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Review

A Comprehensive Review on Lithium-Ion Battery Lifetime Prediction and Aging Mechanism Analysis

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Abstract: Lithium-ion batteries experience degradation with each cycle, and while aging-related deterioration cannot be entirely prevented, understanding its underlying mechanisms is crucial to slowing it down. The aging processes in these batteries are complex and influenced by factors such as battery chemistry, electrochemical reactions, and operational conditions. Key stressors including depth of discharge, charge/discharge rates, cycle count, and temperature fluctuations or extreme temperature conditions play a significant role in accelerating degradation, making them central to aging analysis. Battery aging directly impacts power, energy density, and reliability, presenting a substantial challenge to extending battery lifespan across diverse applications. This paper provides a comprehensive review of methods for modeling and analyzing battery aging, focusing on essential indicators for assessing the health status of lithium-ion batteries. It examines the principles of battery lifespan modeling, which are vital for applications such as portable electronics, electric vehicles, and grid energy storage systems. This work aims to advance battery technology and promote sustainable resource use by understanding the variables influencing battery durability. Synthesizing a wide array of studies on battery aging, the review identifies gaps in current methodologies and highlights innovative approaches for accurate remaining useful life (RUL) estimation. It introduces emerging strategies that leverage advanced algorithms to improve predictive model precision, ultimately driving enhancements in battery performance and supporting their integration into various systems, from electric vehicles to renewable energy infrastructures.

Keywords: lithium-ion batteries; battery lifetime modeling; aging mechanisms; state of health (SOH); RUL; degradation factors; battery health assessment; battery durability; predictive model precision; temperature fluctuation

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1. Introduction

As the world moves towards sustainable energy systems and decarbonization, lithium-ion batteries (LIBs) play a crucial role in supporting clean energy solutions, facilitating the shift to electric mobility and renewable energy storage. While there have been notable advancements in LIB technology, much of the current research tends to neglect the interactions among various aging factors, resulting in a lack of comprehensive models that address all relevant degradation mechanisms. The aging processes of LIBs in electric cars, LIBs in stationary energy storage systems, and their integration into grid systems are the main topics of this paper. "Grid integration" refers to the use of LIBs to store energy harvested from renewable sources, such as wind and solar, and then the use of that energy to balance and stabilize the grid. Conversely, non-mobile energy storage devices, such as microgrids that are independent of renewable energy sources and industrial and residential energy storage, are referred to as "stationary applications". Data-oriented and model-oriented methods were greatly used to examine the aging processes in EVs and stationary storage systems. Data-driven approaches to battery aging modeling usually use an experimental dataset to estimate battery aging and performance, whereas model-driven approaches usually estimate the electrochemical processes occurring inside the battery [1–3].

While aging factors in EVs are critical, similar challenges impact the broader application of LIBs in energy storage systems, including temperature extremes and infrastructure limitations. The emergence of EVs has been seen as a viable solution to combat global carbon emissions. However, their widespread adoption faces significant challenges, including range anxiety and battery degradation [4]. The range of an EV heavily relies on the energy density and specific energy of the battery, while battery degradation is influenced by driving behavior and environmental conditions. The deployment of LIBs in EV applications is complicated by a number of additional issues in addition to range anxiety and battery deterioration. Because the infrastructure of fast charging is not universal and its thermal management is sophisticated, charging time remains an issue. The high energy density of LIBs raises safety concerns, particularly regarding thermal runaway. Furthermore, supply chain risks are introduced, and battery production costs are impacted by the balance of vital raw materials like nickel, cobalt, and lithium. Additionally, the energy needed for battery recycling and disposal raises environmental concerns. Furthermore, LIB performance is significantly impacted by temperature extremes: hot weather leads to aging, while cold weather reduces efficiency. The viability and sustainability of EVs will suffer if these problems are not resolved [5–8]. Accurate battery lifetime prediction is not only crucial for EV performance but also impacts the reliability and cost-efficiency of renewable energy storage systems, military technology, and off-grid applications in remote areas where replacement access is limited. In this context, understanding battery lifetime prediction and aging mechanisms becomes essential for optimizing battery technology in a way that enhances EV viability [9,10].

While EVs face challenges related to battery performance and sustainability, similar issues arise in grid applications, where LIBs also encounter unique aging and operational concerns due to their stationary use and varying environmental factors. The value of lithium extends beyond its use in electric vehicles. It is also necessary for power integration and moving energy storage. Energy reliability is ensured by the widespread use of backup power systems, energy load shifting, and microgrid operations in the commercial, industrial, and residential sectors. In addition to improving energy dispatch efficiency, LIBs linked into the grid also aid in stabilizing voltage variations brought on by sporadic renewable energy sources like wind and solar. The aging processes in these applications of LIBs, however, differ from those in EVs. The aging process of the calendar is much more harmful because these batteries cycle slowly and remain unused for extended periods of time. Problems including capacity fade, electrode cracking, and lithium plating prevent grid storage batteries from cycling quickly. These issues are made more difficult by the fact that, unlike EV aging models, fixed and grid storage systems have to take into consideration seasonal variations, yearly energy flow, and shifting load patterns over time. For battery-powered technologies to be practical and sustainable in multipurpose energy storage systems, these issues require immediate consideration. In grid-scale applications, data-driven and model-based approaches are essential for enhancing the longevity and dependability of LIBs. By accurately predicting battery behavior, these techniques assist in controlling energy flow, preserving grid stability, and guaranteeing long-term performance even in the face of load and seasonal fluctuations [11,12].

Building on the challenges faced by LIBs in grid applications, reutilizing EV batteries for second-life applications offers potential solutions, but it also brings new concerns related to aging, efficiency, and thermal management. Reutilizing EV batteries presents an opportunity to use their remaining energy capacity and extend their lifespan. Second-life applications for these batteries typically require lower power and energy density than EVs. However, the technical and economic feasibility of these systems still faces uncertainties. It is crucial to understand the aging and lifespan of reused batteries to facilitate their development [13]. Such battery reuse contributes to environmental sustainability and offers economic and resource-saving benefits, particularly when supported by accurate aging predictions and cost-effective assessment strategies. Accurately estimating battery life often requires lengthy and costly testing processes. To address this, efficient methods need to be explored to minimize testing requirements by leveraging existing knowledge of aging patterns from different battery chemistries [14]. These predictions hold significance for industries where reliable battery life forecasting directly impacts operational efficiency, including hybrid vehicles and remote monitoring systems, and even critical applications such as defense and aerospace. Heat generation and thermal transport are crucial factors affecting LIBs' performance, aging, and safety. Elevated battery temperatures significantly accelerate aging. Managing temperature and aging during battery operation presents a complex challenge spanning multiple scales, from the micro/nanoscale within individual material layers to large integrated LIB packs [15,16]. The multi-scale approach to temperature management is vital for extending battery life and critical for ensuring battery safety and reliability in both primary and second-life applications.

The fire and explosion risks associated with LIBs pose significant concerns for their use and transportation in aircraft. Therefore, studying thermal safety issues specific to flight conditions is crucial. Lithium-ion batteries are prone to overcharging, which can lead to thermal runaway and potentially dangerous situations. Inconsistent battery performance, charging devices, or failures in the battery management system (BMS) can contribute to such incidents [17]. Addressing these safety challenges is crucial for expanding lithium-ion battery use across sectors that have stringent safety standards, including aviation and military. In recent years, there has been growing confidence among stakeholders that end-of-life batteries can be repurposed for less demanding applications, such as stationary energy storage, providing new value in the electric grid and transportation sectors. Assessing the feasibility of second-life battery applications from economic and technological perspectives becomes imperative in this context. This paper acknowledges the significance of LIBs in various applications. However, it also highlights the limitation of battery aging as a challenge that needs to be addressed. By addressing the complexities of aging and incorporating them into battery design and management strategies, it becomes possible to improve the overall performance and lifespan of lithium-ion batteries in different applications [18]. Battery aging directly influences the feasibility and maintenance planning of these systems. For example, reliable lifetime prediction in second-life batteries could support energy storage for grid stability, backup power for critical infrastructure, and electrification in remote communities. Understanding the economic feasibility of second-life applications could greatly enhance resource efficiency in sectors such as energy management for hybrid vehicles or maintenance planning for isolated regions.

Data-driven approaches for estimating the state of LIBs primarily employ machine learning and deep learning techniques to predict essential parameters such as state of charge (SOC), state of health (SOH), and future performance or lifespan. Unlike model-based methods, these approaches bypass complex electrochemical models and instead derive insights from experimental data. They typically require extensive datasets to ensure accurate and reliable predictions, as illustrated in Figure 1 [19–23]. Data-driven approaches, therefore, enable scalable solutions for battery lifecycle management, which are essential for applications requiring real-time and long-term reliability [24].

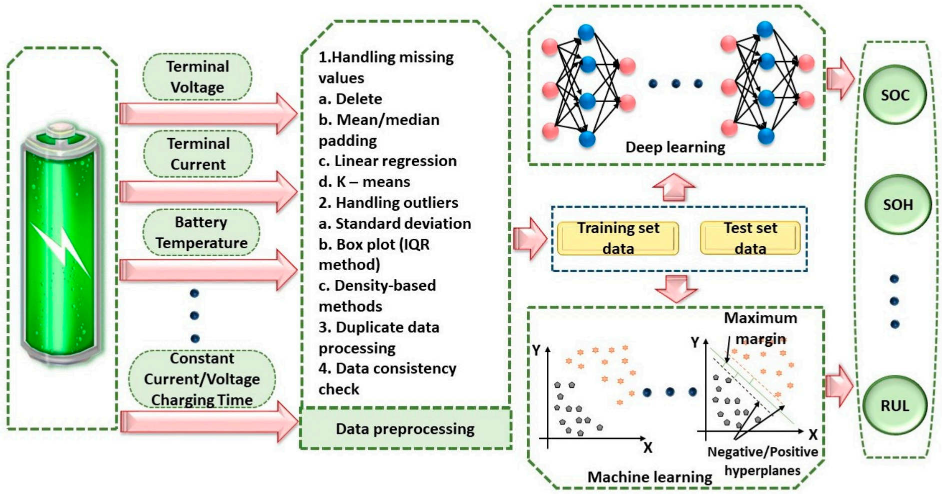

Figure 1. Flowchart of data-driven state estimation based on the Liion battery modified version from [19–23].

Due to their accuracy in predicting a battery's state of charge (SOC), state of health (SOH), and prognostics or life expectancy, data-driven methods for evaluating the state of LIBs (Lithium-Ion Batteries) have grown in popularity. Model-based prediction attempts are predicated on intricate electrochemical models that replicate battery function. In contrast to these, data-driven approaches apply deep learning (DL) and machine learning (ML) models directly to the experimental data. This presents the chance to extract insightful information with consistent accuracy from large amounts of data. Real-time and long-term sustainable applications require sophisticated battery lifecycle management solutions, which are supported by data-driven approaches. Nevertheless, in certain situations, other methods, such as model-based ones, are still helpful, particularly where precise physical modelling is needed. These techniques provide insight into the internal electrochemical processes of batteries, despite the fact that they are frequently more expensive and complex. Additionally, there are now integrated approaches that combine data-driven and model-based methodologies in an effort to strike a balance between prediction accuracy and computation time. This study examines the benefits and limitations of data-driven methods in comparison to other conventional approaches, as well as how they can aid in the development of battery management systems for broader applications. A thorough grasp of battery aging mechanisms and internal processes can be gained using model-based approaches, which are based on intricate electrochemical simulations. On the other hand, data-driven approaches are more scalable and require less computing power than these computationally costly approaches, which may also be less effective in real-time applications [25–29].

Monitoring a battery's SOH has become a critical challenge in the field of hybrid electric vehicles (HEVs) and EVs, as it significantly impacts vehicle performance and lifespan. This poses challenges in real-world scenarios where batteries are expected to deliver reliable and consistent performance over extended periods. To optimize battery designs, it is crucial to have a deep understanding of aging behavior. Empirical and semiempirical models are frequently used to estimate battery aging. However, it is essential to recognize that these models may introduce errors if they do not consider the limitations and interdependencies among various stress factors that contribute to aging. Neglecting these factors can lead to inaccurate estimations, and can potentially impact the performance and reliability of batteries [19–23]. This underscores the importance of robust models that incorporate multiple aging factors, which help ensure that battery performance meets application-specific requirements over time.

In [30], Wang et al. focused on investigating the degradation of a $LiFePO_4$ (LFP) battery resulting from cycling and developing cycle-life models. The researchers collected extensive data on cell lifespan through a comprehensive cycle-test matrix. This matrix incorporated three key parameters: temperature (−30 to +60 °C), depth of discharge (DOD) (10–90%), and discharge rate (C-rate) ranging from C/2 to 10 C (with 1 C equivalent to 2 A). The experimental findings revealed that, at lower C-rates, the battery's capacity loss was primarily influenced by time and temperature, with the impact of DOD being relatively less significant. However, the charge/discharge rate had a more pronounced effect on capacity loss at higher C-rates. To establish a life model, the researchers utilized a power law equation that linked capacity loss to either time or charge throughput. Additionally, the temperature effect was accounted for using an Arrhenius correlation. By allowing the model parameters to vary with C-rates, the researchers observed that the model effectively represented a wide range of life cycle data. Finally, the paper discusses ongoing efforts to develop a comprehensive battery life model considering Ah throughput (time), C-rate, and temperature. Figure 2 shows the test matrix for a cycle-life model for graphite-$LiFePO_4$ cells. This study exemplifies the nuanced impact of aging factors on battery performance, reinforcing the need for a comprehensive review of current predictive models and their effectiveness across varying conditions.

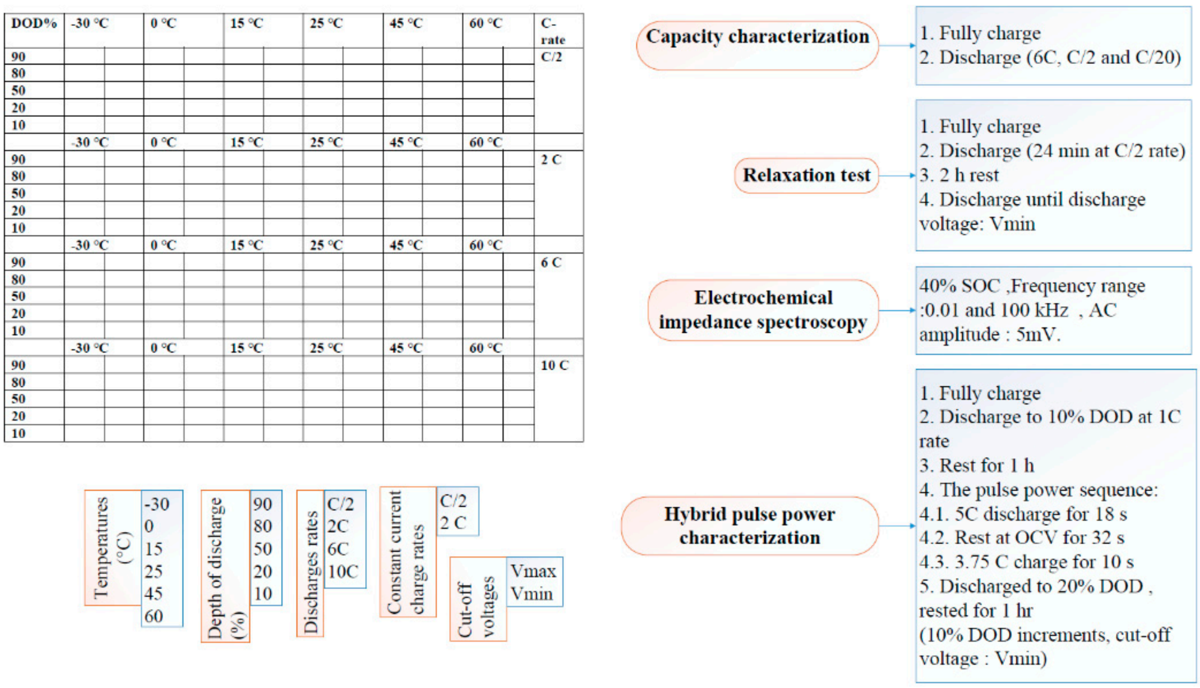

Figure 2. Cycle−life model test matrix for graphite−$LiFePO_4$ cells [30].

Mechanical stress in Nickel Manganese Cobalt (NMC) particles is a significant factor in the aging of LIBs using NMC cathodes. Repeated expansion and contraction during charge/discharge cycles lead to the formation of microcracks, which gradually degrade the material. This degradation reduces the amount of active material and disrupts electrical contact within the electrode, ultimately diminishing the battery's capacity and efficiency over time. Moreover, these cracks allow for electrolyte penetration into the particles, initiating side reactions that further accelerate degradation. The resulting thermal hotspots worsen these effects, hastening capacity loss and overall battery aging. Extending battery lifespan requires optimized particle design and stress-mitigating materials to address these issues effectively [31–34].

Lithium-ion battery aging is driven by Solid Electrolyte Interphase (SEI) degradation, high voltage, temperature, and poor charging/storage conditions, leading to capacity loss and increased resistance. The quality of electrolyte and electrode materials also impacts aging. Mitigating strategies like optimizing charge cycles and improving thermal management can extend battery life. It highlights key areas of focus, including SEI formation, temperature effects, and charge cycles, offering insights into ongoing efforts to mitigate aging and improve battery longevity [35]. Aging is the gradual degradation of the battery cell's performance parameters. Negative electrodes in batteries are commonly composed of materials such as graphite, carbon, titanate, or silicon. Graphite plays a crucial role in battery aging and safety. Upon the initial charge of a battery, a SEI forms between the electrolyte and the electrode, shielding the electrode from corrosion. This SEI is typically stable and helps extend the lifespan of lithium-ion batteries by minimizing capacity loss. However, over time, factors like high voltage, temperature, or improper charging can cause the SEI to degrade. This degradation can lead to gas formation, cracking, and increased electrode impedance, ultimately diminishing the battery's performance. A high state of charge along with conditions such as high temperatures or overcharging can accelerate the breakdown of the SEI. Conversely, low temperatures can hinder lithium diffusion, resulting in lithium plating. These effects contribute to the loss of cyclable lithium and reduce the battery's efficiency. While the SEI provides protection, it becomes unstable when the battery operates beyond the electrolyte's electrochemical stability range, leading to further capacity loss and electrolyte breakdown [35]. Figure 3 illustrates all these phenomena occurring at the SEI. These processes can occur both during the operation of the battery and while it is in storage.

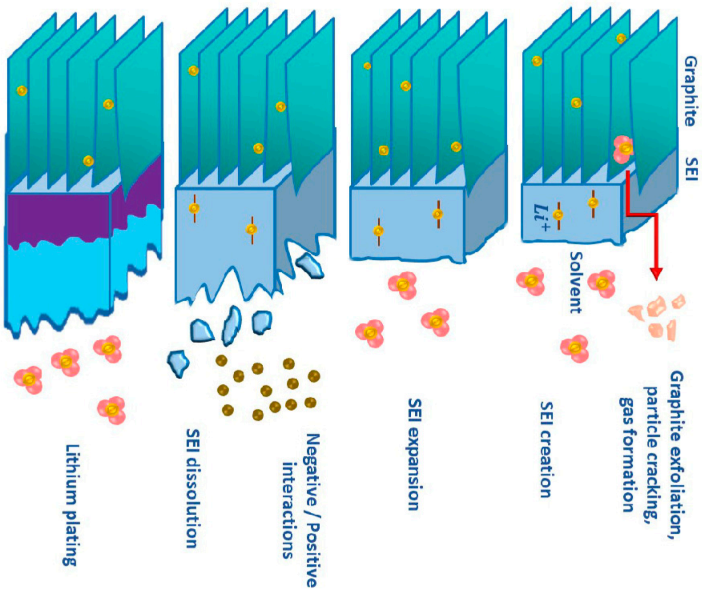

Figure 3. Illustration of the aging effects on the battery's negative electrode: the decrease in capacity and the growth of the SEI layer, modified version from [35].

Structure of the Review

Given the complexity and diversity of factors impacting battery aging and lifetime prediction, a comprehensive review is essential to synthesize current approaches, address knowledge gaps, and identify trends that could drive future advancements in battery technology. This paper provides a structured review of these complex aging mechanisms, the multitude of predictive models developed internationally, and the implications of these insights on the advancement of battery technology. The following sections present the detailed framework of this review, beginning with an analysis of aging mechanisms and progressing to data-driven prediction models and their applications. Section 2 introduces aging in lithium-ion batteries, with a focus on calendar and cycle aging processes, followed by Section 3, we examine various modeling approaches, highlighting physics-based, empirical, and electrochemical models, along with the importance of validation through case studies. Section 4 delves into factors affecting battery aging, such as temperature, SOC, DOD, and electrolyte composition, while Section 5 presents lifetime modeling specific to NCA cathodes, covering degradation mechanisms, mathematical models like the Doyle–Fuller–Newman (DFN) model, and experimental validation. Section 6 discusses key indicators used to quantify battery health, including SOH, End of Life (EOL), and RUL. In Section 7 aging estimation models, contrasting electrochemical models and equivalent circuit-based approaches are presented. Section 8 addresses both the prospects and challenges associated with LIB lifetime modeling, emphasizing its potential for performance enhancement, cost reduction, sustainability, and safety. Section 9 evaluates precise models for describing aging, including calendar aging, using single-particle models, the DFN model, and empirical approaches. In Section 10, we analyze the role of lithium-ion battery materials and their impact on aging, exploring developments in electrode materials and essential lifetime modeling components. Section 11 provides a comparative analysis of different lithium-ion chemistries, followed by Section 12, which outlines future research directions in lithium-ion battery aging. Finally, Section 13 offers a comprehensive discussion synthesizing insights from across the paper followed by the conclusions in Section 14.

2. Aging of Lithium-Ion Batteries

In the context of Li-ion batteries, aging refers to the gradual decline of the battery's performance characteristics over time due to regular usage and charging/discharging cycles. Calendar aging specifically relates to the gradual deterioration of the Li-ion battery's performance parameters during periods of storage or inactivity, taking place under various environmental conditions. Even when not actively used, the battery undergoes chemical changes that can impact its overall performance. Cycling aging, on the other hand, refers to the gradual degradation of the Li-ion battery's performance parameters occurring during the repetitive charging and discharging cycles it experiences during regular operation. Lifetime represents the duration for which the Li-ion battery can be effectively operated until its performance parameters reach predefined threshold values. Once the battery's performance degrades to the specified levels, it may be considered at the end of its usable life, with reduced efficiency and capacity that might no longer meet practical application requirements [36]. The aging of lithium-ion batteries is summarized in Figure 4. To differentiate between "power capability decay" and "internal resistance increment", it should be noted that the former refers to a decrease in the battery's ability to supply power over time, while the latter specifically refers to an increase in resistance inside the battery brought on by electrolyte and electrode degradation. Deterioration of power capability is largely caused by internal resistance, although it is also influenced by capacity loss, structural deterioration, and thermal effects. Therefore, although while an increase in internal resistance is a significant indicator of power capability decay, power capability decay encompasses a variety of degradation mechanisms in addition to an increase in internal resistance, therefore the two terms are not entirely interchangeable [37].

