fire investigation using FMEA, FTA and practical experiments, Microelectron. Reliab. 64 (2016) 705–710.
[44] P.V. Chombo, Y. Laoonual, A review of safety strategies of a Li-ion battery, J. Power Sources 478 (2020) 228649.
[45] J. McDowall, A guide to lithium-ion battery safety, Battcon 1 (2014) 1–23.
[46] Y. Wang, Q. Gao, G. Wang, P. Lu, M. Zhao, W. Bao, A review on research status and key technologies of battery thermal management and its enhanced safety, Int. J. Energy Res. 42 (13) (2018) 4008–4033.
[47] Y. Chen, Y. Kang, Y. Zhao, L. Wang, J. Liu, Y. Li, Z. Liang, X. He, X. Li, N. Tavajohi, et al., A review of lithium-ion battery safety concerns: The issues, strategies, and testing standards, J. Energy Chem. 59 (2021) 83–99.
[48] D.H. Doughty, E.P. Roth, A general discussion of li ion battery safety, Electrochem. Soc. Interface 21 (2) (2012) 37.
[49] A. Vezzini, Lithium-ion battery management, in: Lithium-Ion Batteries, Elsevier, 2014, pp. 345–360.
[50] J. Zhao, X. Feng, M.-K. Tran, M. Fowler, M. Ouyang, A.F. Burke, Battery safety: Fault diagnosis from laboratory to real world, J. Power Sources 598 (2024) 234111.
[51] H.A. Gabbar, A.M. Othman, M.R. Abdussami, Review of battery management systems (BMS) development and industrial standards, Technologies 9 (2) (2021) 28.
[52] T.-H. Tseng, C. Liang-Rui, Z. Yu-Jia, X. Bo-Rui, L. Jin-An, Battery management system for 24-V battery-powered electric wheelchair, Proc. Eng. Technol. Innov. 10 (2018) 29.
[53] S. Abada, G. Marlair, A. Lecocq, M. Petit, V. Sauvant-Moynot, F. Huet, Safety focused modeling of lithium-ion batteries: A review, J. Power Sources 306 (2016) 178–192.
[54] S. Chen, Z. Gao, T. Sun, Safety challenges and safety measures of Li-ion batteries, Energy Sci. Eng. 9 (9) (2021) 1647–1672.
[55] W. Waag, C. Fleischer, D.U. Sauer, Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles, J. Power Sources 258 (2014) 321–339.
[56] C. Fleischer, W. Waag, H.-M. Heyn, D.U. Sauer, On-line adaptive battery impedance parameter and state estimation considering physical principles in reduced order equivalent circuit battery models: Part 1. Requirements, critical review of methods and modeling, J. Power Sources 260 (2014) 276–291.
[57] C. Fleischer, W. Waag, H.-M. Heyn, D.U. Sauer, On-line adaptive battery impedance parameter and state estimation considering physical principles in reduced order equivalent circuit battery models part 2. Parameter and state estimation, J. Power Sources 262 (2014) 457–482.
[58] D. Andrea, Battery Management Systems for Large Lithium-Ion Battery Packs, Artech house, 2010.

[59] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, B. Liu, State estimation for advanced battery management: Key challenges and future trends, Renew. Sustain. Energy Rev. 114 (2019) 109334.
[60] S. Sarkar, D. Swamy, M.T. Amin, M. El-Halwagi, F. Khan, Safer operating areas (SOA) of cylindrical lithium-ion battery–a probabilistic approach, Process. Saf. Environ. Prot. 190 (2024) 708–725.
[61] E. Cabrera-Castillo, F. Niedermeier, A. Jossen, Calculation of the state of safety (SOS) for lithium ion batteries, J. Power Sources 324 (2016) 509–520.
[62] L.D. Couto, R. Romagnoli, S. Park, D. Zhang, S.J. Moura, M. Kinnaert, E. Garone, Faster and healthier charging of lithium-ion batteries via constrained feedback control, IEEE Trans. Control Syst. Technol. 30 (5) (2021) 1990–2001.
[63] G. Dong, Y. Feng, Y. Lou, M. Zhang, J. Wei, Data-driven fast charging optimization for lithium-ion battery using Bayesian optimization with fast convergence, IEEE Trans. Transp. Electr. (2023).