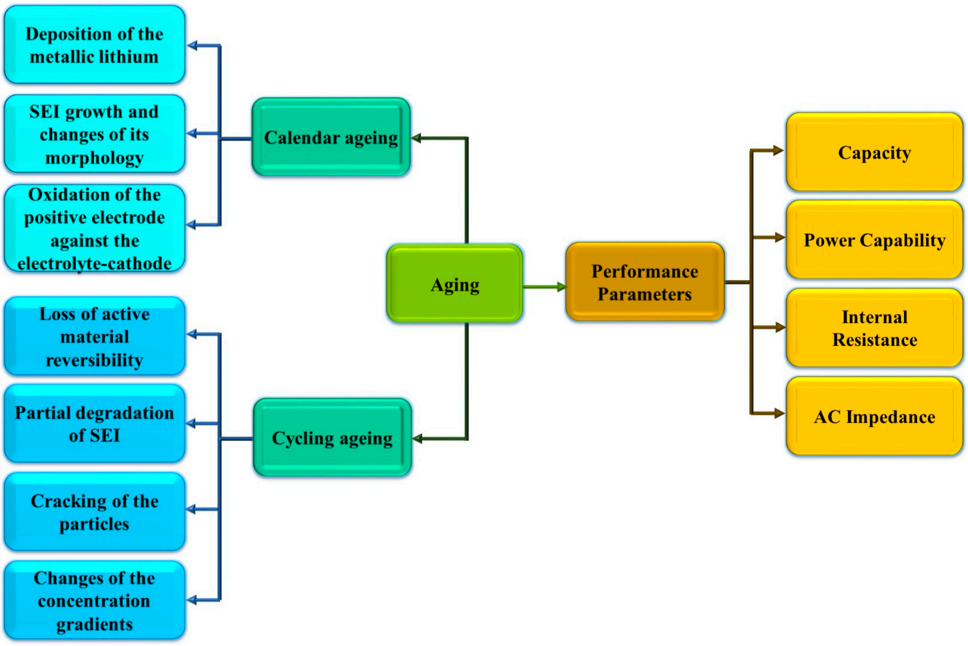

Figure 4. Aging of lithium-ion batteries.

Battery aging in lithium-ion systems is influenced by a combination of chemical, thermal, and mechanical factors, which can differ significantly between calendar and cycle aging processes. Understanding these influences is crucial for optimizing performance in various applications.

2.1. Calendar Aging

Lithium-ion batteries experience performance degradation even when not in use, such as when electric or hybrid vehicles remain parked. This phenomenon, known as calendar aging, occurs over time and significantly impacts the overall lifespan of lithium-ion batteries in electric vehicles. As a result, understanding and predicting calendar aging is crucial for developing long-lasting electric vehicles [38].

Battery degradation plays a vital role in quality management and customer satisfaction across applications such as electric scooters and EVs. The overall health of a battery directly influences its value and depreciation, making it essential to monitor battery performance throughout its lifespan. This includes both cycle aging, which results from usage, and calendar aging, which occurs in stationary conditions. By effectively managing both aspects of battery degradation, manufacturers can optimize battery performance and extend durability [39–43].

A novel approach to studying calendar aging involves radiolysis, a process using ionizing radiation to accelerate the degradation of battery electrolytes. Souid et al. [44] demonstrated that radiolysis can simulate long-term calendar aging up to 30 times faster than natural aging. Using electrochemical impedance spectroscopy (EIS), researchers analyzed symmetrical coin cells with various electrolyte additives, finding that irradiation produces degradation compounds similar to those formed during natural aging. Low radiation doses increased cell resistance by affecting both the solid electrolyte interphase (SEI) layer and charge transfer, while higher doses altered the SEI composition depending on the additive used. Notably, vinylene carbonate (VC) and fluoroethylene carbonate (FEC) enhanced SEI formation, creating more uniform layers than those observed in natural aging. These findings suggest that radiolysis could serve as a valuable tool for rapidly screening electrolyte additives, aiding in the identification of compounds that improve battery lifespan.

In a separate study, Plattard et al. [45] aimed to improve the reliability of lithium-ion batteries by developing accurate aging models. Their research focused on a weighted ampere-hour throughput model, incorporating temperature, current intensity, and state of charge (SOC) as key stress factors influencing aging. To refine this model, they utilized Incremental Capacity Analysis (ICA), which evaluates dQ/dV as a function of voltage to assess a cell's state of health and detect material degradation. When applied to NMC/graphite cells, ICA revealed two peaks: one linked to cycling-induced aging and another potentially associated with calendar aging. However, distinguishing between the two remains challenging since both mechanisms overlap. A key trend observed was that one ICA peak correlated with initial capacity loss (first 10%), primarily driven by lithium inventory loss (LLI). Further research is required to explore degradation at later stages, where loss of active material (LAM) becomes more pronounced.

2.2. Cycle Aging

Cycle aging in lithium-ion batteries results in gradual performance degradation due to repeated charge and discharge cycles. Key factors influencing this process include electrode material degradation, mechanical stress, thermal effects, and electrolyte decomposition. High current rates and deep discharges accelerate capacity loss, while environmental conditions, such as humidity, further contribute to aging. To mitigate these effects and extend battery lifespan, optimized charging protocols and advanced materials are employed [46]. Table 1 presents a comparative summary of lithium-ion battery cycle aging studies.

Electrolyte additives and pulse charging techniques play crucial roles in enhancing lithium-ion battery performance, efficiency, and longevity. Electrolyte additives improve the stability of the solid electrolyte interphase (SEI) layer, minimize undesirable side reactions, and slow electrolyte degradation. These benefits contribute to better battery performance, particularly under varying environmental conditions such as low temperatures. Pulse charging, which applies intermittent rather than continuous charging currents, helps manage heat generation, reduce internal component stress, and improve ion diffusion. By mitigating capacity fade and increasing cycle life, these strategies collectively enhance battery efficiency and longevity [47–53].

Understanding degradation processes in lithium-ion cells is crucial for battery-powered applications. Degradation arises from temperature variations, current load, SOC operating range, and cycle depth, leading to reduced capacity and increased internal resistance. Laboratory aging studies provide insights into these influences, enabling prediction of cell degradation under specific conditions and identification of detrimental operating practices [54,55] However, most studies focus on steady-state conditions, such as constant-current profiles, while dynamic influences like variable current and temperature profiles remain underexplored. Addressing this gap by incorporating real-world dynamic conditions into aging studies can improve the accuracy of degradation assessments and optimize battery performance strategies [56,57].

Battery aging is categorized into calendar aging, driven by factors like temperature and SOC, and cycle aging, influenced by charge/discharge current rates and cut-off voltages. While studies confirm that higher current rates accelerate aging, research on mitigating these effects remains ongoing [58,59]. At high SOC levels, particularly above 4 V in NMC cathodes, increased electrochemical activity accelerates degradation. This leads to electrolyte oxidation, SEI layer instability, cobalt leaching, thermal instability, and increased internal resistance, all contributing to reduced capacity retention and battery lifespan [60–62].

Accurate lithium-ion battery lifetime prediction requires considering both calendar and cycle aging. Future research should focus on developing accelerated aging tests that simulate real-world operational conditions, particularly for EV applications. Incorporating dynamic conditions and comprehensive offline training data can enhance battery lifetime predictions, aiding successful market integration.

Ecker et al. [63] developed a lifetime prediction approach for NMC/graphite lithium-ion batteries by analyzing temperature and SOC effects on impedance rise and capacity loss. Using experimental data, they parameterized a semi-empirical aging model integrated with an impedance-based electro-thermal model, allowing evaluation of drive cycles and battery management strategies. This approach improves lifetime prediction accuracy and provides insights for optimizing vehicle battery design.

Gu et al. [64] introduced a data-driven grey model for predicting life-ending indices in lithium-ion batteries. Unlike traditional aging models that require detailed mechanistic knowledge, the grey model relies on limited test data and employs a smoothing method to enhance accuracy. Applied to phosphate iron and manganese oxide lithium-ion batteries, the model demonstrated effectiveness in reducing the number of cycles needed for operational evaluations in EVs.

Schmalstieg et al. [65] conducted calendar life and cycle aging tests to evaluate the effects of voltage, temperature, cycle depth, and mean SOC on capacity loss and resistance increase. Their results informed a mathematical aging model, which was integrated with an impedance-based electro-thermal model. This approach enabled the simulation and optimization of different drive cycles and battery management strategies, considering seasonal temperature variations for diverse applications.

Stroe et al. [66] proposed a three-stage methodology for accelerated lifetime testing in wind power applications. By collecting capacity fade and power degradation data, they developed a performance degradation model incorporating both calendar and cycle aging. Validation under normal operating conditions confirmed the model's reliability, offering insights for optimizing battery selection, operation, and maintenance strategies.

Sandia National Laboratories developed accelerated life test protocols for high-power lithium-ion cells in hybrid EV applications. Aging experiments on 18,650-size cells revealed power loss, capacity fade, and increased cathode interfacial impedance. Inductive models describing power fade, capacity loss, and impedance rise enabled precise lifetime predictions under varied conditions, contributing to the development of reliable lithium-ion cells for hybrid EVs [67].

Stroe et al. [68] conducted accelerated aging tests on EV batteries, simulating real-world driving conditions using the Worldwide Harmonized Light Vehicles Test Cycle (WLTC) and representative temperature profiles. Focusing on NMC batteries, the study investigated capacity fade and internal resistance increase, enhancing understanding of degradation mechanisms and improving battery management strategies. These findings support more effective BMS designs, contributing to EV performance improvements and wider adoption.

Takei et al. [69] developed testing methods to estimate lithium-ion battery lifespan efficiently. Their experiments on $LiCoO_2$/hard carbon cells revealed that most degradation reactions occur above 4 V. They demonstrated that while straight-line approximations can extrapolate limited cycle data, early short-cycle data introduces significant errors. Accelerated aging tests under high charge rates and elevated temperatures confirmed rapid degradation, emphasizing the importance of voltage control and stress factor analysis for accurate lifespan prediction and effective battery management strategies.

Table 1. Comparative summary of lithium-ion battery cycle aging studies.

Focus Area	Methodology	Battery Type	Degradation Model	Key Findings	Ref.
Lifetime prediction of high-power batteries	Experimental investigation and parameterization of semi-empirical aging model coupled with impedance-based electrical-thermal model	NMC/Graphite	Semi-empirical aging model	Accurate lifetime prediction based on drive cycles and management strategies	[30,63,70]
Cycle-life prediction using the grey model	Data-driven grey model with smoothing methods to predict cycle life	Phosphate Iron & Manganese Oxide Lithium-ion batteries	Grey model for life-end prediction	Efficient lifetime prediction with fewer cycles, without needing detailed aging mechanism knowledge	[64,71]
Calendar and cycle aging tests	Mathematical equations derived from voltage, temperature, cycle depth, and SOC	-	Impedance-based electrical-thermal model	Comprehensive aging model for optimizing different drive cycles and battery management strategies	[65,72]
Accelerated lifetime testing for wind power applications	Accelerated aging conditions and performance-degradation model validation with mission profiles	-	Performance-degradation lifetime model	Optimized battery selection, operation, and maintenance for improved performance and longevity	[66,73,74]
Establishment of life test protocols for high-power lithium-ion cells in HEV applications	Aging experiments on 18,650-size cells; developed inductive models	High-power lithium-ion cells	Inductive models for power fade, capacity loss, and impedance rise	Accurate lifetime predictions under various operating conditions	[22,37,67]
Aging tests on NMC batteries for EV applications	Accelerated aging tests using standardized driving cycle (WLTC) and temperature profiles	NMC	-	Insights into capacity fade and internal resistance increase in NMC batteries	[68,75]
Lifespan estimation of lithium-ion batteries	High-voltage testing, accelerated aging tests with high charge rates and elevated temperatures	$LiCoO_2$/Hard carbon cells	-	Highlighted degradation above 4 V, importance of avoiding high voltage for lifespan prediction	[69]

3. Modeling the Lifespan and Aging of LIBs

LIBs are prevalent in our modern world, powering various devices, from smartphones to electric vehicles. It is vital to comprehend and accurately forecast the lifespan of these batteries to optimize their performance, reduce expenses, and ensure the sustainability of energy storage systems. This chapter explores the intricate science behind modeling the longevity of lithium-ion batteries, drawing from extensive scientific research and references to offer a comprehensive overview.

3.1. Mechanisms of Battery Aging

The duration of LIBs' usability is primarily dictated by the gradual deterioration of their essential components.

3.1.1. Electrochemical Breakdown

An anode solid electrolyte interphase (SEI) is created during the battery's charge and discharge cycles by electrochemical deterioration, which over time may reduce the battery's capacity. Researchers now have a better understanding of how SEIs occur and how they impact battery life thanks to the substantial amount of work that has been done [76,77].

3.1.2. Lithium Deposition

Lee et al. [78] addressed the commercialization challenges of LIBs with Li metal anodes, primarily caused by unpredictable dendrite growth and performance degradation. While prior studies have examined factors influencing dendrite formation, their complex interactions remain unclear. To bridge this gap, the authors developed a multiscale model that combines a kinetic Monte Carlo model for microscopic dendrite formation with a macroscopic electrochemical model. This framework tracks macroscopic variables (e.g., current density, Li-ion concentration, voltage, and state of charge), analyzes their impact on dendrite growth, and optimizes LIB operation to mitigate dendrite formation.

3.1.3. Thermal and Mechanical Stress

Thermal modeling and heat generation are crucial for managing lithium-ion battery safety and performance. As heat from internal resistance and reactions increases with higher charge rates, it risks uneven temperatures and accelerated aging. Modeling techniques predict hotspots, aiding thermal management strategies to prevent overheating. Compressive loads can also deform internal structures, raising resistance and causing micro-cracks, which further accelerate aging. Micro-crack formation is linked to the charge/discharge depth, which causes volume expansion of cathode active materials. Thermal modeling in lithium-ion batteries spans from simple lumped parameter models, assuming uniform temperature, to more advanced finite element and electrochemical-thermal coupled models, which consider spatial and electrochemical variations. Heat generation is influenced by charge/discharge rates, state of charge, ambient temperature, and battery structure. Effective thermal management, using either passive (conductive materials) or active cooling (liquid or air cooling), is vital for preventing overheating and ensuring longevity, particularly in high-power applications such as electric vehicles [79–84].

In EV applications, lithium-ion batteries experience compressive loads from thermal expansion, vibrations, and potential impacts, which can affect mechanical integrity and performance. These forces may deform battery components, accelerate electrochemical degradation, and, in severe cases, cause thermal runaway. Characterization methods include mechanical compression testing, finite element modeling, and in situ stress monitoring to understand how compressive loads impact safety and longevity. To mitigate these effects, battery pack designs often incorporate high-strength materials and protective structures, which help ensure the battery's resilience and reliability under operational stresses [85]. LIBs face safety risks throughout their lifecycle, particularly related to internal short circuit (ISC) triggering, ISC modes, and subsequent TR. For aged LIBs, ISC triggering delays with declining SOH, and "soft" ISC modes occur more frequently, likely due to changes in current collectors' mechanical properties. This delay and soft ISC process result in milder TR events, as aged cells show lower temperature rises and peak temperatures. In thermal front propagation (TFP) within cells, the TR velocity stabilizes away from the initial heat source, with the energy release rate being inversely proportional to cell dimensions. Anisotropic cells exhibit ellipsoid-shaped TFP with long and thin cells releasing less energy than shorter, thicker ones. These insights advance thermal hazard modeling and inform design strategies for safer, next-generation LIBs [86–88]. The longevity of lithium-ion cells during high-voltage cycling can be enhanced by choosing specific electrolyte additives, as demonstrated in tests on NMC442/graphite and cobalt-free NMC640/graphite cells under accelerated degradation conditions (4.4 V at 40 °C). Promising additives effectively reduced degradation by minimizing the dissolution of transition metals (primarily manganese) from the positive electrode, which otherwise leads to increased cell impedance through the formation of a rock salt layer on NMC particles. Additionally, blending LiFePO4 (LFP) with NMC640 in a 90% to 10% ratio notably improved stability in high-temperature cycling and reduced iron deposition on the anode, achieving a synergistic performance boost over cells with pure LFP. Cells with high-nickel positive electrodes ($LiNi_{0.95}Mn_{0.04}Co_{0.01}O_2$) also showed stable cycling at lower cut-off voltages (4.04 V or ~75% SOC), as higher voltages (4.18 V) raised positive electrode impedance due to parasitic electrolyte reactions. Adding

1 wt% lithium difluorophosphate to a 1.2 M $LiPF_6$ electrolyte composed of fluoroethylene carbonate and ethyl methyl carbonate effectively curbed impedance growth, thereby extending cycle life without compromising electrode particle structure. These insights inform electrolyte and material selection for high-energy, long-lasting LIBs designed for rigorous cycling conditions [45]. Galushkin et al. [89–91] demonstrated that the probability of TR in commercial lithium-ion cells, specifically the 18,650 types, increases with the number of charge/discharge cycles and the cells' SOC. Experiments conducted in an accelerating rate calorimeter (ARC) revealed a significant decrease in the initiation temperature of exothermic reactions, leading to TRand increased released energy as the number of charge/discharge cycles increased. Further ARC experiments, along with gas analysis, indicated the accumulation of hydrogen during cycling in the anode graphite. It was confirmed that the recombination of atomic hydrogen released from the graphite anode is a powerful exothermic reaction, leading to increased released energy and decreased initiation temperature of TR. Thus, TR initiation in lithium-ion cells is attributed to this recombination reaction of accumulated atomic hydrogen in the anode graphite during cycling. A possible mechanism for initiating TR is proposed based on the experimental findings.

3.2. Battery Aging and Modeling Approaches

The challenge in simulating and optimizing battery lifetime lies in balancing accuracy with computational efficiency. While ECMs are commonly used in the automotive industry for their efficiency, they rely on empirical relations for aging extensions, limiting their applicability. The choice of a precise model to depict the aging of lithium-ion batteries is contingent on various factors, including the unique battery chemistry and usage pattern. Researchers frequently employ a combination of empirical models, electrochemical models, and statistical models to make accurate forecasts about battery aging. The selection of the most suitable model should align with the available data and the particular application [92]. Recent scientific literature in this field has shown an increased utilization of advanced modeling techniques, machine learning, and data-driven methodologies to enhance the precision of battery aging predictions. These models are customized for different battery chemistries and provide valuable insights into the aging process, contributing to developing more robust battery management strategies [93]. To sum up, lithium-ion battery aging is influenced by many factors, with temperature, cycling rate, and depth of discharge ranking among the most crucial. Accurate models are continuously advancing, harnessing advanced techniques to gain a better understanding and projection of battery aging, facilitating the creation of longer-lasting and more dependable energy storage solutions [94–96].

Numerous calendar aging models exist for LIBs, and their complexity can differ depending on specific applications and the required level of detail. Understanding and modeling battery aging is crucial to ensure cost optimization and safety. Calendar aging analysis involves a periodic cycle of aging and cell characterization. So far, the influence of characterization on calendar aging results has been considered insignificant. However, different studies use varying characterization measurements, particularly in capacity measurement, which could affect capacity and resistance change in calendar aging [97]. Researchers employ various modeling methodologies to predict the longevity of lithium-ion batteries accurately. These models aim to capture the intricate interplay of degradation mechanisms over time. Some commonly used modeling techniques encompass:

3.2.1. Physics-Based Models

Physics-based models replicate the behavior of lithium-ion cells by incorporating fundamental electrochemical processes. These models consider critical variables such as electrode composition, temperature effects, mechanical expansion, and current flow. They typically rely on partial differential equations (PDEs) to describe the internal dynamics of the battery, including ion transport, reaction kinetics, and thermal behavior [98].

Jianing et al. [99] proposed an improved approach for modeling the micro-health parameters of $LiFePO_4$ batteries by analyzing negative electrode materials and electrolytes. Their method simplifies complex liquid and solid diffusion processes using a pseudo-two-dimensional (P2D) model, refining liquid-phase diffusion boundary conditions to enhance electrolyte concentration predictions. A terminal voltage model, employing lumped parameters and nonlinear optimization, enables efficient identification of battery health characteristics. Experimental validation under 1 C constant-current charging demonstrated improved accuracy and reliability compared to conventional techniques.

Single-Particle Model (SPM)

To replicate the behavior of a single particle in a LIB, a mathematical model known as the SPM was developed. Calendar aging can be investigated by observing the changes in the particle's characteristics over time. The battery's aging process can be examined holistically by extending this model to include additional components [100].

Doyle–Fuller–Newman (DFN) Model

Single Particle Models (SPMs) offer a simpler electrochemical approach, potentially suitable for automotive use. Despite their distinct development paths, there's a discussion about connecting EEMs and SPMs. A new empirical aging model called SPM-EEM, derived from simplified SPM aging relations, was proposed by Rechkemmer et al. [100] and compared to existing models, particularly tailored to $LiMn_2O_4$ (LMO) cell chemistry. SPM-EEM demonstrates promising initial results for enhancing accuracy. Although SPMs are somewhat more predictable than EEMs, their complexity often hinders implementation on control devices. Thus, enhancing the predictability of EEMs is crucial for improving aging estimation and optimization in automotive applications.

3.2.2. Empirical Models

Zhang et al. [101] addressed the challenge of increasing longevity in LIB technology by proposing a health-conscious advanced BMS. The system incorporates monitoring and control algorithms to extend battery lifespan while preserving performance. Central to these algorithms are real-time battery capacity estimates. The paper introduces an online capacity estimation scheme for LIBs, which relies on two key innovations: (1) utilizing thermal dynamics for capacity estimation and (2) developing a hierarchical estimation algorithm with guaranteed convergence properties. This algorithm comprises two stages working sequentially. The first stage estimates battery core temperature and heat generation using a two-state thermal model, while the second stage utilizes these estimates to determine state-of-charge and capacity. Numerical simulations and experimental data are presented to demonstrate the effectiveness of the proposed capacity estimation scheme [102,103]. Krupp et al. [97] quantified, for the first time, the impact of characterization using periodic measurements. It reveals a significant influence, manifesting as capacity increase and resistance decrease, attributed to an increase in active electrode surface area due to characterization. Consequently, cell characterization emerges as a potential source for capacity increase in calendar aging. The study suggests that future capacity measurements should use small currents below 1 C to mitigate the influence of characterization on results. Moreover, a method for correcting the characterization effect is proposed.

3.2.3. Electrochemical Models

The electrochemical battery model is valued for its physical interpretability but requires precise parameter settings for accuracy. Conventional parameter identification methods are often time-intensive and may compromise interpretability. Chang et al. [104]

addressed these challenges by developing a framework that: (1) incorporates lithium plating and SEI film growth into the electrochemical model, (2) employs sensitivity analysis using voltage and impedance characteristics to efficiently identify key parameters, and (3) integrates machine learning with optimization in a two-step parameter identification process to improve initialization and prevent convergence issues. This approach enhances accuracy while maintaining efficiency and physical interpretability.

Electrochemical Impedance Spectroscopy (EIS)

EIS serves as a valuable non-invasive method for characterizing Lithium-ion cells, enabling the identification and monitoring of cell degradation processes within a short testing period. Iurilli et al. [105] reviewed and compiles existing studies that utilize EIS spectra for characterizing Li-ion cell degradation or developing ECMs. The objectives include highlighting the impact of various aging test conditions on EIS spectra, establishing correlations between EIS spectra changes and underlying degradation mechanisms, and outlining options for formulating ECMs from EIS spectra of aged cells. Following a comprehensive analysis of the current state-of-the-art, the review offers a critical examination to discuss the connections between degradation mechanisms and the most dependable approaches for modeling them.

3.2.4. Volume Change Models

The development of high-capacity lithium-ion batteries faces challenges due to the large volumetric changes in anode materials during electrochemical cycling, leading to degradation and reduced cycle life. Coupled electrochemical-mechanical models, which account for the interaction between electrochemical processes and mechanical stresses, have been developed to understand and mitigate these issues. These models highlight the importance of considering particle size distributions, as non-uniform particle utilization significantly impacts the rate-dependent volume changes at the electrode and cell levels. Strategies such as surface coatings and porosity adjustments can help alleviate degradation. Future work will focus on improving the understanding of delithiation effects, SEI growth, and the interplay between active materials, as well as refining models for automotive applications to predict the impact of volume changes on battery fatigue and stress [106,107]. By combining mechanical and electrochemical models, the behavior of blended silicon oxide-graphite anodes shows a notable tradeoff in volume expansion during cell operation. Although silicon oxide accounts for just 20% of the anode's capacity, it contributes to half of the total volume change in the cell, underscoring its significant effect on the cell's mechanical performance. This modeling framework enables virtual assessment of design changes at both the cell and pack levels, offering insights into balancing energy density and managing volume expansion. Integrating this model with aging predictions will provide better estimations of irreversible volume changes, supporting more accurate long-term performance and lifespan evaluations. Future work will focus on refining the model to account for rate-dependent volume changes and investigating microstructure modeling to differentiate between dimensional and porosity-related volume changes, further improving volume expansion predictions [108].

3.2.5. Combined Multiphysics- and Data-Based Models

Silva et al. [109] presented a comprehensive overview of recent aging modeling methods, using a multiscale approach that explores aging at the particle, cell, and battery pack levels, and identifies future research opportunities in LIB aging modeling. They also reviewed battery testing strategies to demonstrate how numerical aging models are validated, offering a holistic modeling framework. Additionally, they proposed a combined multiphysics- and data-based modeling approach to achieve accurate, computationally efficient LIB aging simulations. Figure 5 illustrates the typical progression of a LIB over its lifetime, emphasizing key aging events. In Stage I, manufacturing conditions play a crucial role, with early-cycle capacity increases followed by declines due to SEI layer formation. In Stage II, aging processes such as SEI growth, electrode cracking, dissolution, and electrolyte breakdown occur at a constant rate. Stage III sees a rapid, non-linear decrease in state of health (SOH), mainly due to lithium plating. While these stages are defined by specific mechanisms in this paper, real-world applications experience variable paths depending on usage requirements.

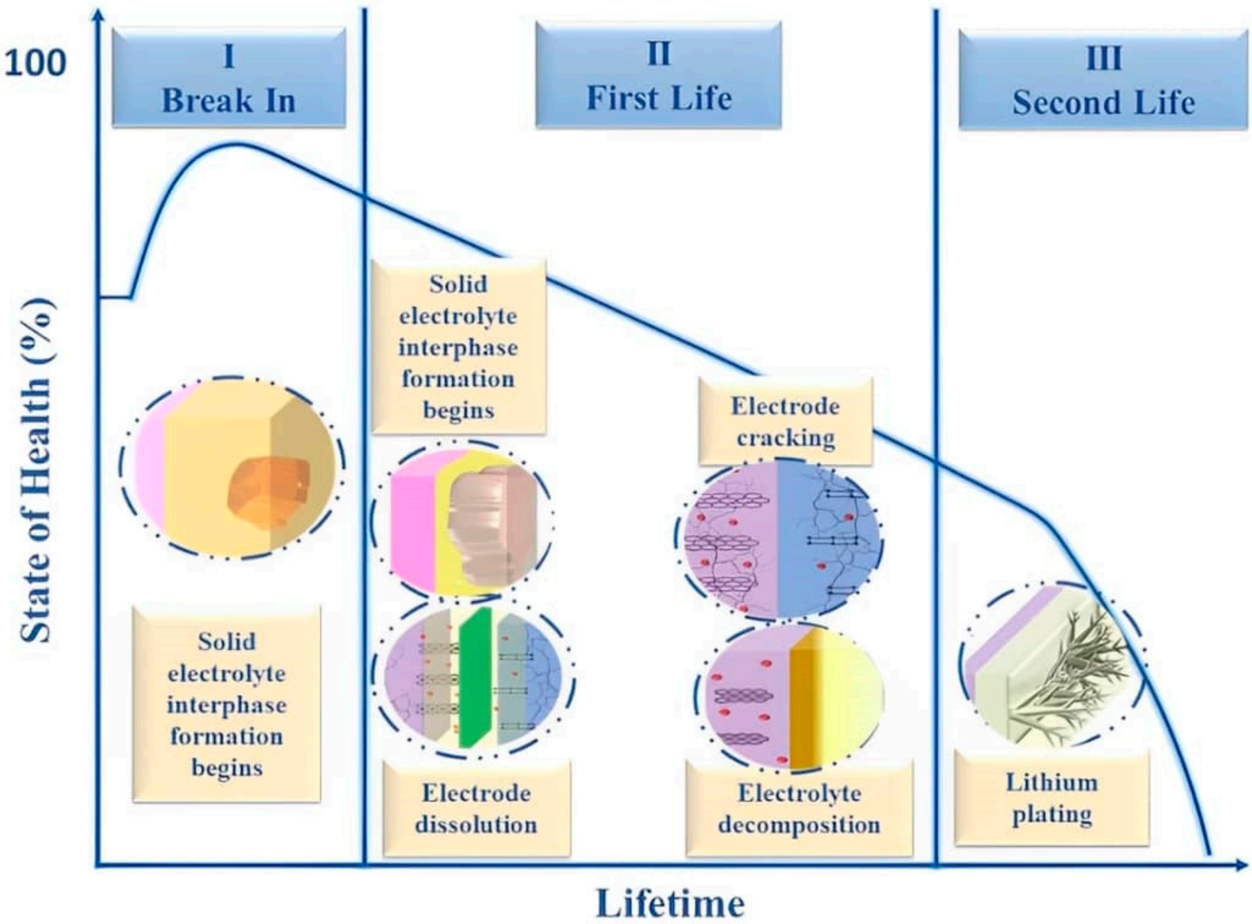

Figure 5. Common progression of state of health and aging processes throughout the battery's lifespan. Modified version from [109].

4. Factors Affecting Lithium-Ion Battery Aging

Because they power everything from cellphones to electric cars, LIBs have become essential to our daily lives. However, Li-ion batteries age like any other energy storage technology, which can have a big impact on how well they work and how long they last. Several external variables can impact the lifespan of LIBs. These variables must be taken into account when formulating lifespan models:

4.1. Operating Conditions

Several variables, including operating temperature, charging and discharging rates, and battery drain, influence battery lifespan. High temperatures, rapid charging, and full discharges can significantly accelerate degradation [110]. Crawford et al. [111] investigated the potential of LIBs in stabilizing the electrical grid as renewable energy sources like solar and wind become more integrated. They tested two commercial Li-ion batteries, one with NCA chemistry and the other with LFP chemistry, under grid duty cycles designed for frequency regulation (FR) and peak shaving (PS), both with and without EV drive cycles. The study compares the lifecycle performance of the two battery chemistries based on metrics such as capacity, round-trip efficiency, resistance, charge/discharge energy, and total used energy. It finds that LFP chemistry offers better stability for energy-intensive PS services, while NCA chemistry is more suitable for FR services under the studied conditions. These results provide insights into selecting, deploying, operating, and analyzing the costs of Li-ion batteries for different grid applications.

4.2. Cycling Frequency

Elmahallawy et al. [112] emphasized the environmental impact of gasoline consumption and the importance of reducing fuel usage through the adoption of hybrid electric vehicles (HEVs) and EVs powered by renewable energy sources. It highlights the concern regarding the degradation of EV batteries over time, which can compromise both performance and safety. Assessing and predicting battery health, referred to as SOH, is crucial for ensuring EV safety. While various techniques exist for estimating and predicting SOH, they may not cover all degradation scenarios. The paper focuses on Li-ion EV batteries and aims to (1) present Li-ion battery models, (2) discuss factors causing degradation and safety issues, (3) review SOH estimation and prediction techniques, and (4) provide recommendations for improving battery lifetime estimation. Overall, it aims to serve as a valuable resource for researchers in the battery community to enhance EV battery safety. The factors contributing to Li-ion battery aging and the resulting degradation effects are illustrated in Figure 6.

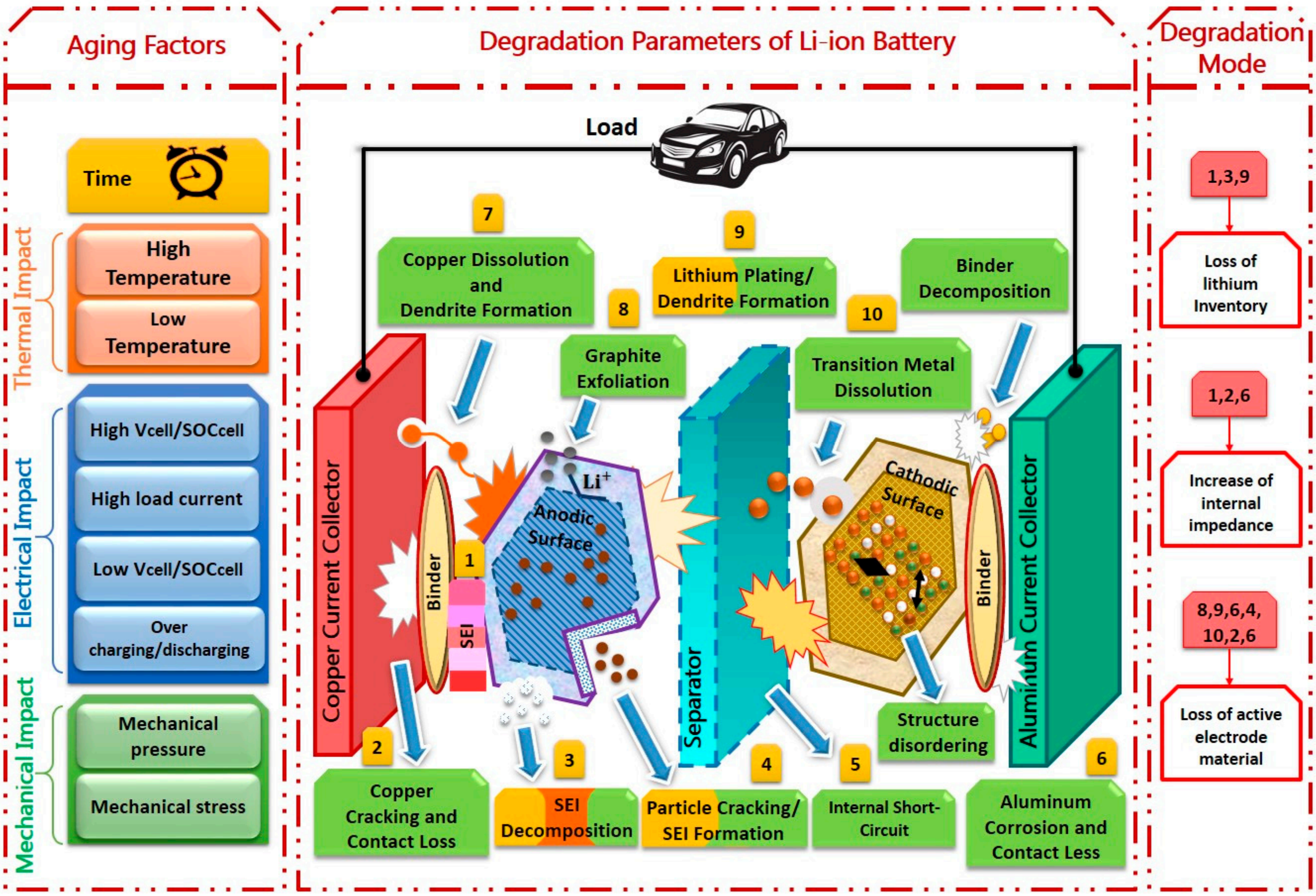

Figure 6. Representation of Li-ion battery aging factors and their associated degradation effects, modified version from [112].

Feng et al. [113] proposed an integrated state-of-charge (SOC) estimation algorithm combining an advanced ampere-hour counting method with a multistate open-circuit voltage (OCV) method. While the ampere-hour counting method is widely used, it can be affected by temperature and current, leading to SOC estimation errors. To address this, the enhanced method adjusts available capacity and coulombic efficiency based on temperature. Additionally, battery SOCs at different temperatures are converted considering capacity loss. The OCV method addresses errors from current sensors and initial SOC estimation, using rated and non-rated OCV-SOCs to estimate initial SOCs. The method was validated through constant- and alternated-temperature tests, demonstrating accurate SOC estimation across various ambient temperatures.

Multi-scale modeling, combining micro- and macro-level perspectives, provides a comprehensive understanding of LIB lifespan by capturing degradation mechanisms at different structural levels. Several case studies have highlighted the practical value of battery lifespan modeling. For example, electric vehicle manufacturers use these models to predict battery degradation and optimize charging strategies, enhancing lifespan and efficiency [114]. However, existing research has not focused on predicting capacity degradation paths for entire battery packs, creating a gap in real-world applications. To address this, Chen et al. [115] introduced the MMRNet model, a multi-horizon time series forecasting approach comprising MOSUM, flash-MUSE attention, and RNN core modules. The model leverages domain knowledge to extract features from large battery aging datasets. MOSUM and flash multi-scale attention effectively capture capacity curve mutations and trends. Dynamic dropout training, transposition linear architecture, residual connections, and module stacking improve model generalization and accuracy. Experimental results show that MMRNet outperforms six baseline time series models, offering effective prediction of battery degradation trajectories with significant implications for condition monitoring and EV safety. Table 2 offers a comparative analysis of lithium-ion battery aging modeling methodologies.

Table 2. Comparative analysis of lithium-ion battery aging modeling methodologies.

Focus/Contribution	Methodology	Key Findings	Ref.
Formation of solid-electrolyte interface (SEI) and its impact on capacity	Literature review	Investigates the electrochemical breakdown and its effects on battery lifespan.	[76,116]
Impact of SEI on battery lifespan	Experimental study	Provides insights into the mechanisms of SEI formation and its role in degradation.	[77,117–119]
Dendrite growth in Li metal anodes	Multiscale modeling (kinetic Monte Carlo and electrochemical model)	Proposes a model to track dendrite growth and its influence on performance, emphasizing the complexity of dendrite formation.	[78,120,121]
Thermal runaway in commercial lithium-ion cells	Accelerating rate calorimeter (ARC) experiments	Shows the correlation between charge/discharge cycles and increased risk of thermal runaway, elucidating the underlying exothermic reactions.	[91]
Physics-based modeling for lifespan prediction	Partial differential equations (PDEs)	Highlights the significance of fundamental electrochemical principles in predicting battery behavior.	[98,118,122]
Advanced battery management system for longevity	Online capacity estimation scheme with thermal dynamics	Introduces a dual-stage estimation algorithm for real-time capacity estimation, enhancing battery longevity.	[101,123,124]
Parameter identification in electrochemical models	Sensitivity analysis and machine learning	Proposes a systematic approach for parameter identification, balancing accuracy and interpretability in electrochemical models.	[104,125–127]
Impact of operating conditions on battery longevity	Literature review	Discusses how temperature, charging rates, and depth of discharge affect degradation rates.	[110,128,129]

Table 2. *Cont.*

Focus/Contribution	Methodology	Key Findings	Ref.
Performance comparison of Li-ion battery chemistries	Experimental testing	Compares lifecycle performance of NCA and LFP chemistries in grid applications, highlighting suitability for different services.	[112,130,131]
State of health (SOH) estimation for EV batteries	Literature review and recommendations	Addresses degradation and safety issues in EV batteries, focusing on SOH estimation techniques.	[132–135]
SOC estimation algorithm development	Combined ampere-hour counting and OCV methods	Proposes an integrated algorithm for accurate SOC estimation across varying temperatures, enhancing battery management.	[113,136–139]
Practical utility of battery lifespan modeling in EVs	Case study	Demonstrates real-world application of lifespan models in forecasting degradation and improving charging strategies.	[114,140–143]
Multi-horizon forecasting model for battery capacity degradation	MMRNet (MOSUM, flash-MUSE attention, RNN)	Develop a data-driven model that effectively predicts degradation trajectories, enhancing condition monitoring in EVs.	[144–147]

4.3. Temperature

Zhang et al. [148] examined the effects of ambient temperature, charge/discharge rate, and cut-off voltage on capacity degradation and internal resistance growth in commercial LIBs. Results highlight the charging rate as the most influential factor, especially in low-temperature aging. Understanding these risks can inform strategies to prevent safety incidents and optimize battery performance in energy storage and electric vehicle applications, including vehicle-to-grid interactions.

4.4. State of Charge (SoC)

State-of-charge (SOC), which represents the amount of energy stored in the battery relative to its capacity, plays a key role in battery aging. Operating a Li-ion battery at extreme SOCs accelerates aging. Ramadass et al. [149] showed that maintaining a high SOC leads to increased capacity degradation due to side reactions, while low SOCs can promote copper dendrite formation, causing internal short circuits. Proper charge and discharge management is essential for extending LIB lifespan.

Accurate SOC estimation is crucial for battery safety, and several techniques are used, including machine learning, voltage-based methods, and Coulomb counting. However, temperature and measurement errors can affect accuracy. As SOC is highly influenced by temperature, parameters are often evaluated together, though challenges remain due to battery manufacturing variations and environmental factors. Zhang et al. [150] introduced a method using ultrasonic reflection waves to measure battery states, considering the effects of SOC and temperature on the ultrasonic signal. Sliding windows help optimize feature selection, and the MD-MTD technique generates virtual samples to address sparse data. The approach, verified in constant-current discharge mode, showed adequate accuracy, though real-world operating conditions may impact its reliability. Future studies could use ICP-OES to measure lithium content at the anode or cathode during SOC and temperature changes in lithium iron phosphate batteries.

Yao et al. [151] reviewed the use of lithium-ion power batteries in transportation, highlighting safety concerns from inaccurate battery health state estimation and prediction. The paper discusses degradation mechanisms and critical definitions of state-of-health (SOH), evaluating model-based, data-driven, and fusion technology methods for SOH estimation and prediction. It also assesses the strengths and weaknesses of current techniques and suggests future research may focus on innovative feature extraction, multi-algorithm coupling, and integration with cloud platforms to improve SOH estimation and prediction.

4.5. Cycling Rate

Sun et al. [152] focused on investigating the characteristics of Li[$Ni_{0.85}$Cox$Mn_{0.15-x}$]O_2 cathodes synthesized through a coprecipitation method, with varying Mn to Co ratios (x = 0–0.15). These cathodes exhibit similar discharge capacities around 206 mAh g^{-1} at room temperature and 213.8 mAh g^{-1} at 55 °C between 2.7 and 4.3 V at a 0.2 C rate. However, their cyclability, thermal stability, and rate capability vary based on the Mn and Co ratio. Among the evaluated cathodes, Li[$Ni_{0.85}Co_{0.05}Mn_{0.10}$]$O_2$ shows the most promising electrochemical properties, with high rate capacity (approximately 163 mAh g^{-1} at 5 C rate) at 25 °C and good thermal stability (main exothermic temperature of 233.7 °C and relatively low heat evolution of 857.3 J g^{-1}).

Ouyang et al. [153] investigated the capacity fading behavior of large format lithium-ion batteries with a Liy$Ni_{1/3}Co_{1/3}Mn_{1/3}O_2$ + LiyMn_2O_4 composite cathode under overcharge conditions. It employs a prognostic/mechanistic model and ICA to understand the capacity degradation mechanism. The overcharge process is divided into four stages: Stage I has no obvious capacity degradation until the battery is overcharged to 120% SOC. In Stage II, lithium deposition leads to LLI LAM in the LiyMn_2O_4 of the composite cathode. Increased internal resistance indicates the thickening of the SEI film. Stage III sees LAM in both the cathode and anode as the battery is overcharged beyond 140% SOC, accompanied by battery swelling due to electrolyte oxidation. In Stage IV, the battery ruptures due to an internal short circuit, instantly releasing stored energy. Pinholes on the separator surface are observed in batteries overcharged to 150% SOC or more.

Choi et al. [154] highlighted the growing importance of analytical methods for assessing the condition of secondary batteries, with a particular focus on EIS that is noted for its convenience, speed, accuracy, and cost-effectiveness. However, interpreting EIS data requires understanding the entire electrochemical system to extract meaningful insights. The review emphasizes constructing a physically sound circuit model tailored to the battery cell system's characteristics. By doing so, the circuit elements representing various aspects of the cell's behavior can be identified. These elements include bulk resistance (Rb), charge transfer resistance (Rct), interface layer resistance (RSEI), and diffusion process (W). The review further discusses the relationship between these resistances and battery parameters, such as SOC, SOH.