[64] Z.M. Konz, P.J. Weddle, P. Gasper, B.D. McCloskey, A.M. Colclasure, Voltage-based strategies for preventing battery degradation under diverse fast-charging conditions, ACS Energy Lett. 8 (10) (2023) 4069–4077.
[65] N. Wassiliadis, M. Ank, A. Bach, M. Wanzel, A.-S. Zollner, K.A. Gamra, M. Lienkamp, A systematic approach for the parameter identification of electrochemical battery models enabling health-aware fast charging control of battery electric vehicles, J. Energy Storage 56 (2022) 105951.
[66] J. Sieg, J. Bandlow, T. Mitsch, D. Dragicevic, T. Materna, B. Spier, H. Witzenhausen, M. Ecker, D.U. Sauer, Fast charging of an electric vehicle lithium-ion battery at the limit of the lithium deposition process, J. Power Sources 427 (2019) 260–270.
[67] C. Liu, Y. Gao, L. Liu, Toward safe and rapid battery charging: Design optimal fast charging strategies thorough a physics-based model considering lithium plating, Int. J. Energy Res. 45 (2) (2021) 2303–2320.
[68] D. Lee, B. Kim, C.B. Shin, Modeling fast charge protocols to prevent lithium plating in a lithium-ion battery, J. Electrochem. Soc. 169 (9) (2022) 090502.
[69] H. Perez, S. Dey, X. Hu, S. Moura, Optimal charging of li-ion batteries via a single particle model with electrolyte and thermal dynamics, J. Electrochem. Soc. 164 (7) (2017) A1679.
[70] K.A. Smith, C.D. Rahn, C.-Y. Wang, Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries, IEEE Trans. Control Syst. Technol. 18 (3) (2009) 654–663.
[71] H. Perez, N. Shahmohammadhamedani, S. Moura, Enhanced performance of li-ion batteries via modified reference governors and electrochemical models, IEEE/ASME Trans. Mechatronics 20 (4) (2015) 1511–1520.
[72] W. Li, Y. Fan, F. Ringbeck, D. Jöst, D.U. Sauer, Unlocking electrochemical model-based online power prediction for lithium-ion batteries via Gaussian process regression, Appl. Energy 306 (2022) 118114.
[73] Q. Wang, P. Ping, X. Zhao, G. Chu, J. Sun, C. Chen, Thermal runaway caused fire and explosion of lithium ion battery, J. Power Sources 208 (2012) 210–224.
[74] T.M. Bandhauer, S. Garimella, T.F. Fuller, A critical review of thermal issues in lithium-ion batteries, J. Electrochem. Soc. 158 (3) (2011) R1.
[75] P. Balakrishnan, R. Ramesh, T.P. Kumar, Safety mechanisms in lithium-ion batteries, J. Power Sources 155 (2) (2006) 401–414.
[76] J.B. Goodenough, Y. Kim, Challenges for rechargeable batteries, J. Power Sources 196 (16) (2011) 6688–6694.
[77] S. Zheng, L. Wang, X. Feng, X. He, Probing the heat sources during thermal runaway process by thermal analysis of different battery chemistries, J. Power Sources 378 (2018) 527–536.
[78] Q. Wang, B. Mao, S.I. Stoliarov, J. Sun, A review of lithium ion battery failure mechanisms and fire prevention strategies, Prog. Energy Combust. Sci. 73 (2019) 95–131.
[79] X. Feng, S. Zheng, D. Ren, X. He, L. Wang, H. Cui, X. Liu, C. Jin, F. Zhang, C. Xu, et al., Investigating the thermal runaway mechanisms of lithium-ion batteries based on thermal analysis database, Appl. Energy 246 (2019) 53–64.
[80] S.M. Rezvanizaniani, Z. Liu, Y. Chen, J. Lee, Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility, J. Power Sources 256 (2014) 110–124.
[81] W. Li, J. Zhu, Y. Xia, M.B. Gorji, T. Wierzbicki, Data-driven safety envelope of lithium-ion batteries for electric vehicles, Joule 3 (11) (2019) 2703–2715.
[82] B.R.D. Goswami, Y. Abdisobbouhi, H. Du, F. Mashayek, T.A. Kingston, V. Yurkiv, Advancing battery safety: Integrating multiphysics and machine learning for thermal runaway prediction in lithium-ion battery module, J. Power Sources 614 (2024) 235015.