The capacity of lithium-ion batteries diminishes over cycles due to various mechanisms stemming from unwanted side reactions. These reactions, occurring during overcharge or over-discharge, lead to electrolyte decomposition, formation of passive films, dissolution of active materials, and other phenomena. Unfortunately, existing mathematical models for lithium-ion batteries lack the incorporation of these capacity loss mechanisms. As a result, Arora et al. [155] fall short in predicting cell performance during cycling and under abusive conditions. They reviewed current literature on capacity fade mechanisms and proposed avenues for integrating these mechanisms into advanced lithium-ion battery models, highlighting the requisite information and directions for future research. A comparison of the factors influencing the aging of lithium-ion batteries is presented in Table 3.

Beyond thermal and operational factors, external environmental conditions such as humidity and atmospheric pressure play a role in battery aging, particularly in applications within extreme climates or high-altitude regions. The most significant factors for lithium-ion battery aging include temperature, cycling rate, and depth of discharge (DOD), which are often regarded as the most pivotal elements impacting aging. Elevated temperatures considerably expedite chemical reactions and intensify the aging process, while frequent cycling and deep discharges place a substantial mechanical and electrochemical load on the battery. Meta-analyses have consistently identified temperature and DOD as leading contributors to battery aging, underscoring the critical need for precise control of these variables in real-world applications. To address this, it's imperative to better understand and mitigate battery aging effects by leveraging predictive aging modeling methods. The significance of these factors can vary depending on the specific battery chemistry, usage scenario, and application.

Table 3. Comparison of factors affecting lithium-ion battery aging.

Factor	Key Findings	Methodology	Ref.
Temperature	Ambient temperature and charge rate significantly affect capacity degradation, especially in low temperatures.	Experimental analysis of commercial LIBs to assess the impact of temperature and charging conditions.	[149,156,157]
State of Charge (SoC)	High SoC accelerates degradation through side reactions, while low SoC promotes dendrite formation. Effective change management is essential for longevity.	Empirical study on how different SoC levels impact battery aging.	[149,158–160]
State of Health	Reviews methods for estimating state of health (SOH) and highlights degradation mechanisms in lithium-ion batteries.	Literature review synthesizing findings on SOH estimation and degradation mechanisms from various sources.	[151,161]
Cycling Rate	Investigates $Li[Ni_{0.85}CoxMn_{0.15-x}]O_2$ cathodes, showing varying cyclability and thermal stability based on composition.	Synthesis and characterization of cathodes with evaluation of electrochemical properties under different conditions.	[152,162]
Depth of Charge	Examines capacity fading under overcharge, identifying stages of degradation, including lithium deposition and active material loss.	Mechanistic modeling and incremental capacity analysis to study overcharge effects in large format LIBs.	[153,163,164]
Electrolyte Composition	Highlights the role of electrochemical impedance spectroscopy (EIS) in assessing battery health, emphasizing circuit model construction for data interpretation.	Analytical review of EIS techniques, focusing on developing circuit models to represent battery behavior.	[154,165,166]
Calendar Aging	Discusses side reactions causing capacity fade and identifies gaps in predictive models for battery performance under stress.	Literature review summarizing capacity fade mechanisms and suggesting improvements for predictive battery modeling.	[155,167,168]

4.6. Environmental Factors

Wang et al.'s study [169] showed that when LIBs are subjected to saline conditions, humidity accelerates the aging process to its greatest degree. The primary aging factor resulting from continuous SEI film breakdown and restoration procedures is lithium inventory loss (LLI). According to the findings of the structural study, there is observable cathode degradation, indications of material cracking, and an increase in impedance rating as capacity falls. In order to control humidity-triggered degradation rates, new design strategies and prediction models should be created.

To investigate the thermal safety of cycling-aged LIBs under various pressure settings, Xie et al. [170] used a dynamic pressure chamber. The time it takes for thermal runaway to start and happen at lower temperatures is shortened by higher cycle aging and lower ambient pressure. Shorter times between gas release and ignite are the result of aging and decreased operating pressure. Battery safety is adversely affected by three factors: pressure imbalances, side chemical reactions, and cathode structural failure. According to the study, for 18,650 LIBs in flight systems, measuring voltage changes offers better early notice capabilities than smoke monitoring systems.

5. Multi-Factor Interactions in Battery Aging

Temperature, SOC, DOD, and charge rate are some of the factors that affect how batteries naturally age. High SOC levels and elevated temperatures combine to promote lithium plating and electrolyte breakdown, while deep cycling at elevated temperatures results in increased mechanical stress and active material loss. Fast charging and high state of charge levels increase the risk of material plating and cause the internal resistance to heat up more. In addition to machine learning techniques that capture non-linear dependencies, effective battery lifetime prediction models employ semi-empirical and Arrhenius-based formulations with exponential or power-law correlations. Performance models are improved and management systems for battery lifetime systems are optimized by laboratory research and experimental testing under real-world aging situations [72].

5.1. Combined Effects of Temperature and SOC

The aging behavior of Samsung INR21700-50E lithium-ion battery cells (Samsung SDI Co., Ltd., Suwon-si, Republic of Korea.) was investigated by Florian et al. [171] using a combination of calendar and cycle aging experiments. The study involved 279 cells under 71 experimental circumstances over the course of a year, or 250 years of data collecting. Various experimental techniques were used throughout the research project's stages: Stage 2 used model-based parameter individual optimum experimental design, while Stage 1 used non-model-based experimental design. Better insight into degradation was made possible by these two methods. By facilitating the calibration of performance models and the investigation of unknown aging mechanisms, this dataset accomplishes three goals.

In order to reconcile the manufacturer's stated battery lifespan from marketing claims with actual usage performance, Sai Krishna et al. [172] developed a sophisticated cycle testing process. By taking into consideration temperature, charging and discharging rules, and rest periods, this approach employs 1000 distinct test cycles to examine realistic driving patterns. Important findings on battery deterioration were revealed by experimental data, which showed that capacity decline was caused by both SEI layer expansion and lithium plate development. Research indicates that whereas cycle time is the primary determinant of SEI formation, lithium plating responds to rest period duration independent of charge/discharge speed. While the development of an SEI layer improves the durability of lithium plating across cycles, dimensional and time-related variations in operating temperatures are important factors that accelerate capacity fading rates. The study demonstrates that safe operating temperatures affect battery lifetime, but it also calls for more investigation into how to replicate actual driving habits and develop innovative charging techniques to improve management systems.

5.2. Impact of Temperature and Discharge Rate

In order to determine how temperature and discharge rate affect cycle-life performance, the authors Yao et al. [173] assessed lithium-ion pouch cells using graphite anode cells and $LiCoO_2/LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ blended cathode cells. These cells are less affected by discharge rate, but exposure to low temperatures causes increasing degradation, mostly in the $LiCoO_2$ component in the cathode area. At discharge rates as high as 5 C, the cells show the ability to function for 3000–5000 cycles before their capacity drops by 20%. Although low temperatures accelerate aging by increasing charge transfer impedance in aged cathodes, rising temperatures accelerate the production of SEI layers and electrolyte breakdown. By design, the pouch cell distribution lessens the effects of rapid discharge rates while lowering mechanical and thermal stress. This work demonstrates why it is still crucial to monitor the cathode's condition in low-temperature applications.

5.3. DOD and Capacity Degradation

Guoqing et al.'s study [174] examined the aging processes of lithium-ion batteries by examining several operational characteristics, such as ambient temperature, DOD, and SOC range. The report describes four main degradation processes, including as particle breakage, active material reduction (LAM), lithium (Li) plate creation, and solid-electrolyte interface (SEI) expansion. The investigation reveals that while temperature extremes accelerate degradation, ideal battery operation temperature ranges between 25 and 35 °C effectively slow down the aging process. The study found that there is constructive feedback between particle cracking and LAM, and destructive feedback between Li plating and SEI growth. Low temperatures accelerate the rate of capacity degradation because Li plating intensifies, whereas high temperatures decrease Li plating but accelerate SEI development. Blocking anode pores results in electrolyte potential gradients, which causes nonlinear capacitance degradation.

6. Lifetime Modeling of Lithium-Ion Batteries with Different Cathode

6.1. (Nickel Cobalt Aluminum) NCA

Torregrosa et al. [175] addressed lithium-ion battery calendar aging, proposing a semi-empirical model with physically interpretable parameters. It incorporates temperature and state of charge dependencies through a pre-exponential factor and a power law coefficient calibrated via a two-step optimization process. This model accurately predicts capacity loss across various conditions and chemistries over 50 years. Findings indicate that NMC chemistry offers superior longevity under specific temperatures and state of charge conditions, which is crucial for automotive and deep-space applications. LFP chemistry shows resilience at higher temperatures and state of charge levels.

Zhang et al. [176] investigated the degradation of lithium-ion battery cells containing nickel–cobalt-aluminum-oxide electrodes due to cyclic overcharging. It suggests non-destructive methods for detecting overcharging-induced degradation. The study finds that battery capacity decreases notably with increased overcharge depth and cycles, particularly in the initial three cycles and when the charging termination voltage is set to 5 V. The tolerance to overcharge also diminishes with cyclic overcharging. The authors employ electrochemical impedance spectroscopy, incremental capacity, and differential voltage analysis to diagnose cell degradation. Three main degradation modes are identified: loss of lithium inventory, loss of active materials, and a unique increase in the third peak on incremental capacity curves, indicative of overcharging degradation in batteries with NCA cathodes.

NCA ($LiNiCoAlO_2$) LIBs, commonly used in electric vehicles and power grid applications, are prone to degradation, raising safety concerns. To monitor changes in the battery's state of health, it's essential to analyze degradation under various stress conditions. While methods like EIS, GITT, and ICA have been used individually, there are few studies combining them to assess NCA battery degradation [177].

High temperatures can hasten NCA cathode deterioration, which lowers capacity and shortens cycle life. To reduce this degradation mechanism, efficient thermal management techniques are essential [178].

Mathematical models play a key role in forecasting the lifespan of NCA cathodes in Lithium-Ion Batteries by modeling degradation processes like capacity loss, cycling effects, and chemical reactions. They factor in variables such as voltage, temperature, and impedance to predict battery behavior. These models are vital for enhancing battery design and extending performance [179].

An electrochemical model called the DFN model is used to explain how NCA cathodes behave during cycles of charge and discharge. A number of variables are considered, including as SOC, temperature, cycling rate, and DOD [180].

Hu et al. [181] emphasized the critical importance of ensuring the reliability of rechargeable LIBs due to the potential for significant economic losses and safety hazards resulting from battery failures. To address this concern, the study introduces a methodological framework for the quantitative analysis of degradation mechanisms in LIBs while they are in operation. The framework involves two main phases: (1) offline characterization of half-cell differential voltage behavior to collect precise voltage and capacity data, and (2) online (on-board) analysis of degradation mechanisms using recursive Bayesian filtering to estimate degradation parameters based on full-cell voltage behavior. These parameters quantify the extent of degradation from different mechanisms. Simulation results using $LiCoO_2$/graphite Li-ion cells demonstrate the effectiveness of the proposed framework in the online estimation of degradation parameters [182,183].

Reduced cyclable lithium inventory is the main source of capacity fade, while anodic side reactions such as electrolyte decrease and SEI growth have been found to be the main culprits. The impacts of anodic and cathodic side reactions during storage are shown by coulomb tracking, while differential voltage analysis (DVA) indicates a change in electrode balance that is highly correlated with anode potential. Reversible self-discharge can happen with high SoCs, which could lead to a misconception of slower aging. The lowest graphite potential should be avoided in order to limit aging and prolong battery life. Cells should be stored at low temperatures and lower SoCs [184].

Data-driven models, founded on machine learning and artificial intelligence techniques, are emerging as potent tools for predicting NCA cathode lifespan. These models can capture intricate patterns and dependencies within extensive datasets [185]. Lifetime modeling for NCA cathodes in LIBs may differ from other chemistries, such as NMC or LFP, due to distinctions in material attributes, charge and discharge characteristics, thermal stability, and the effects of degradation mechanisms [186]. Material Properties: NCA cathodes typically have a higher cobalt content than NMC cathodes, making them more costly but potentially offering greater energy densities. LFP cathodes possess a different olivine crystal structure than the spinel structure of NCA and NMC, impacting ion transport and overall performance [187]. Charge/Discharge Characteristics: NCA and NMC cathodes are commonly employed in applications prioritizing high energy density and power, like electric vehicles, due to their higher specific capacity. In contrast, LFP has higher structural stability and potential for longer cycle life, albeit with a slightly lower energy density [188]. Thermal Stability: Distinct cathode materials show varied thermal stability. For instance, NCA tends to be less thermally stable than LFP, influencing operating temperature ranges and safety considerations [189]. Degradation Mechanisms: Each cathode chemistry has unique degradation mechanisms that can influence lifetime modeling. For example, NCA and NMC may experience capacity fade due to side reactions at the electrode-electrolyte interface, while LFP might be more susceptible to mechanical degradation due to its brittleness [110]. Performance vs. Cycle Life: The selection of cathode material can impact the trade-off between performance and cycle life. NCA and NMC may offer higher specific energy but have a shorter cycle life than LFP [190]. Overall, lifetime modeling for NCA cathodes must consider these differences and variations in properties and performance compared to other cathode chemistries. This involves understanding the kinetics of electrochemical processes, capacity fading mechanisms, thermal stability, and other factors influencing long-term battery performance [191–193]. Transfer learning approaches, which adapt models trained on related chemistries or systems, may help overcome data limitations, particularly in predicting NCA cathode behavior under varied operating conditions.

Accurate lifespan modeling relies on experimental data and validation. Researchers conduct accelerated aging tests under extreme conditions to gather valuable data for calibrating models. These tests involve subjecting batteries to high temperatures, rapid charge/discharge rates, and other stressors. Validation of lifespan models entails comparing model predictions with real-world battery performance data. This step ensures that the models accurately depict the degradation behavior of NCA cathodes in practical scenarios. Modeling the lifespan of NCA cathodes in lithium-ion batteries is a multidisciplinary endeavor that integrates elements of electrochemistry, materials science, and mathematical modeling. Precise models are indispensable for optimizing battery design management strategies and guaranteeing the long-term performance and safety of LIBs. As research progresses in this domain, enhancements in the durability of NCA cathodes will contribute to more dependable and long-lasting lithium-ion battery technologies [194].

6.2. Lithium Cobalt Oxide (LCO)

Two major issues must be resolved in order to increase the energy density and functionality of lithium cobalt oxide (LCO)-based batteries for 3 C electronics: interfacial instability with electrolytes and structural deterioration, which includes phase transitions, cobalt dissolution, and oxygen evolution. Techniques including coating, doping, and electrolyte optimization have worked well; coating improves surface protection, while doping increases structural stability. To improve cycling stability, particularly at higher cut-off voltages above 4.5 V, future developments should concentrate on integrating sophisticated characterization techniques, creating innovative electrolytes, and combining numerous modification tactics [195].

6.3. Lithium Iron Phosphate (LFP)

Lithium iron phosphate (LFP) battery deterioration is primarily influenced by environmental temperature (T) and charging voltage limit (Vchg), with charging current (Ichg), discharging current (Idis), and discharging voltage limit (Vdis) following closely behind. Higher charging voltage limits speed up the degradation of accessible lithium and positive electrode materials, while higher charging current speeds up the degradation of negative electrode materials. Future studies on the aging mechanisms of lithium-ion batteries are also essential for enhancing battery management techniques and aging test optimization [196].

6.4. Nickel Cobalt Aluminum (NCA)

NCA batteries' capacity fade is accelerated by high-rate pulse discharge; after 400 cycles, when pulse-discharge cell's capacity fade was 20.5%, whereas the high-rate continuous discharge's was 5.68% and the control cell's was 0%. EIS demonstrates that the degradation under high-rate pulse discharge is associated with increased passive layer development and higher charge transfer resistance. Using additional methods such as material analysis and three-electrode EIS, more research is required to ascertain if the observed degradation is due to the peak current or the pulsed character of the discharge [197].

6.5. Lithium Manganese Oxide (LMO)

A semi-empirical life model was created by Wang et al. [198] to explain both calendar-life and cycle-life losses. In graphite/composite metal oxide cells, the DOD, temperature, and rate have the biggest effects on capacity loss. According to the differential voltage approach, lithium loss happens more quickly than active material loss. The cycle-life loss is linearly dependent on time or charge throughput and exponentially dependent on rate, while the calendar-life loss is controlled by an Arrhenius correlation for temperature effects and a square root of time relation.

It can be concluded that the main reasons for capacity fading in lithium-manganese oxide and lithium-nickel-cobalt mixed oxide batteries include structural and mechanical changes that occur during cycling, as well as adverse reactivity with the electrolyte. Doped materials have helped to lessen these problems, but more research is still needed to fully understand concerns like manganese dissolution and electrolyte interactions. The cathode chemistry (NCA, LCO, LFP, LMO) affects the temperature, charging voltage, current rates, and discharge depth, among other aspects that affect the aging and deterioration of LIBs. Enhancing battery performance, longevity, and safety requires an understanding of these systems. Although semi-empirical and data-driven models shed light on degradation processes, more study is required to improve thermal and structural stability, optimize battery management strategies, and improve testing techniques to anticipate and lessen capacity fade. These advancements will eventually result in more dependable and long-lasting battery technologies for cutting-edge applications.

7. Indicators to Quantify the Health Level of the Battery

Figure 7 illustrates an EEC-based method for lifetime modeling of Li-ion battery cells. Accurately estimating the SOC, SOH, RUL, and EOL of (LIBs is of paramount importance for effective BMS [66,199]. The assessment of the SOH is critical for evaluating batteries' usability and remaining capacity. In the context of repurposing retired batteries, there is a growing interest in rapid methods for evaluating the SOH of battery modules.

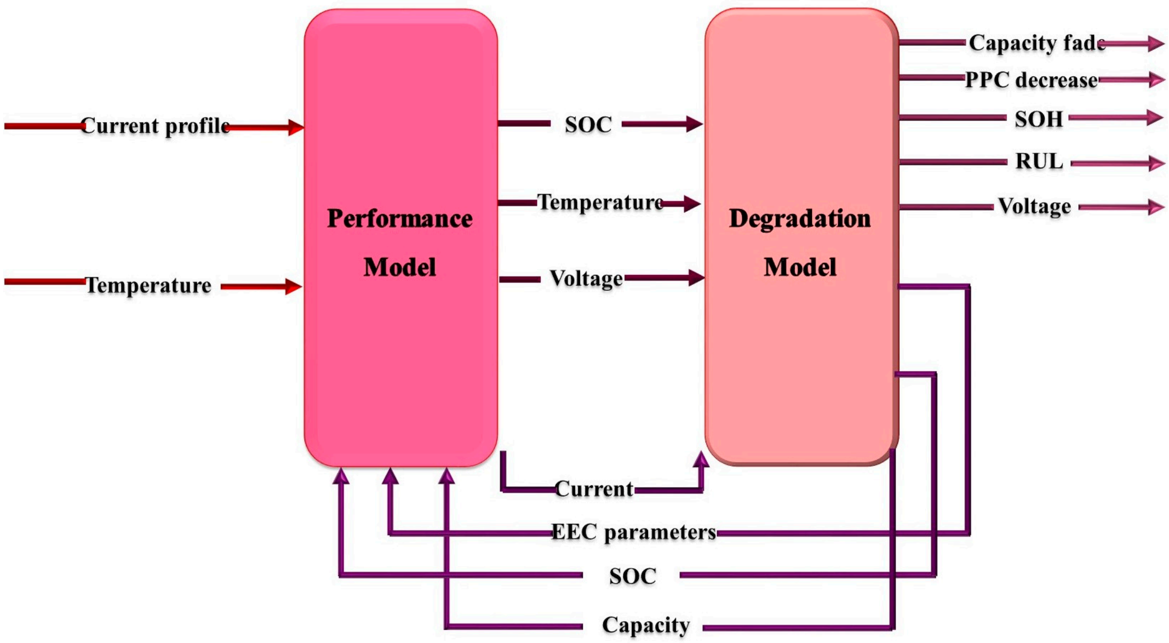

Figure 7. An EEC-based method for lifetime modeling of Li-ion battery cells [66].

As batteries are increasingly integrated into complex systems such as aircraft and electric vehicles, monitoring and predicting SoC and SoH become critical. Accurate prediction of remaining battery power is essential for informed operational decision-making and supporting system operations. However, it is important to consider age-dependent changes in battery dynamics to ensure precise and reliable predictions [200].

7.1. State of Health

LIBs have gained widespread use as the primary power source for battery electric vehicles (BEVs) due to their superior performance characteristics. However, these batteries undergo aging and performance degradation over time, influenced by external and internal factors. Evaluating the SOH of LIBs is crucial to ensure their longevity and support safe driving in BEVs. While various SOH prediction methods exist, many are primarily tested under simulated environments and face challenges when implemented in real-world industrial production settings [201]. Tian, Huixin, et al. [202] investigated the elements contributing to the aging of LIB, presented a classification-oriented method to predict the SOH, and evaluated the pros and cons of each approach. Ultimately, they offered practical recommendations and solutions tailored to the specific demands of industrial production. Mawonou et al. [203] introduced two innovative indicators for evaluating the aging of LIBs to improve the existing diagnosis-based state of health (DB-SOH) solutions. These indicators, known as charging event-based (CDB-SOH) and driving event-based (DDB-

SOH) indicators, utilize data collected during charging and driving activities, incorporating variables like distance, speed, temperature, charging power, and more. Both indicators offer reliable assessments of the state of health with a significantly reduced estimation error. Additionally, the researchers proposed a data-driven battery aging prediction model that utilizes the random forest (RF) algorithm, considering real-world user behavior and ambient conditions. This model achieved an estimation error of only 1.27%. Finally, a method for ranking the factors contributing to battery aging was proposed, and the obtained ranking aligns with known causes of aging in existing literature. This ranking can be applied to mitigate the rapid aging of lithium-ion batteries in electrified vehicle applications.

Feng et al. [204] presented the probability density function (PDF) method as a means of evaluating the SOH of electric storage batteries. The PDF method was compared to other techniques, such as cyclic voltammogram (CV), ICA, and differential voltage analysis (DVA), revealing their mathematical agreement. When applied to $LiFePO_4$ and $LiMn_2O_4$ batteries and coin cells, the PDF method produced results similar to those of the ICA/DVA methods, demonstrating its effectiveness. Durability tests conducted on commercial batteries using the PDF method indicated a reduction in peak height as battery capacity declined, facilitating the development of an algorithm for online SOH assessment.

Zhang et al. [205] studied the aging behavior of a 15P4S battery module using a specific cycle protocol. They employed various evaluation methods, including EIS, charge/discharge curves, ICA, and average Fréchet distance (AFD). The findings indicated that certain internal resistances increased as the module aged, and the combined value of two resistances served as a health factor for evaluating the offline SOH. The characteristic peak height observed on the ICA curves offered a quick assessment of the module's SOH. The AFD method demonstrated high accuracy in estimating the SOH, surpassing ICA regarding online module evaluation.

Eddahech et al. [206] investigated the kinetics of the constant current–constant voltage (CC-CV) charging process at 1 C and focused explicitly on the voltage regulation kinetics during the CV step. The CV step is considered crucial in assessing the battery SOH, particularly concerning calendar aging. The study compared the aging behavior of four different battery technologies and observed variations in battery behavior throughout the aging process. In the case of lithium–nickel–manganese–cobalt-oxide, lithium–nickel–cobalt–aluminum-oxide, and lithium-ion–manganese batteries, the current during the CV charging phase proved valuable in determining the SOH. However, for lithium-iron-phosphate batteries, a simple calculation of the duration of the CV step showed high accuracy compared to traditional capacity measurements.

Tang et al. [207] presented an innovative algorithm for estimating the SOH of LIBs through incremental capacity analysis. The algorithm leverages regional capacity and voltage data to develop a precise SOH model with a high goodness of fit. Notably, this method is computationally efficient, resilient to noise, and does not necessitate the direct derivation of characteristic parameters. It accurately estimates SOH without relying on the state of charge and impedance measurements, which are commonly utilized in other approaches.

Weng et al. [208] tackled the challenge of capacity degradation in lithium-ion batteries, specifically in the context of EVs and plug-in hybrid electric vehicles (PHEVs). They proposed a monitoring scheme for battery SOH based on partial charging data to track capacity loss during on-board operations. ICA was employed to identify a robust signature associated with battery aging. Several algorithms, including support vector regression (SVR), were developed and evaluated for on-board SOH monitoring. The SVR model consistently delivered accurate identification results, capable of predicting capacity degradation in other cells within a 1% error margin [209,210].

Zhang et al. [211] presented a thorough overview of the most recent advancements in impedance spectroscopy measurement technology and its application for estimating the health state of LIBs. The paper discusses the benefits and constraints associated with this approach and highlights potential future directions. This review article addresses a significant gap in the field and contributes to the continued progress of this technology.

Feng et al. [212] conducted a study to examine the thermal behavior and heat accumulation of commercial lithium-ion batteries under various SOH during overcharging. The findings revealed that thermal runaway, caused by separator melting and subsequent internal short circuits, was the triggering factor regardless of the SOH. The safety of the batteries decreased after aging, as evidenced by temperature, voltage, and duration changes leading up to thermal runaway. This decrease in safety was primarily attributed to the loss of lithium ions and changes in negative capacity following high-rate overcharging. The SOH did not significantly influence the contribution of heat from side reactions to thermal runaway. The study provides valuable insights into the risks associated with overcharging lithium-ion batteries and recommends safety measures to be implemented within 3 min of reaching a voltage inflection point.

7.2. EOL

The limited lifespan of EV batteries is attributed to their declining capacity and power capabilities over time. However, there is a lack of understanding regarding the EOL value chains, their interdependencies, and the dynamic conditions that influence decision-making and monetary outcomes for EOL options [213]. The increasing global usage of LIBs necessitates effective management of their EOL. While numerous studies have focused on managing their EOL within closed-loop supply chains, safety has been largely overlooked [214]. The EV industry has grown significantly, with major players now manufacturing EVs worldwide. As the number of EVs continues to rise, it becomes crucial to establish well-defined EOL strategies for the batteries removed from these vehicles, aligning with efforts to make the automotive industry more environmentally friendly [215]. E-mobility, particularly electric cars, has experienced rapid growth driven by LIB technology advancements. However, LIBs degrade over time and usage, resulting in diminished performance. With the increasing adoption of EVs, a substantial volume of retired LIB packs that no longer meet the performance requirements for powering an EV will soon be available. Various EOL options, including recycling and recovery processes, are being developed to address this challenge [216].

Daigle et al. [217] utilized an electrochemistry-based model to examine the variations in key parameters of batteries throughout the aging process. By developing models that capture the aging effects on these parameters, the authors could (i) accurately forecast the end-of-discharge for aged batteries and (ii) predict the EOL of a battery based on anticipated usage patterns. To validate their approach, they conducted experiments using randomized discharge profiles. The results demonstrated the efficacy of their models in accurately predicting battery behavior and showcased their potential for practical implementation in BMS.

Stroe et al. [218] conducted a study comparing the performance of a Lithium-ion battery at the beginning of its life (BOL) and at two higher levels of degradation. The research involved measuring the capacity, internal resistance, and open circuit voltage of a high-power 13 Ah battery under various temperature conditions, C-rates, and SOC levels. Two cells underwent aging processes, resulting in 40% and 60% capacity losses, respectively. These degraded cells were characterized in a similar manner to the fresh cell at BOL. The results indicated significant changes in battery performance parameters, such as temperature, C-rate, and SOC, between the fresh and highly degraded cells. These findings underscore the impact of degradation on battery performance and emphasize the need to consider these variations in real-world applications.

Rohr et al. [219] created a dynamic model for EOL batteries to examine the economic aspects of battery value chains and estimate residual values. This model addresses a research gap and employs cost-benefit and net present-value approaches. The findings from a survey conducted in Germany indicate an economic potential for all EOL strategies, namely Recycling, Remanufacturing, and Second-Life. Second-Life already proves to be economically feasible, while the economic viability of Remanufacturing and Recycling depends on the quantity of discarded batteries. Recycling is expected to reach a break-even point within 5 to 10 years. The model provides flexibility for future parameter surveys to evaluate the impact of evolving battery characteristics on EOL value chains. It is a valuable tool for devising strategies concerning the end-of-life of electric vehicle batteries.

Chen et al. [220] highlighted the significance of these research inquiries in materials science, supply chain management, and fire protection engineering. The study emphasizes the importance of addressing safety considerations in managing EOL of LIBs. By doing so, the research aims to contribute to the establishment of a comprehensive and secure approach for handling LIBs at the conclusion of their life cycle.

Kupper et al. [221] introduced an electrochemical model for a lithium iron phosphate/graphite (LFP/C6) cell that encompasses various aging mechanisms, including SEI formation, SEI breaking, and electrode dry-out. To address inadequate electrolyte penetration, the model incorporates an activity-saturation relationship. A time-upscaling methodology is utilized to make long-term aging predictions. The model demonstrates accurate predictions of both calendric and cyclic aging, aligning with experimental data. Valuable insights are obtained concerning the impact of temperature, cycling depth, and average state of charge on capacity loss. Additionally, the model captures the non-linear aging behavior observed towards the end of the battery's life, commonly referred to as "sudden death". This study provides a comprehensive understanding of aging mechanisms and capacity loss in LFP/C6 cells.

Ramoni et al. [222] underscored the importance of conducting thorough research to tackle the diverse challenges related to the remanufacturing of EV batteries. These challenges encompass areas such as comprehending battery degradation, optimizing remanufacturing procedures, devising effective testing and quality control techniques, and exploring viable business models for remanufactured EV batteries. By addressing these research concerns and advocating for remanufacturing as a feasible EOL option, the paper seeks to contribute to establishing a sustainable and efficient EOL strategy for EV batteries.

Santhira Sekeran et al. [223] addressed two key research questions related to battery life estimation. Firstly, they tackled the issue of incomplete battery cell testing data by proposing the application of survival analysis. This statistical technique can handle censored data and estimate the remaining lifespan of cells that have not yet reached the EOL threshold. By implementing survival analysis, the researchers aimed to overcome the challenge posed by limited testing data availability. Secondly, the study focused on the reusability of prediction models trained on one battery cell chemistry to predict EOL for a different chemistry using transfer learning. They developed a workflow that enables training a prediction model for one chemistry and subsequently reusing it to improve the prediction accuracy for a different chemistry. This approach reduces the need for extensive testing and enhances efficiency in battery life estimation. The work presented by Santhira Sekeran et al. [223] contributes to the development of effective methods for battery life estimation by addressing the challenges associated with incomplete data and leveraging transfer learning techniques across different battery cell chemistries.

Using historical data, Kandasamy et al. [224] conducted a study focused on the proactive identification of EOL for LIBs. The research employed multiple machine learning (ML) methods to predict the EOL of batteries, aiming to forecast the EOL at least 30 cycles in advance. Such predictions aim to facilitate timely maintenance and effective battery replacement. The paper thoroughly analyzes the performance of different ML methods to enhance the accuracy of EOL predictions. Furthermore, it establishes a correlation between the predictions and data obtained from a practical BMS, thereby demonstrating the practical applicability of the approach. By leveraging ML techniques and historical data, this study contributes to the proactive management of stationary battery systems (SBSs) by providing timely EOL predictions. The findings underscore the potential for improving battery maintenance strategies and optimizing battery replacement schedules to ensure the reliable and efficient operation of SBSs.

Zhu et al. [225] offered valuable insights into the feasibility of repurposing retired LIBs for second-life applications. The study examined the viability of utilizing these retired batteries by considering both economic factors and technological considerations. Through an analysis informed by industry reports and technical literature, the research provided a comprehensive perspective on the potential benefits and challenges associated with repurposing retired LIBs for second-life applications. This evaluation contributes to a better understanding of the feasibility and practicality of implementing second-life battery strategies.

7.3. RUL

Accurately predicting future capacities and RUL of batteries while managing uncertainty is challenging in battery health diagnosis and management. To address this challenge, advanced machine learning techniques can be applied to achieve effective predictions of future capacities and RUL for LIBs, while also providing reliable uncertainty quantification [226]. The accurate prediction of RUL and the diagnosis of SOH are essential for ensuring the safety, durability, and cost-effectiveness of energy storage systems that rely on Li-ion batteries. However, the prediction of RUL and the diagnosis of SOH present significant challenges due to the complex aging mechanisms inherent in batteries [227,228]. Maximizing the longevity of Li-ion batteries is a major concern, and Intelligent BMS plays a critical role in achieving this goal while maintaining performance. To optimize battery performance and minimize degradation, accurate information on the battery's RUL is required. However, accurately predicting RUL remains a challenging task [229].

Liu et al. [230] proposed a data-driven approach for predicting battery capacity and estimating RUL. The study utilized empirical mode decomposition (EMD) to decompose capacity data into intrinsic mode functions (IMFs) and a residual component. The residual component was estimated using a long short-term memory (LSTM) submodel to capture long-term dependencies, while the IMFs were fitted using a Gaussian process regression (GPR) submodel to quantify uncertainty. Comparative evaluations with other models demonstrated that the combined LSTM + GPR model outperformed alternative approaches, providing accurate forecasts for both short-term and long-term battery capacity. The proposed approach also exhibited good adaptability and reliable uncertainty quantification for battery health diagnosis, including RUL prediction. This study significantly contributes to battery health diagnosis and management by presenting an effective solution for capacity prediction and RUL estimation, while effectively managing uncertainty.

Wei et al. [231] proposed a comprehensive method for predicting the RUL and estimating the SOH of batteries. Their approach involved developing a battery SOH state-space model based on SVR. The model incorporated representative features extracted from a CC and CV protocol. The state variable of the model was battery capacity, and the output variables were estimated impedance values, considering the correlation between capacity and charge transfer resistance plus electrolyte resistance. A particle filter was employed to mitigate measurement noise and enhance the accuracy and robustness of SOH estimation. Experimental tests were conducted to validate the method, and the results demonstrated accurate and reliable SOH estimation and RUL prediction. This approach contributes to advancing BMS for energy storage applications by providing a comprehensive framework for RUL prediction and SOH estimation.

Zhang et al. [232] presented a novel online scheme for estimating Li-ion batteries' RUL from a thermal perspective. The approach leverages thermal dynamics to predict the RUL and incorporates a hierarchical estimation algorithm with provable convergence properties. The algorithm has three stages that estimate core temperature, SOC, battery capacity, and capacity fade aging model. Sliding mode observers and nonlinear least-squares algorithms are employed to design the estimators for each stage. Simulation results demonstrate the effectiveness of the proposed scheme, showcasing accurate and reliable RUL predictions. This paper makes a valuable contribution to the field by introducing an innovative approach to RUL estimation that considers thermal dynamics. The proposed scheme can potentially enhance BMS and optimize battery performance.

Zhang et al. [233] introduced a novel fusion technique for predicting LIBs' RUL LIBs. The technique reduces the training data requirement while maintaining high prediction accuracy. The study also introduces a validation and verification framework, which provides a robust approach for evaluating the prediction performance. This framework ensures that the predictions are reliable and can be effectively assessed. The results of the study demonstrate the effectiveness of the proposed fusion technique in accurately predicting battery failure and estimating the RUL. This highlights the technique's potential to enhance BMS by improving RUL predictions and optimizing battery maintenance strategies.

Zhang et al. [234] introduced practical methods for battery health diagnosis and RUL prediction. The study focused on analyzing the charging voltage curve of batteries using a feature extraction-based approach to estimate the battery's SOH. Additionally, the authors identified different aging stages in the battery's lifespan to predict its RUL. The proposed methods were validated using data from acceleration aging tests conducted on multiple battery cells under various current rates. The capacity estimates achieved high accuracy, with less than 1% estimation errors in most cycles. RUL prediction was also rapid, even when subjected to dynamic current rates, with prediction errors remaining below 10 cycles for most cycles after 300 cycles. The results demonstrated the effectiveness of the proposed methods in accurately estimating battery capacity and predicting RUL. These approaches provide practical and efficient battery health diagnosis and RUL prediction solutions. They enable informed decision-making and optimize battery performance in a wide range of applications.

Zhang et al. [235] introduced a novel approach to predicting LIBs' RUL. The method utilizes the Box-Cox transformation and Monte Carlo simulation to achieve accurate and efficient RUL predictions. Unlike traditional approaches, this method does not rely on offline training data, which offers advantages in terms of flexibility and adaptability. The proposed approach has the potential to significantly reduce the acceleration aging test time for lithium-ion batteries. Providing reliable RUL predictions without the need for extensive offline training contributes to the development of more practical and effective BMS for EVs. Overall, Zhang et al.'s approach presents an innovative solution for RUL prediction in lithium-ion batteries, offering improved efficiency and applicability for BMS in the EV industry.

Xu et al. [236] introduced a novel method for predicting LIBs' RUL under varying temperature conditions. Their approach combines a stochastic degradation rate model, an aging model based on the Wiener process, and a two-step estimation method that integrates maximum likelihood estimation (MLE) with a genetic algorithm (GA). By incorporating these elements, the proposed method enhances accuracy and reduces uncertainty in RUL prediction compared to existing approaches. A case study demonstrated the improved performance of the method, showcasing its ability to provide more reliable predictions. The method presented by Xu et al. offers a comprehensive solution for RUL prediction by considering stochastic degradation, parameter estimation, and online parameter update. This contributes to a better understanding and managing battery health, enabling more informed decision-making in various applications.

Wang et al. [237] introduced a model-free method for predicting the RUL of LIBs in EVs. Their approach utilizes the discrete wavelet transform (DWT) to incorporate real operational factors and overcome the limitations of previous methods that relied on specific models or identification techniques. The proposed method offers several advantages, including flexibility and adaptability to different battery systems and operating conditions. It considers dynamic stress tests and accounts for the non-stationary behavior of batteries, enhancing the accuracy of RUL predictions. Experimental tests conducted on a commercial battery with various aging levels validated the accuracy of the method in predicting RUL. The results demonstrated the effectiveness of the model-free approach in enhancing BMS for EVs, ensuring safety and reliability throughout the battery's lifespan. Overall, Wang et al.'s approach contributes to the field by providing a practical and efficient method for RUL prediction that takes into account real operational factors and avoids the need for specific models or identification methods.

Qiu et al. [238] conducted a study on predicting batteries' RUL. They extracted eight aging features from battery data and examined their correlation using gray relation analysis. To create an RUL prediction model, the researchers employed the improved gray wolf constrained optimization algorithm to determine coefficients for combining kernel functions in the multi-kernel relevance vector machine. The validation of the proposed model was carried out using NASA's battery dataset. The results showed that the improved model outperformed single-kernel and other multi-kernel models. It achieved high accuracy in RUL prediction, with a prediction error of less than 10 cycles and a mean absolute error (MAE) of less than 0.05. The study demonstrated that the improved model has superior long-term prediction capability and robustness in RUL prediction, indicating its effectiveness in accurately estimating the RUL of batteries.

Sadabadi et al. [239] developed an algorithm for predicting the RUL of LIBs using an enhanced single particle model (eSPM) and vehicle charging data. The researchers collected experimental aging data and estimated eSPM parameters associated with battery aging. They established a correlation between these parameters and the battery's SOH, from which they derived a composite SOH metric. The RUL predictor, based on a particle filter (PF) algorithm, utilized the evolution of the SOH metric to estimate the RUL of the battery. The algorithm was validated using experimental data, demonstrating its feasibility for predicting SOH and RUL using readily available charging data from electric or hybrid vehicles. This approach holds significant implications for battery health monitoring and management in the automotive industry. By leveraging the eSPM model and vehicle charging data, the algorithm provides a valuable tool for assessing the battery RUL and facilitating informed decision-making in battery maintenance and replacement strategies [240].

Table 4 offers an overview of major findings and approaches for measuring battery health indicators. Recent advancements in health monitoring leverage sensor-based data collection and machine learning to assess battery health in real time, enhancing accuracy in SOH, EOL, and RUL predictions.

Table 4. Summary of key findings and methodologies in indicators to quantify the health level of the battery.

Key Findings	Methodology/Approach	Ref.
Analyzed the effect of environmental conditions on LIB aging.	Systematic examination of various environmental stressors.	[202]
Presented a mechanistic model to understand the degradation processes in LIBs.	Developed model based on electrochemical and thermal behavior.	[203]
Examined how cycling frequency affects the aging of LIBs.	Long-term cycling tests under varying frequencies.	[204]
Addressed the challenges in predicting battery life due to aging variability.	Discussed statistical approaches to enhance prediction accuracy.	[205]
Reviewed different techniques for estimation of battery state of health (SOH).	Evaluated methods including impedance spectroscopy and machine learning.	[206]
Highlighted the importance of second-life applications for used LIBs.	Comprehensive analysis of potential repurposing strategies.	[207]
Discussed the economic implications of LIB recycling and remanufacturing.	Cost-benefit analysis of different end-of-life strategies.	[208]
Examined the role of battery management systems (BMS) in enhancing battery life.	Analysis of BMS features that optimize battery usage and longevity.	[211]
Reviewed advancements in battery diagnostics and health monitoring.	Summarized recent innovations in diagnostic technologies.	[212]
Investigated the relationship between battery composition and aging behavior.	Comparative study of different battery chemistries.	[213]
Analyzed the life cycle assessment (LCA) of lithium-ion batteries.	Environmental impact analysis of LIBs throughout their lifecycle.	[214]
Explored the safety challenges associated with aging LIBs.	Discussed failure modes and safety measures.	[215]
Reviewed regulatory frameworks affecting LIB end-of-life strategies.	Analysis of current regulations and their impact on LIB management.	[216]
Evaluated innovative recycling techniques for LIBs.	Investigated advanced recycling processes and technologies.	[217]
Presented a framework for sustainable battery management practices.	Developed best practices for battery use and end-of-life strategies.	[218]
Created a dynamic model for end-of-life (EoL) batteries, addressing economic aspects and estimating residual values.	Cost-benefit and net present value approaches; survey conducted in Germany.	[219]
Highlighted the significance of safety considerations in managing end-of-life lithium-ion batteries (LIBs).	Focused on materials science, supply chain management, and fire-protection engineering.	[220]
Introduced an electrochemical model for LFP/C6 cells, covering aging mechanisms and predicting capacity loss.	Utilized a time-upscaling methodology to make long-term predictions.	[221]
Emphasized the need for research on remanufacturing challenges related to EV batteries.	Addressed battery degradation, optimization of procedures, and viable business models.	[222]
Tackled incomplete battery testing data through survival analysis and transfer learning.	Developed a workflow for reusing prediction models across different battery chemistries.	[223]
Focused on proactive identification of EoL for lithium-ion batteries using historical data.	Employed multiple machine learning methods to predict EoL at least 30 cycles in advance.	[241]
Explored the feasibility of repurposing retired lithium-ion batteries for second-life applications.	Analysis based on economic factors and technological considerations.	[225]
Proposed a data-driven approach for battery capacity prediction and RUL estimation.	Empirical mode decomposition (EMD) and long short-term memory (LSTM) models were used.	[230]
Developed a SOH state-space model for predicting RUL and estimating SOH of batteries.	Incorporated features from a constant-current and constant-voltage protocol.	[231]
Presented a novel online scheme for estimating RUL of Li-ion batteries from a thermal perspective.	Thermal dynamics and a hierarchical estimation algorithm were used.	[232]
Introduced a fusion technique for RUL prediction of lithium-ion batteries.	Created a validation framework for evaluating prediction performance.	[233]
Analyzed charging voltage curves for battery health diagnosis and RUL prediction.	Validated methods using data from acceleration aging tests.	[234]
Utilized Box-Cox transformation and Monte Carlo simulation for RUL prediction.	Offered advantages in flexibility and adaptability without offline training data.	[235]

Table 4. *Cont.*

Key Findings	Methodology/Approach	Ref.
Combined stochastic degradation rate model and aging model for RUL prediction.	Integrated maximum likelihood estimation with a genetic algorithm.	[236]
Introduced a model-free method for RUL prediction considering real operational factors.	Used discrete wavelet transform (DWT) for enhanced accuracy.	[237]
Developed an RUL prediction model using gray relation analysis.	Employed improved gray wolf optimization algorithm for kernel functions in multi-kernel relevance vector machine.	[238]
Developed an algorithm for RUL prediction using an enhanced single particle model (eSPM).	Utilized vehicle charging data to estimate parameters and derive a composite SOH metric.	[239]

7.4. Aging Estimation

Modeling lithium-ion batteries simulates electrochemical, thermal, and electrical behaviors to predict performance, aging, and efficiency. Techniques such as equivalent circuits and electrochemical models help understand charge dynamics and degradation. SOC and SOH are key for optimizing energy use and lifespan, while SOX estimation enhances performance monitoring. System-level modeling integrates these factors to predict aging and optimize battery management in real-world conditions [241–245]. LIB aging modeling methods can generally be divided into electrochemical, statistical, and machine learning approaches, with each focusing on specific aging factors like capacity fade, resistance increase, and thermal effects. Figure 8 demonstrates a classification of aging models for lithium-ion batteries. Recent research has introduced machine learning-based models that enhance the accuracy of RUL predictions by incorporating real-time data and accounting for operational variability. Additionally, emerging technologies, including solid-state batteries and new electrolyte formulations, offer the potential to slow down aging processes and extend battery life, opening up promising avenues for future research.