[83] J.A. Carcone, Performance of lithium-ion battery systems, in: Proceedings of WESCON'94, IEEE, 1994, pp. 242–248.
[84] P. Keil, A. Jossen, Charging protocols for lithium-ion batteries and their impact on cycle life—An experimental study with different 18650 high-power cells, J. Energy Storage 6 (2016) 125–141.
[85] K. Smith, C.-Y. Wang, Power and thermal characterization of a lithium-ion battery pack for hybrid-electric vehicles, J. Power Sources 160 (1) (2006) 662–673.
[86] N.A. Chaturvedi, R. Klein, J. Christensen, J. Ahmed, A. Kojic, Algorithms for advanced battery-management systems, IEEE Control Syst. Mag. 30 (3) (2010) 49–68.
[87] A. Boehm, J. Weber, Adaptives verfahren zur bestimmung der maximal abgebaren oder aufnehmbaren leistung einer batterie, 2011, DE Patent WO 2011/095368 Al.
[88] J. Do Yang, et al., Method of estimating maximum output of battery for hybrid electric vehicle, 2009, US Patent 7, 518, 375.
[89] X. Sun, N. Xu, Q. Chen, J. Yang, J. Zhu, J. Xu, L. Zheng, State of power capability prediction of lithium-ion battery from the perspective of electrochemical mechanisms considering temperature effect, IEEE Trans. Transp. Electr. 9 (2) (2022) 2453–2463.
[90] F. Sun, R. Xiong, H. He, W. Li, J.E.E. Aussems, Model-based dynamic multi-parameter method for peak power estimation of lithium–ion batteries, Appl. Energy 96 (2012) 378–386.
[91] G.L. Plett, High-performance battery-pack power estimation using a dynamic cell model, IEEE Trans. Veh. Technol. 53 (5) (2004) 1586–1593.
[92] R.D. Anderson, Y. Zhao, X. Wang, X.G. Yang, Y. Li, Real time battery power capability estimation, in: 2012 American Control Conference, ACC, IEEE, 2012, pp. 592–597.
[93] L. Pei, C. Zhu, T. Wang, R. Lu, C. Chan, Online peak power prediction based on a parameter and state estimator for lithium-ion batteries in electric vehicles, Energy 66 (2014) 766–778.
[94] R. Xiong, H. He, F. Sun, K. Zhao, Online estimation of peak power capability of li-ion batteries in electric vehicles by a hardware-in-loop approach, Energies 5 (5) (2012) 1455–1469.
[95] R. Xiong, H. He, F. Sun, X. Liu, Z. Liu, Model-based state of charge and peak power capability joint estimation of lithium-ion battery in plug-in hybrid electric vehicles, J. Power Sources 229 (2013) 159–169.
[96] W. Waag, C. Fleischer, D.U. Sauer, Adaptive on-line prediction of the available power of lithium-ion batteries, J. Power Sources 242 (2013) 548–559.
[97] S. Wang, M. Verbrugge, J.S. Wang, P. Liu, Power prediction from a battery state estimator that incorporates diffusion resistance, J. Power Sources 214 (2012) 399–406.
[98] R. Guo, W. Shen, A review of equivalent circuit model based online state of power estimation for lithium-ion batteries in electric vehicles, Vehicles 4 (1) (2021) 1–29.
[99] W. Li, Y. Fan, F. Ringbeck, D. Jöst, X. Han, M. Ouyang, D.U. Sauer, Electrochemical model-based state estimation for lithium-ion batteries with adaptive unscented Kalman filter, J. Power Sources 476 (2020) 228534.
[100] T.-K. Lee, Y. Kim, D.M. Rizzo, Z.S. Filipi, Battery power management in heavy-duty HEVs based on the estimated critical surface charge, Int. J. Veh. Des. 61 (1–4) (2013) 108–127.
[101] Y. Li, Z. Wei, M. Vilathgamuwa, Power capability prediction of lithium-ion batteries using physics-based model and NMPC, in: 2022 IEEE 1st Industrial Electronics Society Annual on-Line Conference, ONCON, IEEE, 2022, pp. 1–6.
[102] L. Zheng, J. Zhu, G. Wang, D.D.-C. Lu, T. He, Lithium-ion battery instantaneous available power prediction using surface lithium concentration of solid particles in a simplified electrochemical model, IEEE Trans. Power Electron. 33 (11) (2018) 9551–9560.