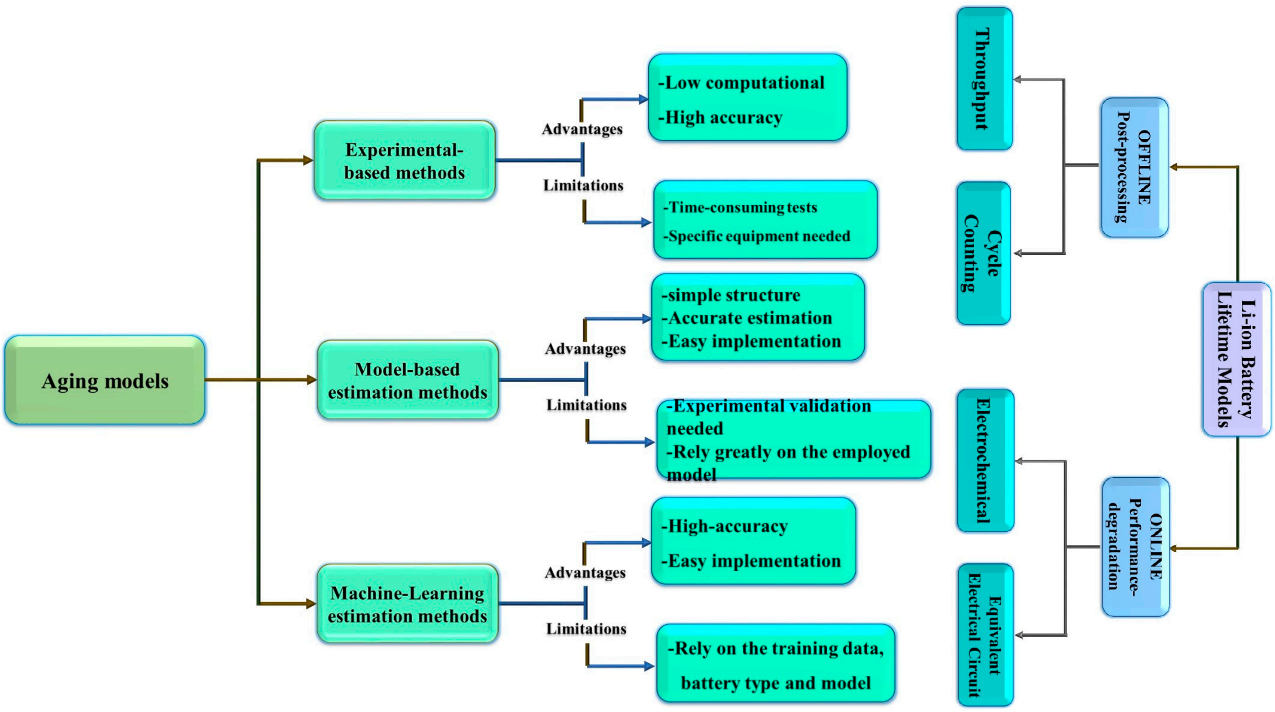

Figure 8. A classification of aging models for lithium-ion batteries.

Figure 9 illustrates different aging estimation methods for lithium-ion batteries. Aging estimation of lithium-ion batteries predicts their RUL and performance degradation using modeling approaches like electrochemical and empirical models. Key indicators include

SOC, SOH, and cycle count, which correlate with capacity fade. Techniques such ICA and EIS help evaluate the effects of aging. Considering temperature and usage patterns is essential for accurate aging predictions and effective battery management [246]. A comparison of research studies on lithium-ion battery aging and degradation estimation is offered in Table 5.

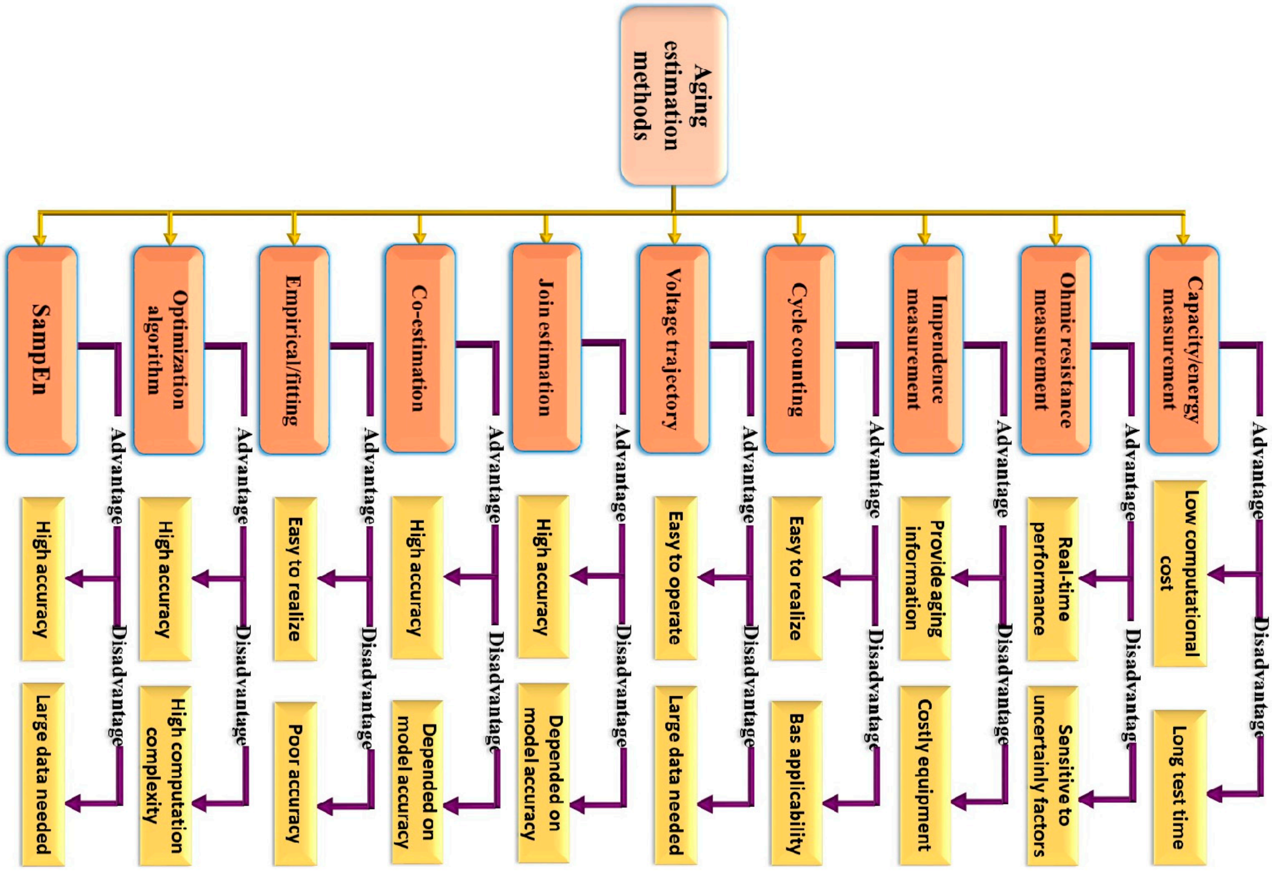

Figure 9. Different aging estimation methods for lithium-ion batteries.

Having a comprehensive understanding of battery degradation and aging in an in operando setting is crucial for designing effective BMS and ensuring the safe use and optimizing the manufacturing of LIBs in large-scale applications. EIS is a nondestructive technique that enables the investigation of electrode kinetic processes occurring within batteries across different time domains. This method reveals information about charge transfer reactions, interfacial resistance, and mass diffusions. EIS has emerged as a powerful diagnostic and predictive tool in battery aging research. It provides significant insights into the changes occurring in internal electrochemical processes by correlating the evolution of impedance with degradation mechanisms. By analyzing the impedance spectra, researchers can gain important knowledge about the degradation mechanisms affecting the battery's performance and longevity [247]. Figure 10 illustrates a lifetime model comparison of LIBs.

Using EIS, researchers can unravel the intricate electrochemical processes within batteries during their operation. This knowledge is essential for improving battery designs, optimizing manufacturing processes, and developing effective strategies for prolonging the lifespan of LIBs in real-world applications [248]. Narayanrao et al. [249] proposed and validated a phenomenological model to investigate the degradation of lithium-ion cells caused by charge/discharge cyclic fatigue. The model considers factors such as SEI formation, fractures, and the isolation of electrode material, which lead to capacity loss and increased electronic resistance. The study incorporates these phenomena into Newman's Porous Composite Electrode framework, implementing the model in COMSOL.

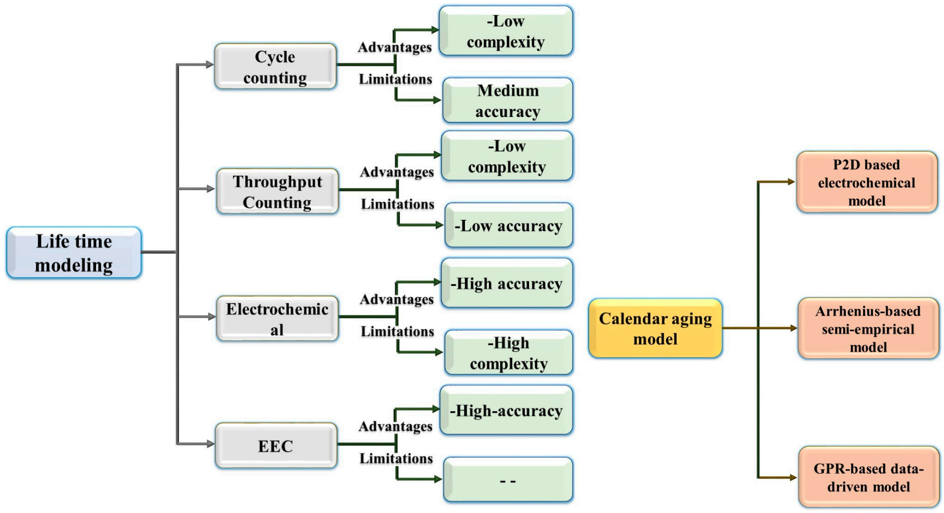

Figure 10. Lifetime model comparison.

Horstkoetter et al. [250] conducted an experimental study to examine the impact of current gradients, specifically the change in current per time interval, on battery degradation. Their research focused on discharging dynamics and its effect on battery aging. The study revealed that current gradients play a significant role in battery degradation. Higher current gradients were found to lead to a larger degradation rate, and even moderate gradients contributed to this trend. The results indicated a linear relationship between current gradient and degradation rate. These findings underscore the importance of considering dynamic influences and steady-state conditions for a comprehensive understanding of battery aging. By recognizing the impact of discharging dynamics, strategies can be developed to mitigate degradation, enhance battery performance, and extend battery longevity. The research by Horstkoetter et al. emphasizes the need to consider not only the average current but also the dynamic changes in current over time for a more accurate assessment of battery degradation and effective battery management strategies.

Weng et al. [251] developed a semi-empirical model describing SEI growth process during lithium-ion battery formation cycling and aging. The model combines a full-cell model, a SEI growth kinetics model, and a representation of cell expansion. Experimental trends observed in a pouch cell, including first-cycle efficiency and SEI layer thickness changes, were successfully reproduced using the model. The model's capability to simulate SEI growth and multi-component reactions makes it valuable for studying solvent and additive consumption in industrial battery manufacturing. It serves as a bridge between electrochemical understanding and practical application, aiding in predicting formation protocols and electrolyte effects on SEI passivation. This contributes to improved battery formation strategies, electrolyte optimization, and enhanced battery longevity and performance.

Langner et al. [252] investigated corrosion in LIBs with $LiNi_{0.6}Co_{0.2}Mn_{0.2}O_2$ (NMC) as the cathode material. Moisture-induced water accumulation on the NMC surface increased pH, leading to corrosion of the carrier foil. Corrosion extent was quantified by measuring the relative area of holes in the aluminum foil, influenced by exposure duration and ambient humidity. Analysis techniques detected lithium, aluminum, sulfur, and oxygen in the corrosion products, revealing local degradation in the NMC layer. These insights contribute to strategies for mitigating corrosion and improving the longevity and performance of NMC-containing batteries.

Yan et al. [253] investigated the formation and evolution of SEI film during the initial lithium intercalation into graphite electrodes in lithium-ion batteries. They developed a model that describes the SEI film formation as a precipitation process with nucleation and growth phases. The model, based on classical nucleation theory, explains the observed two-layer structure of the SEI film. The inner layer, close to the graphite electrode, is thin and compact with inorganic species such as LiF and Li_2O. The outer layer, farther from the graphite, is thicker and porous, composed mainly of organic compounds. Understanding the mechanisms and structure of the SEI film is crucial for improving battery performance, stability, and longevity. The findings contribute to developing strategies for optimizing SEI formation and controlling its properties to enhance lithium-ion battery performance.

Yan et al. [254] developed three phenomenological models to predict mechanical phenomena during Li-ion intercalation in batteries. These models estimate the forces induced by intercalation, predict dynamic swelling behavior, and determine the swelling shape on the battery surface. Incorporating these models into BMS can enhance understanding, control, and performance of Li-ion batteries, contributing to improved safety and lifespan. These models simplify the measurement and correlation of mechanical aspects, advancing battery technology.

Li et al. [255] investigated diffusion-induced stress in elastoplastic hollow spherical silicon electrodes using analytical modeling and molecular simulations. The research showed that controlling electrode parameters and achieving low yield strength reduced diffusion-induced stress. It identified concentration and stress gradients, particularly at the interface and interior of the electrode. Molecular dynamics simulations revealed plastic deformation in these regions. The findings emphasize the importance of managing mechanical stress to enhance the lifespan of lithium-ion batteries and provide valuable insights for designing more durable electrode materials. Understanding diffusion-induced stress in these electrodes helps develop strategies to improve battery performance and longevity.

Li et al. [256] highlighted the application of atomistic modeling in discovering and designing materials for lithium-ion batteries. It emphasizes how atomistic modeling provides insights into material mechanisms, predicts properties, and guides material design, particularly in processes like lithium-ion diffusion and intercalation reactions. Collaboration between experimentalists and computational researchers is essential for advancing the field. The review demonstrates how atomistic modeling accelerates the development of electrode and electrolyte materials, contributing to improved battery performance.

Tröltzsch et al. [257] presented a method that addresses challenges in using impedance spectroscopy to characterize aging effects in portable secondary batteries online. They developed a composite electrode model and a hybrid parameter estimation method to represent and analyze battery aging mechanisms accurately. Experimental validation demonstrated the approach's effectiveness in capturing changes during battery aging. The method's potential to enhance the understanding and monitoring of battery aging contributes to developing more reliable and durable energy storage systems.

Monem et al. [258] investigated the impact of three charging methodologies (CC, CC-CV, and CC-CVNP) on the lifetime of high-power $LiFePO_4$ batteries. Their study demonstrated that the CC-CVNP charging method, with low amplitude and fewer negative pulses, resulted in reduced capacity degradation and improved battery performance. This technique minimized impedance-related aging mechanisms, such as concentration polarization resistance and diffusion time constant. The findings offer insights for designing optimized charging systems to extend the lifetime and enhance the performance of high-power $LiFePO_4$ batteries in practical applications.

Guo et al. [259] introduced the universal voltage protocol (UVP) as an innovative charging technique for lithium-ion batteries. The UVP aims to improve charging efficiency and cycle life while requiring less adaptation to changing battery conditions than conventional CC-

CV methods. The paper presents a mathematical formulation of the UVP, demonstrating its effectiveness through comparisons with optimized varying current profiles. The UVP offers adaptability, charging efficiency, and cycle-life advantages, making it a promising option for practical implementation in battery charging systems. Its utilization can lead to better performance and longer cycle life for lithium-ion batteries, contributing to advancements in battery technology.

Prasad et al. [260] investigated key aging parameters in lithium-ion battery models for SOH estimation, explicitly focusing on power and energy fade caused by impedance rise and capacity loss. They proposed using cell resistance and solid phase diffusion time of Li+ species as simplified aging parameters, which exhibit consistent variations with battery age. The study also developed estimation techniques using voltage and current data from fresh and aged cells. These findings enhance the understanding of battery degradation and provide insights for accurate SOH estimation, enabling informed decisions regarding battery usage and replacement based on monitoring the identified aging parameters.

Xia et al. [261] conducted a study on the variations of equivalent circuit model (ECM) parameters in lithium-ion batteries at different SOH levels. The researchers developed an ECM by fitting it to experimentally measured EIS data. The accuracy of the ECM model was then validated using EIS data collected during an accelerated aging experiment. The study found that as battery health deteriorated, certain ECM parameters, such as the series resistor, increased, indicating an increase in internal resistance. On the other hand, capacitance components decreased with decreasing battery health. These findings emphasize the potential of the ECM model in estimating battery state-of-health and its application in BMS. Monitoring and analyzing the variations in ECM parameters makes it possible to assess battery performance, predict RUL, and optimize battery management strategies. The study contributes to understanding battery aging and highlights the importance of utilizing ECM models in battery health estimation and management. It provides valuable insights for developing more accurate and reliable battery diagnostics and prognostics techniques, ultimately enhancing the performance and longevity of lithium-ion batteries [262,263].

Gong et al. [264] conducted a study to improve Li-ion battery modeling and state estimation for electric vehicle applications by addressing uncertainties related to temperature and aging. The researchers introduced an equivalent circuit battery model and utilized an Adaptive Extended Kalman Filter (AEKF) algorithm to accurately estimate SOC. The study further focused on understanding the temperature-dependent performance of LIBs through EIS tests. Compensation functions were derived to account for the temperature effects on battery behavior. Battery aging mechanisms were investigated using ICA for SOH estimation and a bias correction modeling method to account for aging-induced inaccuracies. The study also addressed the inconsistency in parallel-connected battery packs, where varying levels of battery aging can lead to current differences among parallel-connected cells. Simulation and experimental results demonstrated the impact of aging and SOC on current differences in parallel-connected cells. The contributions of this work include the development of analytical compensation functions, the utilization of ICA-based SOH estimation, and the introduction of modeling methods to optimize battery management in electric vehicles, considering temperature and aging uncertainties. This study provides valuable insights and methodologies to enhance Li-ion battery modeling, state estimation, and battery management strategies for electric vehicle applications, considering the complex factors of temperature variations and battery aging.

Stiaszny et al. [265] conducted a detailed analysis of a commercially available lithium-ion battery to understand its decline in capacity. The study revealed the depletion of cyclable lithium and the formation of a SEI layer as key aging processes, aided by impedance spectroscopy and the distribution of relaxation times (DRT) analysis. The research provides valuable insights into battery aging mechanisms and highlights the importance of SEI formation and its influence on capacity decline [266].

Hu et al. [267] conducted a comprehensive analysis of impedance techniques for studying degradation and aging in Li-ion batteries, summarizing variations EIS techniques and discussing modeling approaches. The paper elaborates on classical EIS and dynamic EIS methods, their underlying principles, and data validation. The authors highlight the potential of EIS in understanding battery aging and degradation mechanisms while acknowledging challenges in data complexity, accurate modeling, and interpretation of impedance spectra. This analysis provides a valuable resource for researchers in the field, outlining future directions and challenges in Li-ion battery aging studies.

De Sutter et al. [268] investigated the fractional differential model (FDM) as an alternative to the first-order RC battery model for NMC cells. The FDM improved simulation accuracy, especially in the low SOC range, with up to an 85% improvement, effectively capturing nonlinear battery behavior and offering valuable insights for accurate battery modeling and characterization.

From both economic and technical perspectives, developing models to predict the lifespan of lithium-ion batteries is essential, particularly for evaluating the economic viability of energy storage systems in wind power plants (WPPs). While LIB prices are decreasing due to advancements in portable electronics and automotive industries, they remain costly for energy storage. Accurate lifetime data are crucial during project planning to assess economic feasibility and optimize battery utilization. Given the complexity of LIB performance degradation, EEC-based performance degradation models provide a balance between fast but less accurate pure-lifetime models and highly accurate but complex electrochemical lifetime models [269,270].

Table 5. Comparison of research studies on lithium-ion battery aging and degradation estimation.

Study Focus	Key Findings	Ref.
EIS and Battery Aging	Discusses the importance of EIS in understanding degradation mechanisms.	[247]
Phenomenological Model	Investigates degradation due to cyclic fatigue, including SEI formation.	[249]
Current Gradients	Examines the impact of current gradients on battery degradation.	[250]
SEI Growth Model	Describes SEI growth during cycling and aging.	[251]
Corrosion in Batteries	Investigates corrosion processes in Li-ion batteries.	[252]
SEI Film Formation	Models the formation of the SEI film during lithium intercalation.	[253]
Mechanical Models	Develops models to predict mechanical phenomena during intercalation.	[254]
Diffusion-Induced Stress	Studies stress distributions in silicon electrodes.	[255]
Atomistic Modeling	Highlights the role of atomistic modeling in material design.	[256]
Impedance Spectroscopy	Proposes a method for online characterization of battery aging.	[257]
Charging Methodologies	Investigates the impact of different charging methods on battery life.	[258]
Universal Voltage Protocol	Introduces a new charging technique for improved efficiency.	[259]
Aging Parameters	Explores aging parameters for SOH estimation in Li-ion batteries.	[260]
ECM Parameters	Analyzes variations in ECM parameters at different SOH levels.	[261]
State Estimation	Investigates aging uncertainties in battery modeling for EV applications.	[264]
Capacity Decline	Analyzes aging mechanisms using impedance spectroscopy.	[265]
Impedance Techniques	Reviews various impedance techniques for aging studies.	[267]
Fractional Differential Model	Examines a new battery model for NMC cells.	[268]
Economic and Technical Models	Discusses the importance of lifespan prediction for economic viability.	[269]

Modeling the lifespan of LIBs is a critical aspect of battery management and design, especially in applications where long-term reliability and performance are vital, such as EVs and renewable energy storage systems. To predict a lithium-ion battery's longevity, it is essential to comprehend the factors contributing to its deterioration and employ mathematical models to estimate how these factors impact the battery's capacity and performance over time. Hybrid modeling approaches that combine electrochemical and empirical techniques have gained attention for their ability to balance accuracy and computational efficiency, especially in applications with limited data. ECMs provide a simple method for estimating battery health, while statistical approaches like Weibull distributions and machine learning models offer greater adaptability in capturing intricate aging patterns. A sensitivity analysis of crucial factors such as temperature, charge/discharge rates, and cycling depth indicates that temperature plays the most significant role in accelerating capacity loss in lithium-ion batteries. Validating these models with real-world data from electric vehicle fleets or grid storage systems is crucial to evaluate their relevance and ensure their reliability across various operational conditions.