[103] Y. Li, Z. Wei, C. Xie, D.M. Vilathgamuwa, Physics-based model predictive control for power capability estimation of lithium-ion batteries, IEEE Trans. Ind. Inform. 19 (11) (2023) 10763–10774.
[104] C. Zou, A. Klintberg, Z. Wei, B. Fridholm, T. Wik, B. Egardt, Power capability prediction for lithium-ion batteries using economic nonlinear model predictive control, J. Power Sources 396 (2018) 580–589.
[105] R. Xiong, F. Sun, H. He, T.D. Nguyen, A data-driven adaptive state of charge and power capability joint estimator of lithium-ion polymer battery used in electric vehicles, Energy 63 (2013) 295–308.
[106] C. Fleischer, W. Waag, Z. Bai, D.U. Sauer, Self-learning state-of-available-power prediction for lithium-ion batteries in electrical vehicles, in: 2012 IEEE Vehicle Power and Propulsion Conference, IEEE, 2012, pp. 370–375.
[107] X. Tang, K. Yao, B. Liu, W. Hu, F. Gao, Long-term battery voltage, power, and surface temperature prediction using a model-based extreme learning machine, Energies 11 (1) (2018) 86.
[108] F. Guo, L.D. Couto, G. Mulder, K. Trad, G. Hu, O. Capron, K. Haghverdi, A systematic review of electrochemical model-based lithium-ion battery state estimation in battery management systems, J. Energy Storage 101 (2024) 113850.
[109] C.R. Birkl, M.R. Roberts, E. McTurk, P.G. Bruce, D.A. Howey, Degradation diagnostics for lithium ion cells, J. Power Sources 341 (2017) 373–386.
[110] K. Takahashi, V. Srinivasan, Examination of graphite particle cracking as a failure mode in lithium-ion batteries: a model-experimental study, J. Electrochem. Soc. 162 (4) (2015) A635.
[111] W. Ai, B. Wu, E. Martínez-Pañeda, A coupled phase field formulation for modelling fatigue cracking in lithium-ion battery electrode particles, J. Power Sources 544 (2022) 231805.
[112] X. Zhu, Y. Chen, H. Chen, W. Luan, The diffusion induced stress and cracking behaviour of primary particle for Li-ion battery electrode, Int. J. Mech. Sci. 178 (2020) 105608.
[113] Y. Zhang, C. Zhao, Z. Guo, Simulation of crack behavior of secondary particles in Li-ion battery electrodes during lithiation/de-lithiation cycles, Int. J. Mech. Sci. 155 (2019) 178–186.

[114] A.M. Boyce, E. Martínez-Pañeda, A. Wade, Y.S. Zhang, J.J. Bailey, T.M. Heenan, D.J. Brett, P.R. Shearing, Cracking predictions of lithium-ion battery electrodes by X-ray computed tomography and modelling, J. Power Sources 526 (2022) 231119.
[115] Y. Zhao, P. Stein, Y. Bai, M. Al-Siraj, Y. Yang, B.-X. Xu, A review on modeling of electro-chemo-mechanics in lithium-ion batteries, J. Power Sources 413 (2019) 259–283.
[116] K. Smith, P. Gasper, A.M. Colclasure, Y. Shimonishi, S. Yoshida, Lithium-ion battery life model with electrode cracking and early-life break-in processes, J. Electrochem. Soc. 168 (10) (2021) 100530.
[117] T.R. Tanim, P.J. Weddle, Z. Yang, A.M. Colclasure, H. Charalambous, D.P. Finegan, Y. Lu, M. Preefer, S. Kim, J.M. Allen, et al., Enabling extreme fast-charging: challenges at the cathode and mitigation strategies, Adv. Energy Mater. 12 (46) (2022) 2202795.
[118] K. An, P. Barai, K. Smith, P.P. Mukherjee, Probing the thermal implications in mechanical degradation of lithium-ion battery electrodes, J. Electrochem. Soc. 161 (6) (2014) A1058.
[119] P. Barai, P.P. Mukherjee, Stochastic analysis of diffusion induced damage in lithium-ion battery electrodes, J. Electrochem. Soc. 160 (6) (2013) A955.
[120] J. Christensen, Modeling diffusion-induced stress in li-ion cells with porous electrodes, J. Electrochem. Soc. 157 (3) (2010) A366.
[121] S. Renganathan, G. Sikha, S. Santhanagopalan, R.E. White, Theoretical analysis of stresses in a lithium ion cell, J. Electrochem. Soc. 157 (2) (2009) A155.
[122] A.M. Colclasure, K.A. Smith, R.J. Kee, Modeling detailed chemistry and transport for solid-electrolyte-interface (SEI) films in Li–ion batteries, Electrochim. Acta 58 (2011) 33–43.
[123] R.D. Deshpande, D.M. Bernardi, Modeling solid-electrolyte interphase (SEI) fracture: coupled mechanical/chemical degradation of the lithium ion battery, J. Electrochem. Soc. 164 (2) (2017) A461.
[124] M.T. Lawder, P.W. Northrop, V.R. Subramanian, Model-based SEI layer growth and capacity fade analysis for EV and PHEV batteries and drive cycles, J. Electrochem. Soc. 161 (14) (2014) A2099.
[125] D. Witt, F. Röder, U. Krewer, Analysis of lithium-ion battery state and degradation via physicochemical cell and SEI modeling, Batter. Supercaps 5 (7) (2022) e202200067.
[126] D. Li, D. Danilov, Z. Zhang, H. Chen, Y. Yang, P.H. Notten, Modeling the SEI-formation on graphite electrodes in LiFePO4 batteries, J. Electrochem. Soc. 162 (6) (2015) A858.
[127] K. MANMI, M. Tuchel, E. Kendrick, F. Brosa Planella, A comparison of standard SEI growth models in the context of battery formation, J. Electrochem. Soc. (2024).
[128] V.A. Agubra, J.W. Fergus, The formation and stability of the solid electrolyte interface on the graphite anode, J. Power Sources 268 (2014) 153–162.
[129] A. Wang, S. Kadam, H. Li, S. Shi, Y. Qi, Review on modeling of the anode solid electrolyte interphase (SEI) for lithium-ion batteries, NPJ Comput. Mater. 4 (1) (2018) 15.
[130] E. Peled, S. Menkin, SEI: past, present and future, J. Electrochem. Soc. 164 (7) (2017) A1703.
[131] B. Li, Y. Chao, M. Li, Y. Xiao, R. Li, K. Yang, X. Cui, G. Xu, L. Li, C. Yang, et al., A review of solid electrolyte interphase (SEI) and dendrite formation in lithium batteries, Electrochem. Energy Rev. 6 (1) (2023) 7.
[132] Z. Chen, D.L. Danilov, Q. Zhang, M. Jiang, J. Zhou, R.-A. Eichel, P.H. Notten, Modeling NCA/C6-Si battery ageing, Electrochim. Acta 430 (2022) 141077.
[133] Z. Wang, D.L. Danilov, Z. Chen, R.-A. Eichel, P.H. Notten, A facile physics-based model for non-destructive diagnosis of battery degradation, J. Energy Storage 101 (2024) 113819.
[134] Z. Wang, D.L. Danilov, R.-A. Eichel, P.H. Notten, The implementation of a voltage-based tunneling mechanism in aging models for lithium-ion batteries, J. Power Sources Adv. 29 (2024) 100157.
[135] C.L. Campion, W. Li, B.L. Lucht, Thermal decomposition of LiPF6-based electrolytes for lithium-ion batteries, J. Electrochem. Soc. 152 (12) (2005) A2327.
[136] K. Kumai, H. Miyashiro, Y. Kobayashi, K. Takei, R. Ishikawa, Gas generation mechanism due to electrolyte decomposition in commercial lithium-ion cell, J. Power Sources 81 (1999) 715–719.
[137] M. Kabir, D.E. Demirocak, Degradation mechanisms in li-ion batteries: a state-of-the-art review, Int. J. Energy Res. 41 (14) (2017) 1963–1986.
[138] J. Cabana, B.J. Kwon, L. Hu, Mechanisms of degradation and strategies for the stabilization of cathode–electrolyte interfaces in li-ion batteries, Acc. Chem. Res. 51 (2) (2018) 299–308.
[139] J. Henschel, C. Peschel, S. Klein, F. Horsthemke, M. Winter, S. Nowak, Clarification of decomposition pathways in a state-of-the-art lithium ion battery electrolyte through 13c-labeling of electrolyte components, Angew. Chem. Int. Ed. 59 (15) (2020) 6128–6137.