8. Prospects and Challenges of Lifetime Modeling of LIBs

The widespread adoption of LIBs in various applications, including EVs, renewable energy storage, and consumer electronics, emphasizes the critical need for accurate and dependable lifespan modeling. A comprehensive grasp of the factors influencing LIB longevity is crucial for optimizing their performance, reducing production expenses, and minimizing environmental impact. In this part, we delve deeper into the possibilities and obstacles surrounding modeling LIB lifetimes, backed by scientific references and ongoing research.

8.1. Prospects

8.1.1. Enhanced Battery Performance

Accurate lifetime modeling enhances battery performance by identifying ideal operating settings and usage trends. Variables including temperature, charge/discharge rates, and battery state of charge have a significant impact on battery degradation. Manufacturers can develop more efficient BMS to extend battery longevity by measuring these aspects [270,271].

8.1.2. Cost Reduction

Effective lifespan modeling can lead to significant cost reductions by improving battery design and material selection. Research is focused on creating improved electrode, electrolyte, and separator materials to extend cycle life and capacity retention. Additionally, accurate lifetime projections save production costs by removing the need for overly complicated engineering [272].

8.1.3. Sustainability and Environmental Impact

Extending the life of Li-ion batteries contributes to sustainability objectives by reducing waste and battery manufacture. This reduction in environmental effect, which includes mining, production, and recycling, lowers the carbon footprint associated with energy storage devices [273].

8.1.4. Safety

Zhang et al. [274] examined thermal runaway (TR) behavior in batteries, highlighting challenges due to complex chemical reactions and degradation mechanisms. It focuses on aged 18,650 cells with lithium nickel cobalt manganese oxide cathodes under typical usage scenarios. EIS reveals increased impedance in aged cells, affecting electrochemical properties. TR tests show aging mechanisms significantly impact safety, with lower onset temperatures and shorter delay times observed in cells subjected to low-temperature cycling. This research underscores the importance of understanding degradation effects on battery safety, contributing insights into TR behavior under various conditions. Feng et al. [275] discussed the safety challenges limiting the widespread adoption of lithium-ion batteries in electric vehicles. It highlights the urgency of improving battery safety alongside increasing energy density. The main focus is on understanding thermal runaway, a critical safety issue. The research reviewed the mechanisms leading to thermal runaway, including mechanical, electrical, and thermal abuse, typically featuring internal short circuits. It proposes a novel energy release diagram to quantify reaction kinetics during thermal runaway, clarifying the relationship between internal short circuits and thermal runaway. Finally, it suggests a three-level protection concept to mitigate thermal runaway hazards, including passive defense, enhancing material thermal stability, and reducing secondary hazards like thermal runaway propagation.

8.2. Challenges

A significant challenge in lifetime modeling is the absence of standardized protocols, which hinders consistent cross-comparison and reduces the reliability of model predictions across different applications.

8.2.1. Complex Degradation Mechanisms

Doyle et al. [276] delved into using mathematical modeling and computer simulations to understand the performance of lithium/polymer batteries. It discusses a comprehensive model of these systems, focusing on the underlying assumptions. The model parameters are classified based on whether they relate to transport, thermodynamics, or design-adjustable properties, and the experiments needed to measure these parameters are outlined. Furthermore, the research explored the role of mathematical modeling in the battery design process. It presents dimensionless groups and simple correlations that aid in characterizing primary system limitations. Additionally, it reviews a general approach for determining optimal values of system parameters, such as electrode thicknesses. Degradation in Li-ion cells results from various physical and chemical processes that impact the different cell components, including the electrodes, electrolyte, separator, and current collectors. Figure 11 highlights some of the most frequently reported degradation mechanisms in Li-ion cells. The diverse causes, rates, and interactions of these mechanisms make them highly complex to model. As a result, most physics-based models concentrate on the most significant mechanisms, such as the formation and growth of SEI or the loss of electronic contact due to particle cracking [277–283].

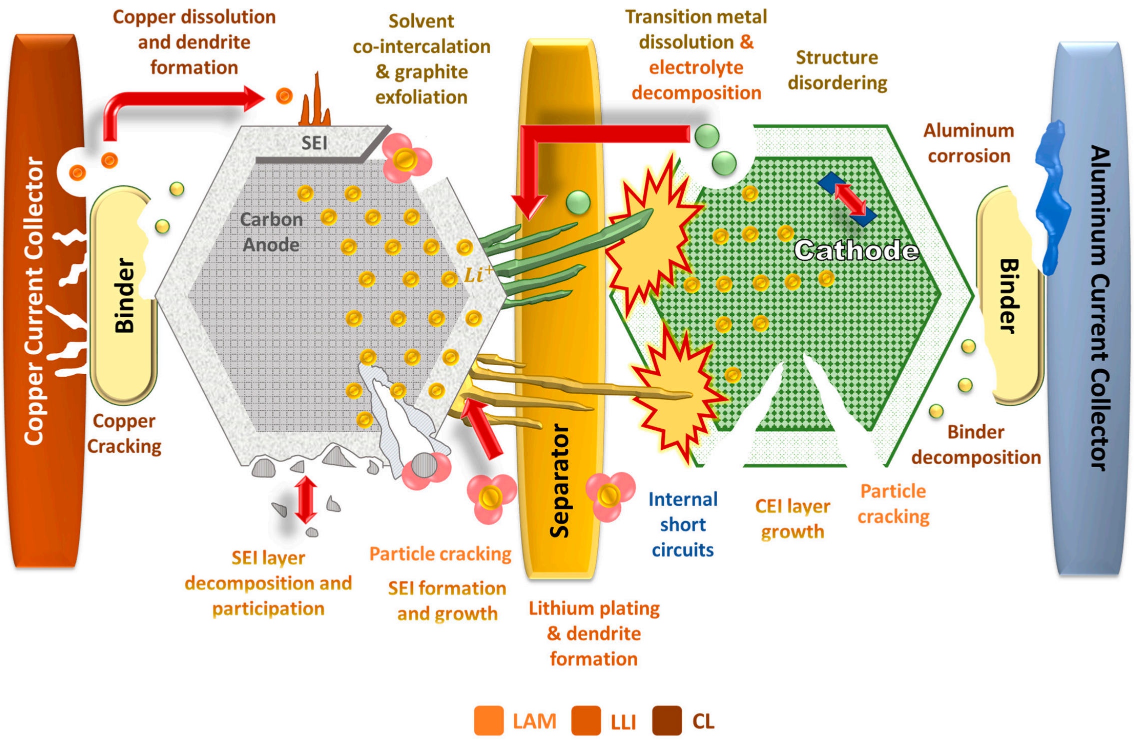

Figure 11. Degradation mechanisms in Li-ion cells. Modified version from [277].

8.2.2. Lack of Standardization

One significant challenge is the absence of standardized testing protocols and data reporting for Li-ion batteries. This inconsistency makes it more challenging to compare and assess life-time models across various studies and businesses. Continuous effort is needed to establish uniform testing protocols and data-sharing protocols [284].

8.2.3. Limited Long-Term Data

Shchurov et al. [285] discussed the challenges of extending the service life of LIBs and presented research methods for understanding LIB degradation. Factors affecting battery lifespan, such as charging/discharging currents and temperature, and the role of BMS are examined. The analysis also covers various operating cycles of electric transport and their impact on LIB degradation, offering recommendations for engineers and designers.

8.2.4. Predicting Real-World Conditions

LIBs operate in diverse and dynamic real-world conditions, making accurately predicting their lifespan challenging. Models need to account for variations in temperature, charge/discharge profiles, and other external factors that affect battery performance. Realistic modeling of these conditions remains an active area of research [286]. Lifetime modeling of Li-ion batteries offers significant potential for enhancing performance, reducing costs, and promoting sustainability. However, addressing the challenges associated with complex degradation mechanisms, standardization, limited long-term data, and predicting real-world conditions is crucial to realizing these prospects. Ongoing research, collaboration among stakeholders, and advancements in modeling techniques will be pivotal in overcoming these challenges and ensuring the longevity and reliability of LIBs across an expanding spectrum of applications [287].

Machine learning techniques, such as reinforcement learning, offer adaptive solutions by optimizing charge/discharge cycles in real time, thus contributing to more accurate lifespan predictions for LIBs. Table 6 offers a comparison of key studies for precise models for describing lithium-ion battery aging.

Table 6. Comparison of key studies for precise models for describing lithium-ion battery aging.

Focus	Methods	Key Findings	Ref.
Overview of aging modeling methods	Multiscale approach, testing strategies	Comprehensive review of aging modeling at particle, cell, and pack levels; proposed a multiphysics and data-based framework.	[109]
Impact of characterization on calendar aging	Periodic measurements, empirical analysis	Identified significant influence of cell characterization on capacity and resistance; recommended small currents for accurate measurements.	[97]
Non-invasive characterization using EIS	Electrochemical Impedance Spectroscopy (EIS)	Discussed the correlation between EIS spectra changes and degradation mechanisms; emphasized modeling degradation through ECMs.	[100]
Development of the SPM-EEM model	Single-Particle Model (SPM), empirical aging model	Proposed SPM-EEM for $LiMn_2O_4$ chemistry, showing enhanced predictability compared to traditional EEMs.	[100]
Electrochemical approach to battery aging	Mathematical modeling	Established a more complex framework for understanding aging processes, though complexity limits control applications.	Doyle–Fuller–Newman (DFN) Model

9. Lithium-Ion Battery Material and Aging

Lithium-ion battery material significantly influences aging mechanisms and performance, with common anode materials like graphite and silicon, and cathode materials such as lithium cobalt oxide (LCO) and lithium iron phosphate (LFP). Aging is affected by factors like SEI formation, lithium plating, and electrolyte stability. Elevated temperatures accelerate degradation, while innovations in nanostructured electrodes and electrolyte additives aim to enhance longevity. Understanding these relationships is crucial for developing durable and efficient batteries [288]. Table 7 offers a comparison of research studies on lithium-ion battery material and aging. LIBs have transformed the landscape of portable electronic devices, electric vehicles, and grid energy storage due to their remarkable energy density and extended life cycles [289–291]. The effectiveness of LIBs relies on various factors, including the selection of electrode materials and their crystalline structures [292].

Chen [293] introduced various carbon-based anode materials for LIBs. It briefly discusses commonly used carbon anode materials and highlights methods to improve their performance, particularly focusing on silicon carbon anode materials and metal oxide/carbon matrix composites. In the case of silicon carbon anode materials, techniques like electrostatic electrospinning and carbon-silicon nanotubes are highlighted as promising for large-scale development. For metal/metal oxide composites, utilizing sodium chloride particles as templates to manufacture Fe_3O_4/C composites is noted for its advantages. Overall, by enhancing the electrochemical performance of LIBs through improved carbon anode materials, the study suggests the potential for batteries with better performance, broader applications, and higher safety standards.

Gao et al. [294] introduced a facile dual-temperature zone heating strategy to fabricate high-purity fibrous phosphorus (FP) with a unique lamellar structure, which, when combined with graphite (G) into an FP-G composite anode, exhibits superior rate performance and cycle stability in LIBs. This approach presents a promising avenue for enhancing LIB electrode materials, leveraging FP's unique properties for improved battery performance and extending their application potential.

Rahman et al. [295] proposed a novel approach utilizing experimental nonlinear frequency response analysis (NFRA) measurements to identify LIB aging history, achieving accurate quantification of degradation modes such as SEI growth, lithium plating, and LAM without prior knowledge of the cell's duty. Combining experimental and simulation approaches, the analysis demonstrates NFRA's potential as a powerful tool for aging diagnosis, emphasizing the importance of correlating NFRA at multiple open circuit voltages (OCVs) and frequencies for comprehensive characterization, thereby enhancing battery management strategies and extending lifespan for various applications, while suggesting avenues for further research to improve analysis robustness and testing conditions.

Mikheenkova et al. [296] Synchrotron X-ray diffraction (XRD) radiography was used to investigate aging heterogeneity in lithium-ion cells with NMC811 and graphite electrodes after ∼2800 cycles. The study revealed degradation near the positive electrode tab, particularly affecting the NMC material. Principal component analysis identified areas of degradation, largely due to lithium plating. Electrochemical characterization highlights the value of a complementary approach, demonstrating the potential of non-destructive techniques for studying large prismatic cells and advancing battery research and industry.

Sulfide solid-state electrolytes (SSEs) show promise for all-solid-state batteries (SSBs) due to their high ionic conductivity and safety benefits. However, challenges like interfacial instability with high-capacity cathodes such as NMC811 hinder their practical use. Issues like oxidation instability, CEI formation, and volumetric changes contribute to performance degradation. New testing protocols and strategies, including optimizing catholytes and exploring interfacial protection, aim to address these challenges. Simulations on electrolyte aging offer insights into factors affecting capacity degradation. Combining experimental studies, advanced modeling, and material optimization is key to improving SSB performance and driving commercial viability [297–299].

9.1. Development of Symmetrical Electrode Materials

Xing Li et al. [300] emphasized the growing demand for flexible energy storage solutions, highlighting flexible LIBs as having potential for wearable electronics due to their high energy density, mechanical elasticity, and stable electrochemical performance.

Specifically focusing on flexible electrode materials, carbon nanomaterials like carbon nanotubes and graphene are explored for their excellent mechanical flexibility, large surface area, and high conductivity. The study identified challenges these materials face and anticipates future directions in electrode material development, offering valuable insights for future lithium battery research and development.

9.2. Structure of Electrode Materials and Lithium-Ion Battery Aging

LIBs depend on the structured materials of their electrodes, such as layered and spinel structures in cathodes and graphite anodes, to enable efficient lithium-ion movement. Over time, aging mechanisms such as mechanical stress, SEI layer formation, lithium plating, and electrolyte breakdown deteriorate these materials, causing capacity reduction, increased internal resistance, and self-discharge. Key factors in aging include chemical reactions during calendar aging and mechanical wear during cycle aging. Strategies like optimizing electrode materials, managing temperatures, using advanced electrolytes, and applying protective coatings are employed to extend battery life and improve performance [288]. Electrolyte composition plays a pivotal role in stabilizing high-energy-density LIBs, as advanced electrolyte formulations can mitigate decomposition and extend cycle life.

9.2.1. Lithium-Ion Diffusion Rate

Electrode material aging in LIBs leads to decreased capacity and increased resistance, affecting overall performance. This complex phenomenon arises from multiple interacting factors. Lin et al. [301] explained the capacity and power fading mechanisms for metallic oxide-based cathodes and carbon-based anodes under cycling and storage conditions. For cathodes, mechanical stress from lithium-ion insertion/extraction causes structural disorder, and metal dissolution from the cathode leads to deposition on the anode. Anode aging is primarily due to the loss of recyclable lithium ions from the SEI growth and mechanical fatigue from diffusion-induced stress. Aging is influenced by electrochemical behavior during cycling and storage and involves structural/morphological changes and side reactions exacerbated by decomposition products and impurities in the electrolyte.

9.2.2. Thermal Stability

Yannick et al. [302] investigated the safety properties of LIB cells by examining thermally induced reactions of active materials. Thermal profiles of anodes and cathodes at various SOCs after electrochemical aging were determined using methods to measure temperature-related mass loss, m/z detection, and heat flow, followed by pyrolysis-GC-MS analysis. Key findings include intense decomposition and reactions of lithiated anodes with binder molecules, confirmation of thermally induced de-lithiation, and phase changes in de-lithiated cathodes detectable via oxygen release. The decomposition properties of the solid electrolyte interphase vary with SOC, showing SOC-dependent behavior with oligocarbonates at 100% SOC and CO_2 at high temperatures for 0% SOC. This study provides a set of methods for thermal profiling to identify reactions that affect the safety of LIBs. Understanding degradation mechanisms, gathering data, modeling mathematically, and taking into account many elements that affect battery aging are all part of the complicated process of calculating the lifespan of LIBs. Accurate lifetime prediction is essential for maximizing battery-powered systems' efficiency and economy [303].

9.3. Degradation Mechanisms

Degradation of LIBs includes electrolyte breakdown, SEI development, lithium plating, and electrode material loss, all of which reduce capacity and performance. Mechanical stress and thermal aging exacerbate these processes even further. Lifetime is also impacted by gas production and cathode degradation. Accurate lifetime models under different settings take these mechanisms into account [304].

9.4. Data Collection and Mathematical Models

Xiaodong et al. [305] addressed the increasing use of lithium-ion batteries in EVs and energy storage stations (ESSs) in the context of carbon neutrality. It highlights how harsh conditions like vehicle-to-grid (V2G) interactions, peak–valley regulation, and frequency regulation accelerate battery degradation, making the development of long-life batteries crucial. It reviews urgent requirements, degradation mechanisms, design methods for suppressing these mechanisms, durability modeling, and management approaches for long-life batteries. The paper emphasizes the significance and urgency of developing durable batteries, discusses design methods to suppress degradation, elaborates on degradation modeling and advanced management strategies, and offers insights into overcoming challenges and seizing future opportunities for the practical application of long-life LIBs.

Binelo et al. [306] introduced a parametrization methodology employing the Genetic Algorithm meta-heuristic for estimating parameters in the Chen and Rincón-Mora model, used to mathematically model the lifetime of lithium-ion polymer batteries in mobile devices. This approach is compared with the conventional method based on visual analysis of pulsed discharge curves. Experimental data from a platform test are utilized for both parametrization procedures and model validation. Results indicate that the Genetic Algorithm method achieves superior efficacy, exhibiting lower mean error, and is more efficient and less subjective than the conventional approach.

9.5. Uncertainty Analysis

Rohr et al. [307] addressed the economic challenges of reusing LIBs from EVs, which are affected by increasing inner resistance and capacity degradation over time. To aid decision-making regarding the use of these batteries post-removal, the article proposes a method for predicting their RUL while accounting for uncertainties. Key risks identified in lifetime prediction include non-linear capacity changes, increasing cell spreading, and critical limit exceedances such as deep discharge events. The article advocates for a separate investigation of linear cell aging and uncertainties up to the battery pack level to establish correlations between operational conditions and failure distribution.

9.6. Analyzing Cell Aging Under Various Duty Cycles

Preger et al. [308] investigated the performance of three lithium-ion battery types (LiFePO4, $LiNi_xCo_yAl_{1-x-y}O_2$, and $LiNi_xMn_yCo_{1-x-y}O_2$) across varying discharge rates, DOD, and temperatures. Despite adherence to manufacturer's guidelines, it highlights that varied cycling conditions significantly impact cell degradation, with 80% capacity loss varying by thousands of hours and cycle counts per cell chemistry. Comparisons are made with previous studies to outline common trends and performance standard deviation.

Kim et al. [309] focused on assessing four commercially available cylindrical cells, each with a distinct Li-ion chemistry, for their performance under standardized testing protocols designed by the U.S. Department of Energy Office of Electricity (DOE-OE) for grid services like frequency regulation, peak shaving, and EV drive cycles. The 15-month investigation compares various parameters, including capacity retention, resistance, OCV, cyclic voltammetry (CV), (dQ/dV, differential voltage (dV/dQ), and AC impedance.

Dubarry et al. [310] explored the performance of a lithium titanate-based battery energy storage system over a seven-year period in an isolated island grid setting. They demonstrated that the modules' capacity loss remains below 10% even after seven years of operation, and the overall battery performance remains within expected specifications. Based on their findings, they projected the battery's full lifespan on the grid, indicating it should easily exceed 15 years. They also identify certain inaccuracies in the current online capacity estimation method, which pose challenges in effectively monitoring the system's performance.

Rosewater et al. [311] detailed the rationale behind establishing a duty-cycle for frequency regulation. A year's worth of publicly available utility frequency regulation control signal data were analyzed, revealing that signal standard deviation could quantify its aggressiveness. Two representative two-hour-long signals, mirroring average and aggressive scenarios, were selected and combined into a 24-h duty cycle. The article reviews the duty cycle's implications and its impact on the energy storage industry.

Crawford et al. [312] developed a pseudo-2D model using COMSOL Multiphysics® to simulate lithium-ion battery degradation during peak shaving grid service. The model accounts for SEI layer formation, breakdown, and cathode dissolution, with high accuracy in simulations of commercial cells. Two models were created: a global model for all chemistries and individual models for each, showing close agreement. A simplified model and a statistics-based model, predicting degradation from current, voltage, and anode expansion, were also developed. These models support an efficient BMS combining machine learning and physics-based algorithms. The reviewed papers focus on battery technology, energy storage systems, and degradation under various cycling conditions. They emphasize the need for accurate models, control systems, and standardized testing to optimize battery performance and lifespan in grid applications, highlighting the importance of collaboration and addressing technical challenges in Li-ion BESS and V2G operations.

Table 7. Comparison of research studies on lithium-ion battery material and aging.