[140] K. Tasaki, Solvent decompositions and physical properties of decomposition compounds in Li-ion battery electrolytes studied by DFT calculations and molecular dynamics simulations, J. Phys. Chem. B 109 (7) (2005) 2920–2933.
[141] K. Leung, S.B. Rempe, M.E. Foster, Y. Ma, J.M.M. Del La Hoz, N. Sai, P.B. Balbuena, Modeling electrochemical decomposition of fluoroethylene carbonate on silicon anode surfaces in lithium ion batteries, J. Electrochem. Soc. 161 (3) (2013) A213.
[142] Y. Liao, H. Zhang, Y. Peng, Y. Hu, J. Liang, Z. Gong, Y. Wei, Y. Yang, Electrolyte degradation during aging process of lithium-ion batteries: Mechanisms, characterization, and quantitative analysis, Adv. Energy Mater. 14 (18) (2024) 2304295.
[143] O. Borodin, X. Ren, J. Vatamanu, A. von Wald Cresce, J. Knap, K. Xu, Modeling insight into battery electrolyte electrochemical stability and interfacial structure, Acc. Chem. Res. 50 (12) (2017) 2886–2894.
[144] J.W. Braithwaite, A. Gonzales, G. Nagasubramanian, S.J. Lucero, D.E. Peebles, J.A. Ohlhausen, W.R. Cieslak, Corrosion of lithium-ion battery current collectors, J. Electrochem. Soc. 146 (2) (1999) 448.
[145] S. Yang, J. Zhong, S. Li, B. Li, Revisiting aluminum current collector in lithium-ion batteries: Corrosion and countermeasures, J. Energy Chem. 89 (2024) 610–634.
[146] A. Gabryelczyk, S. Ivanov, A. Bund, G. Lota, Corrosion of aluminium current collector in lithium-ion batteries: A review, J. Energy Storage 43 (2021) 103226.
[147] L. Guo, D.B. Thornton, M.A. Koronfel, I.E. Stephens, M.P. Ryan, Degradation in lithium ion battery current collectors, J. Phys.: Energy 3 (3) (2021) 032015.
[148] S.-T. Myung, Y. Hitoshi, Y.-K. Sun, Electrochemical behavior and passivation of current collectors in lithium-ion batteries, J. Mater. Chem. 21 (27) (2011) 9891–9911.
[149] P. Arora, M. Doyle, R.E. White, Mathematical modeling of the lithium deposition overcharge reaction in lithium-ion batteries using carbon-based negative electrodes, J. Electrochem. Soc. 146 (10) (1999) 3543.
[150] S.E. O'Kane, I.D. Campbell, M.W. Marzook, G.J. Offer, M. Marinescu, Physical origin of the differential voltage minimum associated with lithium plating in Li-ion batteries, J. Electrochem. Soc. 167 (9) (2020) 090540.
[151] C. von Lüders, J. Keil, M. Webersberger, A. Jossen, Modeling of lithium plating and lithium stripping in lithium-ion batteries, J. Power Sources 414 (2019) 41–47.
[152] N. Legrand, B. Knosp, P. Desprez, F. Lapicque, S. Raël, Physical characterization of the charging process of a Li-ion battery and prediction of Li plating by electrochemical modelling, J. Power Sources 245 (2014) 208–216.
[153] L. Zhang, L. Liu, X. Gao, Y. Pan, X. Liu, X. Feng, Modeling of lithium plating in lithium ion batteries based on Monte Carlo method, J. Power Sources 541 (2022) 231568.
[154] S. Carelli, W.G. Bessler, Coupling lithium plating with SEI formation in a pseudo-3D model: A comprehensive approach to describe aging in lithium-ion cells, J. Electrochem. Soc. 169 (5) (2022) 050539.
[155] M. Ecker, P.S. Sabet, D.U. Sauer, Influence of operational condition on lithium plating for commercial lithium-ion batteries–electrochemical experiments and post-mortem-analysis, Appl. Energy 206 (2017) 934–946.
[156] A.J. Smith, Y. Fang, A. Mikheenkova, H. Ekström, P. Svens, I. Ahmed, M.J. Lacey, G. Lindbergh, I. Furó, R.W. Lindström, Localized lithium plating under mild cycling conditions in high-energy lithium-ion batteries, J. Power Sources 573 (2023) 233118.