Study Focus	Key Findings	Methodologies/Approaches	Implications/Contributions	Ref.
Carbon-based Anode Materials	Discussed various carbon anode materials and methods to improve performance, focusing on silicon carbon anodes and metal oxide/carbon composites.	Review of carbon-based anodes, highlighting electrostatic electrospinning and templates for composites.	Enhanced electrochemical performance and wider applications for LIBs.	[293]
Phosphorus-Graphite Composite	Introduced a dual-temperature zone heating strategy to fabricate fibrous phosphorus for improved battery performance.	Composite fabrication and performance testing.	Demonstrated enhanced rate performance and cycle stability of LIBs.	[294]
Nonlinear Frequency Response Analysis	Proposed NFRA to quantify battery aging modes without prior knowledge of cell's duty.	Experimental NFRA measurements combined with simulations.	Highlighted the importance of NFRA for aging diagnosis and battery management.	[294]
Aging Heterogeneity Investigation	Investigated aging heterogeneity in NMC811 and graphite cells after extensive cycling.	Synchrotron XRD radiography and electrochemical characterization.	Showcased potential for non-destructive techniques in battery research.	[296]
Flexible Lithium-Ion Batteries	Emphasized the potential of flexible LIBs for wearable electronics and explored carbon nanomaterials.	Review of flexible electrode materials.	Identified challenges and future directions for electrode development.	[300]
Capacity and Power Fading Mechanisms	Explained aging mechanisms for cathodes and anodes, focusing on structural disorder and SEI growth.	Analysis of aging mechanisms under cycling and storage.	Provided insights into performance degradation in LIBs.	[301]
Thermal Stability Analysis	Investigated thermal stability and reactions of active materials in LIBs.	Various thermal profiling methods, including pyrolysis-GC-MS analysis.	Identified thermal reactions affecting LIB safety.	[302]
Lifetime Modeling	Reviewed degradation mechanisms, data collection, and modeling for long-life LIBs.	Comprehensive review and analysis of methodologies.	Advanced understanding of battery lifespan and degradation management.	[305]
Parameter Estimation for Lifetime Models	Introduced a Genetic Algorithm methodology for estimating parameters in battery lifetime modeling.	Comparison of parametrization methodologies.	Improved parameter estimation for battery lifespan models.	[306]
Uncertainty in Battery Lifetime Prediction	Proposed a method for predicting remaining battery life, considering uncertainties.	Analytical and predictive modeling.	Aimed to aid decision-making for reused batteries in EVs.	[307]
Performance under Varying Conditions	Analyzed the performance of various LIB types under different discharge rates and conditions.	Experimental performance evaluation and comparison.	Highlighted significant impacts of cycling conditions on degradation.	[308] [309] [310], [311], [312]

10. Limitations of Data-Driven Methods in Battery Life Prediction

10.1. Data Quality, Preprocessing, Overfitting and Underfitting

Due to its efficient handling of handcrafted features, the Random Forest Regressor demonstrated superiority in life prediction challenges for lithium-ion batteries with limited information. The successful operation of these models was found to be largely dependent on feature extraction, particularly when using data from sources of variance. Although deep learning exhibits promise, its limited performance with the available data sets indicates that more data and better network architecture are required to produce more accurate forecasts. Currently, the most effective machine learning techniques for predicting battery life in these situations use handcrafted features [313].

10.2. Insufficient Data for Training

An in-depth analysis of data-driven methods for predicting rechargeable battery longevity in Cyber-Physical Systems (CPS) was presented by Yang et al. [314] The authors examine every stage of battery lifespan prediction, from gathering data to feature engineering and preprocessing to modelling. While addressing the implementation challenges within CPS, the authors look at real-world applications of these strategies in various contexts. The operational challenges of battery duration forecasting in CPS networks are described in this study, along with strategies for improving battery predictions via CPS networks. The authors commit to fostering scholarly investigations and real-world implementations that will foster the long-term advancement of data-driven energy storage methods.

10.3. Generalization Issues

Using a "capacity matrix" representation of electrochemical cycle data, Attia et al. [315] developed simple yet accurate data estimation algorithms to forecast battery lifespan. According to benchmarking experiments on a previously published dataset, univariate and multivariate statistical learning techniques are equivalent to deep learning models, particularly in terms of generalization. Deep learning models perform on par with ridge regression, elastic net, and partial least squares regression (PLSR). Studies suggest that feature engineering creates useful models and that a capacity matrix is a possible standardized format for storing battery cycle data. Novel creative feature extraction techniques, comprehensive testing across battery chemistries and usage conditions for these techniques, and other goals should be the three main topics of future study.

10.4. Data Imbalance

Li et al.'s [316] study offered a cutting-edge method for forecasting smartphone battery life using machine learning and copious amounts of usage data. The technique that uses the concordance index to fill in missing data is beneficial for survival analysis. According to the study, precise battery predictions are made possible by combining status monitoring, sensor data, application tracking, and analysis of current system performance. The results show that predictions now achieve an average reduction of 33 min, allowing users to better manage their smartphone usage. Predictive features are based on user activity patterns and battery discharge records, and tree-based analytical models outperform linear regression techniques. The technique is applicable to prediction systems in electric cars and wearable technology. In order to improve forecast accuracy levels, future studies will employ sophisticated machine learning algorithms and incorporate more data dimensions into the analysis.

10.5. Domain Knowledge Integration

In order to improve the performance of EV batteries, Naresh et al. [317] investigated predictive machine learning (ML) techniques by assessing the states of charge (SoC), health (SoH), function (SoF), and remaining usable life (RUL). Proactive maintenance functions, real-time monitoring, and efficient energy use are all made possible by the method's use of several supervised and unsupervised deep learning algorithms to forecast battery behavior. The study discusses challenges with data collection, model development, and battery prediction accuracy while evaluating EV battery performance optimization using an operation research model. Solid-state and lithium–sulfur batteries will be used to adapt to new battery technologies in the future, and IoT sensors will be included for real-time monitoring and explainable AI system verification for regulatory requirements. This study demonstrates the significance of controlling energy use and grid connection processes, predicting product lifespan, and advocating for sustainable business practices that maximize battery recycling and restoration.

11. Comparison of Lithium-Ion Battery Chemistries

Cathode expansion, lithium anode dendrite growth, and electrolyte breakdown are some of the mechanisms that cause advanced energy storage system Li–S batteries to age. Various aging processes impact material waste, structural degradation, increased internal resistance, and safety risks, all of which contribute to a shorter battery life and worse performance during operation. Research on developing sulfur-host materials is also ongoing, including the development of protective anode coatings and stable electrolyte enhancements. Real-time diagnostic methods and computational models that assist designers in creating long-lasting sulfur batteries make it possible to comprehend battery aging [318–320]. The techniques used to create lithium-ion batteries exhibit significant differences in terms of energy density levels, cycle life, thermal stability, and safety requirements. Although the NCA and NMC chemical families achieve high energy densities, they continue to perform poorly in terms of life cycle and thermal stability. Although these characteristics limit their energy storage capacity, lithium iron phosphate ($LiFePO_4$) and lithium titanate (LTO) provide excellent safety performance, long cycle life, and heat-resistance qualities for power storage systems [321]. Solid-State, Li–S, and Lithium–Air (Li–Air) battery technologies offer greater energy density and safety features, but they still need to be further developed because of their existing cycle performance and manufacturing cost limits. Future electric car ranges will be revolutionized by Li–S and Li–Air batteries, and solid-state batteries will combine safety and maximum efficiency for future use after technological obstacles are resolved [322]. Table 8 summarizes a comparison of lithium-ion battery chemistries and their aging behavior.

Table 8. Comparison of lithium-ion battery chemistries.

Application	Chemistry Type	Energy (Wh/kg)	No. of Charge/Discharge Cycles	Heat Resistance	Power Output	Safety Measures	Price Point	Aging Factors	Ref.
EVs, Energy Storage	Lithium Iron Phosphate (LFP)	90–160	2000–5000	Highly Stable at High Temps	Moderate	Safe	Moderate	Volume Expansion of Electrodes, SEI Development	[323–326]
EVs	Nickel Cobalt Aluminum (NCA)	200–260	500–1000	Needs Better Cooling	High	Improved with Battery Management	Higher	Electrolyte Breakdown, SEI Growth	[327–330]
Electric Tools, Power Storage	NMC	150–220	1000–2000	Sensitive to High Temps	High	Moderate	Moderate-High	Cathode Degradation, SEI Layer Expansion	[331–333]

Table 8. *Cont.*

Application	Chemistry Type	Energy (Wh/kg)	No. of Charge/Discharge Cycles	Heat Resistance	Power Output	Safety Measures	Price Point	Aging Factors	Ref.
High Power, Fast Charging EVs	Lithium Titanate (LTO)	80–120	7000–20,000	Stable at All Temps	Very High	Extremely Safe	Higher	SEI Growth, Lithium Plating, Electrolyte Aging	[334–337]
Portable Electronics	Lithium Cobalt Oxide (LCO)	150–240	500–1000	Overheating Issues	Moderate	Moderate	High	SEI Expansion	[338–340]
Next-Gen EVs, Consumer Electronics	Solid-State Lithium-Ion	300+ (Potential)	>10,000	Non-Flammable	High	Extremely Safe	High	Reduced Side Reactions, Solid Electrolyte Interface	[341–345]
Aerospace, EVs	Lithium–Sulfur (Li–S)	400–600	100–500	Stable at Low and Moderate Temps	Moderate	Moderate	Low to Moderate	Lithium Degradation, Electrolyte Decomposition	[346–352]
EVs, Energy Storage Systems	Lithium–Air (Li–Air)	1000+ (Theoretical)	100–500 cycles	Susceptible to Contamination	High	Low	High	Lithium Degradation	[353–357]

12. Future Research Directions for Lithium-Ion Battery Aging

Research into the aging of LIBs requires more stable material development, ideal thermal management and charging techniques, and effective recycling systems. The application of efficient technologies that reverse material degradation across a variety of environmental circumstances defines the base lifespan of batteries. Accurate precision in diagnostic and predictive modeling technology allows for better management of LIBs through better forecasting of aging processes. Combining novel materials with sophisticated production processes leads to improved system functionality. Research on recycling methods and secondary product usage systems must be prioritized in order to accomplish sustainable product disposal from an ecological and financial standpoint. Table 9 summarizes future research directions for lithium-ion battery aging. Three main areas are the focus of research on lithium-ion battery aging: producing materials that reduce the impacts of aging, creating machine learning algorithms for health assessment, and enhancing battery monitoring systems using cutting-edge methods. To achieve sustainability, a number of improvements in secondary battery applications, recycling systems, and heat management systems must be put into practice. Improved electrode design, sophisticated electrochemical modeling techniques that increase accuracy, and mechanistic research on aging mechanisms under use settings will all help batteries reach their full potential. It is necessary to fully comprehend interfacial phenomena and evaluate the environmental impact using a variety of charging simulations based on multi-scale models in order to select the appropriate battery technology development [358]. The main area of research is the development of sustainable LIB materials that decompose slowly and are likely to be reused. With the help of new battery types, industrial operations can continue economically and sustainably while reducing the need for replacements and protecting the environment.

Table 9. Future research directions for lithium-ion battery aging

Research Focus	Goals	Methods	Potential Impact
Understanding Aging Mechanisms	Enhance comprehension of degradation processes at the molecular level	Advanced characterization methods	More precise modeling
Aging Under Extreme Conditions	Investigate battery performance in extreme temperatures and rapid charging	Low-temperature experiments, fast charging tests, thermal assessments	Enhanced performance in varied climates; safer charging

Table 9. *Cont.*

Research Focus	Goals	Methods	Potential Impact
Novel Materials & Electrolytes	Create new, stable battery materials and safer electrolyte options	Innovative anode/cathode designs, electrolyte additives, solid-state advancements	Improved longevity, enhanced safety, increased energy density
Aging in Real-World Conditions	Examine battery aging during practical use	Machine learning applied to varied duty cycle evaluations	Enhanced predictive maintenance; greater battery reliability
Electrode-Electrolyte Interface Stability	Stabilize battery interfaces	Interface coatings, solid-electrolyte interface research	Reduced degradation; extended cycle life
Aging Mitigation Strategies	Develop technologies to reduce aging rates	Self-healing materials, thermal management techniques, adaptive charging methods	Longer battery lifespan; enhanced safety
Recycling and Second-Life Applications	Optimize battery reuse and recycling efforts	Second-life performance assessments, sustainable recycling methodologies	Lower environmental impact; cost-effective resource recovery
Next-Generation Battery Research	Investigate aging in new chemistries	Research on air contamination	Enables higher energy densities with novel materials
Safety and Failure Mechanisms	Prevent catastrophic events like thermal runaway	Comprehensive analysis of thermal events, electrolyte instability	Safer batteries; mitigated risks in high-stress situations
Standardized Aging Protocols	Establish new testing methodologies for consistent outcomes	Standardization of aging tests, comprehensive data reporting	Enhanced comparability among studies; more reliable forecasting

13. Discussion

Table 10 offers a comparison of aging behavior and performance degradation across LIB chemistries. LIBs have emerged as essential components in the clean energy landscape due to their compact size, high energy density, and suitability for various applications. In particular, Stationary Battery Systems (SBSs), which leverage LIBs, play a crucial role in power distribution networks worldwide, enabling functions such as peak load management, load shifting, voltage regulation, and power quality improvement. These applications underscore the critical importance of effective health management for LIBs to ensure long-term performance and reliability. This study explored various methodologies used to estimate LIB aging, with a focus on the most widely examined degradation mechanisms, such as capacity fade and internal resistance increase. However, existing research often tends to address these degradation factors in isolation, despite the fact that both play significant roles in the overall performance of LIBs, especially in the context of EVs and clean energy systems. Although each method reviewed has its merits, there are notable limitations that must be addressed. For instance, detailed data analysis from single battery cells or large datasets from vehicle applications can provide valuable insights under specific conditions, yet challenges such as reproducibility in chemical studies and the need for diverse datasets to capture all interactions effectively persist.

For EV users, ensuring a consistent range and reliable power output over the lifespan of the battery is paramount. Accurate battery SOH assessment is essential for evaluating battery performance and predicting longevity. Despite significant advances in lifetime modeling, there are still substantial challenges in developing a model-based evaluation system, primarily due to the limited availability of comprehensive data samples. The necessity for extensive battery testing to establish degradation relationships across a range of operating conditions remains a resource-intensive and time-consuming process. Thus, efforts are urgently required to advance our understanding of battery aging mechanisms and the development of reliable techniques to assess the SOH of LIBs. Innovative approaches that overcome the current limitations—such as those related to data availability and the resource demands of traditional testing methods—must be explored. Such advancements would facilitate the development of more efficient and accurate systems for evaluating battery aging, ultimately leading to improved battery performance and increased user confidence in EV technology. For EVs, an ideal method for estimating battery aging should strike a balance between flexibility and simplicity, providing quick results using easily obtainable variables without the need for complex measurements. Real-time models, such as equivalent circuit models or statistical approaches, offer practical advantages, though they are often less accurate compared to direct measurements. Nonetheless, the high accuracy achieved through direct measurements highlights the trade-off between ease of use and precision in battery health assessments.

Table 10. Aging behavior and degradation of li-ion batteries.

Battery Chemistry	Aging Behavior	Capacity Degradation	Resistance Increase	Aging Mechanism	Additional Observations
LFP	Low aging, long life	Minimal loss	Moderate increase	Loss of lithium inventory & anode material	Best for long life services, Umax 3.65 V
NCA	Degrades at 60 °C, high voltage	Drastic loss at high temp/volt	High resistance at 60 °C	Loss of active material & lithium inventory	Performance vs. cycle life compromise
NMC	Degrades at 60 °C, high voltage	Drastic loss at high temp/volt	High resistance at 60 °C	Loss of active material & lithium inventory	Sensitive to high temp, manganese dissolution
LCO	Mixed degradation	Less capacity loss	Lower resistance increase	Loss of active material	Less extreme aging compared to others
LTO	High degradation at high voltages	High degradation at high voltages	Least resistance increase	Minimal loss of anode material	Sensitive to high voltage, high cycle life
LMO	No degradation at 50 °C, moderate at higher	Almost no degradation at 50 °C	Significant resistance increase	Increase in resistance & possible loss of active material	Sensitive to high temp, manganese dissolution
Overall Aging	Higher degradation at high temp/voltage	High degradation at 60 °C	Highest resistance for NMC & NCA	Loss of active material, lithium inventory, & resistance increase	LTO: less resistance increase, LFP: high long life

Table 11 provides a comprehensive summary of the key aspects of LIB aging mechanisms, contributing factors, and mitigation strategies. Battery aging is a multifaceted process influenced by a variety of factors, including usage patterns, environmental conditions (such as temperature), and charging profiles. The inherent complexity of aging dynamics presents significant challenges in achieving accurate characterization, particularly due to the interplay of multiple interdependent factors. One specific area of concern is voltage imbalance in lithium-ion battery packs, often attributed to varying self-discharge rates among individual cells. There is a notable lack of detailed research on the variability of self-discharge currents and their potential implications for battery packs composed of series-connected cells. Given the crucial role that voltage balance plays in the overall performance and longevity of battery packs, further investigation into this phenomenon is required to understand its impact on both performance degradation and the aging process. Developing an ideal method for estimating battery aging in electric vehicles requires a careful balancing of several factors, including flexibility, measurement complexity, accuracy, and precision. While real-time calculations based on easily obtainable variables can provide timely insights into battery health, achieving an accurate and reliable assessment necessitates a deeper understanding of the complex interactions underlying battery aging. Recognizing these complexities is crucial for the accurate prediction of battery performance and the optimization of vehicle operation over the course of the battery's lifetime. In conclusion, LIBs are indispensable for the advancement of clean energy technologies and electric mobility. Their high energy density and compact size make them the preferred choice for numerous applications, with accurate assessment and prediction of aging playing a central role in ensuring optimal performance, longevity, and reliability, particularly in electric vehicles, where users expect consistent performance throughout the battery's lifecycle. Although current methodologies for aging estimation have made significant strides, they also exhibit inherent limitations that must be overcome. The development of more reliable techniques for assessing the SOH of LIBs, including innovative approaches that address data availability and resource constraints, is critical for the continued advancement of battery technologies. The ideal method for estimating battery aging should balance flexibility, ease of use, and precision while accounting for the complex and interdependent factors that drive battery degradation. A comprehensive understanding of these factors will lead to more accurate predictions of battery health, ultimately contributing to the reliability and efficiency of electric vehicles and other clean energy systems. Uncertainties in battery aging predictions, such as variations in cell manufacturing and usage conditions, can result in substantial discrepancies in predicted outcomes. This emphasizes the importance of developing robust, adaptive models that can address these uncertainties, leading to more dependable predictions of battery health and performance.

Table 11. Key aspects of lithium-ion battery aging mechanisms, factors, and mitigation strategies.

Aspect	Key Insights & Implications
Aging Mechanisms	Lithium plating: can result in higher resistance, capacity loss, and potentially safety problems. SEI growth: lowers the ion's mobility and increases resistance. Electrolyte degradation: decreases the electrolyte's function and raises pressure. Cathode degradation: lowers efficiency and energy density. Mechanical stress: reduces performance by causing cracks and the loss of active material. Lithium consumption: traps lithium, increasing self-discharge and reducing the amount of charge that may be released.
Factors Influencing Aging	Lithium plating: can lead to increased resistance, loss of capacity, and possibly safety issues. SEI growth: raises resistance and decreases ion mobility. Electrolyte degradation: increases pressure and reduces the electrolyte's action. Cathode degradation: reduces energy density and efficiency. Mechanical stress: causes loss of active material, which lowers performance. Lithium consumption: reduces the amount of charge that may be released and increases self-discharge by trapping lithium.
Diagnostic Methods	EIS: detects resistance variations and SEI accumulation. Post-cycle analysis: checks for material failure and mechanical damage.
Mitigation Strategies	Thermal management: prevents SEI and plating by controlling temperatures. BMS: minimizes overcharging or discharging by optimizing SOC, voltage, and current. Charging protocols: use more intelligent charging techniques to prolong battery life and lessen stress. Material innovation: creates superior materials to increase energy density, stability, and safety.

14. Conclusions

LIBs have established themselves as a cornerstone of contemporary energy storage solutions, offering high energy density and compact design. Their widespread use spans diverse applications, particularly in SBS systems, which are integral to modern power distribution networks. In these systems, LIBs facilitate essential functions such as peak load management, load shifting, voltage regulation, and power quality enhancement, thus underscoring the importance of efficient health management strategies for maintaining system performance and longevity. This review has critically examined the current state of research on battery aging, focusing on the methodologies used to estimate and predict the degradation of LIBs. Although significant progress has been made, most studies address specific aging aspects, such as capacity fade and internal resistance increase. These factors, while important, cannot be fully understood in isolation, as they jointly impact the performance and reliability of EVs and energy storage systems. The review highlights that the existing methods provide valuable insights but are not without limitations. Challenges such as data reproducibility and the need for extensive, diverse datasets remain significant barriers to developing comprehensive aging models. Also, more effort is needed to understand the mechanisms and predict chemomechanical degradation, which is multiphysics and complex. Accurately assessing the health of LIBs is paramount for ensuring the consistent performance and extended lifespan of EVs, where maintaining a stable range and reliable power output over time is crucial. Despite several proposed solutions, developing an efficient, model-based system for lifetime estimation remains hindered by data constraints and the resource-intensive nature of battery testing. To address these issues, future research must focus on innovative approaches to overcome these limitations, enabling more precise and scalable methods for estimating battery aging. Ideally, a robust battery aging estimation method should be adaptable, simple to implement, and capable of providing rapid assessments using readily accessible operational parameters. While real-time prediction methods offer operational advantages, it is critical to recognize that direct measurement techniques, although more complex to implement, provide the highest accuracy and reliability. Striking a balance between practical usability and precision is essential to optimizing battery health management strategies and ensuring the sustained performance of LIBs in real-world applications. Battery aging is a multifaceted process, influenced by various factors such as usage patterns, environmental conditions, and charging profiles. The complex interplay of these factors makes it challenging to accurately predict the degradation behavior of LIBs. Additionally, issues such as voltage imbalance within battery packs—resulting from variations in self-discharge rates among individual cells—remain underexplored and warrant further investigation. As the adoption of LIBs continues to grow, particularly in the context of EVs and large-scale energy storage systems, it is critical to monitor SOH of these batteries in real time. Ensuring high precision in SOH estimation will be crucial for maintaining the stability and reliability of energy storage systems and optimizing the performance of lithium-ion-based technologies.

This paper has provided a comprehensive review of the current methodologies for modeling the lifespan of LIBs, emphasizing the gaps in existing approaches and presenting a novel framework that integrates various methods and algorithms. The findings underscore significant improvements in the predictive accuracy of aging models, offering a pathway for advancing battery technology. Future work should focus on refining these methodologies and applying them to specific applications, including electric vehicles and renewable energy systems, to enhance battery performance, safety, and reliability. Ultimately, a deeper understanding of the factors influencing battery aging and the development of more accurate estimation models will be crucial for driving the future of sustainable energy systems.

Future research should focus on developing adaptive aging models incorporating real-time data from various sources, such as vehicle performance metrics and environmental conditions, to improve predictive accuracy. Enhancing battery aging prediction models will not only boost the performance and lifespan of electric vehicles but also support the sustainability of energy systems by reducing the frequency of battery replacements. Moreover, extending the lifespan of lithium-ion batteries will significantly minimize the environmental impact linked to battery production and disposal, promoting more sustainable energy solutions worldwide. The findings of this study highlight the essential role of precise battery aging predictions in ensuring the long-term reliability and performance of clean energy technologies.

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