[157] D. Ren, K. Smith, D. Guo, X. Han, X. Feng, L. Lu, M. Ouyang, J. Li, Investigation of lithium plating-stripping process in Li-ion batteries at low temperature using an electrochemical model, J. Electrochem. Soc. 165 (10) (2018) A2167.
[158] X. Lin, K. Khosravinia, X. Hu, J. Li, W. Lu, Lithium plating mechanism, detection, and mitigation in lithium-ion batteries, Prog. Energy Combust. Sci. 87 (2021) 100953.
[159] D. Aurbach, E. Zinigrad, H. Teller, P. Dan, Factors which limit the cycle life of rechargeable lithium (metal) batteries, J. Electrochem. Soc. 147 (4) (2000) 1274.
[160] D. Lu, Y. Shao, T. Lozano, W.D. Bennett, G.L. Graff, B. Polzin, J. Zhang, M.H. Engelhard, N.T. Saenz, W.A. Henderson, et al., Failure mechanism for fast-charged lithium metal batteries with liquid electrolytes, Adv. Energy Mater. 5 (3) (2015) 1400993.
[161] J. Christensen, J. Newman, Stress generation and fracture in lithium insertion materials, J. Solid State Electrochem. 10 (2006) 293–319.
[162] J. Christensen, J. Newman, A mathematical model of stress generation and fracture in lithium manganese oxide, J. Electrochem. Soc. 153 (6) (2006) A1019.
[163] X. Zhang, W. Shyy, A.M. Sastry, Numerical simulation of intercalation-induced stress in Li-ion battery electrode particles, J. Electrochem. Soc. 154 (10) (2007) A910.
[164] R. Purkayastha, R.M. McMeeking, A linearized model for lithium ion batteries and maps for their performance and failure, 2012.
[165] F. Berto, P. Lazzarin, C. Marangon, Brittle fracture of U-notched graphite plates under mixed mode loading, Mater. Des. 41 (2012) 421–432.
[166] B.H. Park, H.C. No, A unified model for strength degradation of oxidized IG-430 graphite column in VHTR, J. Nucl. Mater. 424 (1–3) (2012) 132–137.
[167] M. Eto, T. Oku, T. Konishi, High temperature young's modulus of a fine-grained nuclear graphite oxidized or prestressed to various levels, Carbon 29 (1) (1991) 11–21.
[168] S. Sato, K. Kawamata, A. Kurumada, H. Ugachi, H. Awaji, R. Ishida, Degradations of thermal shock resistance and fracture toughness of neutron irradiated reactor graphite, J. Nucl. Sci. Technol. 24 (7) (1987) 547–556.

[169] C. Zou, C. Manzie, D. Nešić, Model predictive control for lithium-ion battery optimal charging, IEEE/ASME Trans. Mechatronics 23 (2) (2018) 947–957.

[170] M.A. Xavier, A.K. De Souza, K. Karami, G.L. Plett, M.S. Trimboli, A computational framework for lithium ion cell-level model predictive control using a physics-based reduced-order model, IEEE Control. Syst. Lett. 5 (4) (2020) 1387–1392.

[171] R. Klein, N.A. Chaturvedi, J. Christensen, J. Ahmed, R. Findeisen, A. Kojic, Optimal charging strategies in lithium-ion battery, in: Proceedings of the 2011 American Control Conference, IEEE, 2011, pp. 382–387.

[172] A. Abdollahi, X. Han, N. Raghunathan, B. Pattipati, B. Balasingam, K. Pattipati, Y. Bar-Shalom, B. Card, Optimal charging for general equivalent electrical battery model, and battery life management, J. Energy Storage 9 (2017) 47–58.

[173] R. Suresh, R. Rengaswamy, Modeling and control of battery systems. Part II: A model predictive controller for optimal charging, Comput. Chem. Eng. 119 (2018) 326–335.

[174] C. Zhang, J. Jiang, Y. Gao, W. Zhang, Q. Liu, X. Hu, Charging optimization in lithium-ion batteries based on temperature rise and charge time, Appl. Energy 194 (2017) 569–577.

[175] J.M. Reniers, G. Mulder, S. Ober-Blöbaum, D.A. Howey, Improving optimal control of grid-connected lithium-ion batteries through more accurate battery and degradation modelling, J. Power Sources 379 (2018) 91–102.