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Exploring the Aging Dynamics of Lithium-Ion Batteries for Enhanced Lifespan Understanding

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Abstract: This review examines the aging mechanisms and performance decline of lithium-ion batteries under various conditions, focusing on temperature effects, charge/discharge efficiency, and operational limits. It covers high-temperature aging and its impact on the solid electrolyte interphase (SEI) layer, as well as thermal runaway risks. Low-temperature aging is also discussed, emphasizing reversible capacity loss, increased resistance, and lithium plating. The review addresses degradation from overcharge/over-discharge scenarios and explores coulombic efficiency (CE) degradation and its link to capacity loss. By synthesizing current research, it provides insights into optimizing battery management and enhancing performance.

Keywords: lithium-ion batteries; Battery aging mechanisms, Battery degradation

1. Introduction

Lithium-ion batteries (LIBs) are essential for applications such as smartphones, electric vehicles (EVs), and grid energy storage due to their high energy density and longevity. However, over time, LIBs degrade, adversely affecting performance, safety, and reliability. This degradation is particularly critical in EVs, where reduced travel range and power output can hinder adoption. Strategies to mitigate aging include optimizing charging protocols, managing discharge depth, and implementing effective thermal management. When a battery overheats uncontrolled, it can cause thermal runaway, which could result in an explosion or fire. Batteries have safety features like temperature sensors, cooling systems, and functions that turn the battery off when it becomes too hot to avoid this. These measures are crucial for preventing

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accelerated degradation, and safety risks, besides thermal runaway. As EV adoption increases, advanced techniques for estimating battery life and managing aging effects become increasingly necessary. Recent research has significantly enhanced our understanding of LIB aging mechanisms, focusing on electrode materials, degradation modeling, estimation techniques, and aging management strategies.

1.1. Electrode Materials and Battery Design
Tarascon et al. [1] reviewed the historical development of lithium-based batteries, emphasizing the synthesis, performance, and safety of various materials. Their discussion on the evolution of anode, cathode, and electrolyte materials, alongside the impact of the rocking-chair battery, offers valuable insights for improving battery efficiency and reliability.

1.2. Aging Mechanisms and Degradation Modeling
Aging is caused by multiple stressors such as deep cycling, high charge/discharge rates, harsh temperatures, and extended storage. These pressures frequently accelerate the degradation process by amplifying one another rather than acting alone. Xiong et al. [2] systematically summarized the aging mechanisms, emphasizing internal side reactions affecting the anode and cathode and external factors like temperature. They discussed three diagnostic methods: disassembly-based post-mortem analysis, curve-based analysis, and model-based analysis, highlighting their roles in battery aging diagnosis and management for intelligent battery management systems (BMSs).
Collath et al. [3] provided a comprehensive analysis of aging mechanisms and degradation modeling in Battery Energy Storage Systems (BESS). Their study emphasized empirical and semi-empirical degradation models and explored the integration of aging costs into optimization functions. They identified stress factors influencing BESS applications, contributing to a better understanding of battery degradation and performance optimization.
Vermeer et al. [4] examined primary aging mechanisms in LIBs and explored empirical modeling techniques. They stressed the importance of accounting for stress factor interactions and avoiding oversimplifications in aging models, which is critical for improving the accuracy of lifetime predictions. In general, designing tests for lifetime predictions is crucial because it helps us learn how batteries deteriorate by simulating real-world settings. Prediction models are improved with the use of this data, increasing their dependability and assisting battery producers in creating better batteries.

1.3. Battery Capacity Estimation
Li et al. [5] focused on computational techniques for capacity estimation, comparing the performance of three filter-based algorithms. They found that the extended Kalman filter provided the best balance between robustness and computational efficiency. Other filters, such as the particle filter and least-squares-based filter, involved trade-offs between speed, accuracy, and computational resources. This study advanced methods for online capacity estimation by clarifying the balance between performance and computational effort.

1.4. Aging Prediction and Battery Health Management
Chen et al. [6] proposed a transfer learning approach to predict battery aging modes, specifically for electric vehicle batteries (EVBs). Their model, which incorporated experimental data and an enhanced dual-tank model with long- and short-term memory neural networks, demonstrated precise estimation of EVB aging parameters. This innovative approach provided valuable insights into battery health management and aging prediction for real-world EV applications. However, it should be noted that the current estimation methods are deemed insufficient for capturing complex aging interactions. The way that many elements, such as temperature, charge rates, and usage, combine to induce aging is not always captured by current approaches.

Oversimplifying these intricately linked processes makes it challenging to simulate what occurs inside the battery.

Barré et al. [7] offered a broad overview of aging mechanisms and estimation techniques, focusing on methods such as state of health (SOH) and remaining useful life (RUL). Their review examined the strengths and limitations of various approaches, identifying gaps in existing models and offering suggestions for improving aging prediction techniques.

This review offers a comprehensive overview of aging mechanisms in lithium-ion batteries (LIBs), categorizing them into electrode materials, aging models, and estimation techniques. It explores battery degradation principles, evaluates modeling approaches, and highlights recent advancements. The review identifies research gaps and suggests ways to mitigate aging processes, focusing on factors like temperature, charge/discharge rates, and operational stresses. By consolidating findings, it provides a unified perspective to help improve battery technology and extend LIB lifespan. Unlike existing literature, it synthesizes research on material degradation, aging models, and health management strategies, offering insights to guide future research and industrial efforts in enhancing battery performance, safety, and longevity across various sectors.

2. Types of Battery Aging

Figure 1 illustrates categorisation of lithium-ion battery aging. Battery aging results from various processes like cycle aging, calendar aging, and environmental factors, leading to reduced performance and capacity. Addressing these aging mechanisms is vital for improving battery longevity and efficiency.

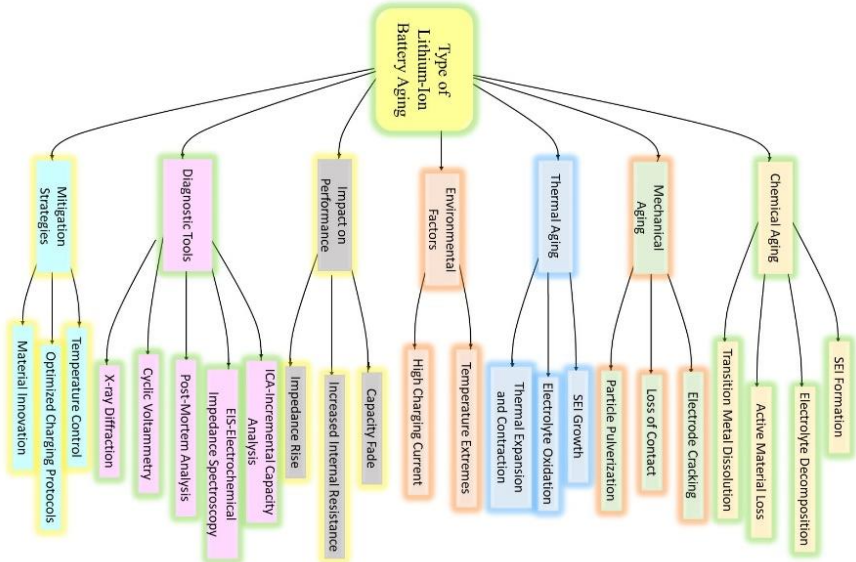

Figure 1. Categorisation of lithium-ion Battery Aging.

2.1. Calendar Aging

Mitigating calendar aging is crucial for extending the lifespan and performance of lithium-ion batteries, especially in electric vehicles. Both calendar and cycle aging impact battery health, capacity influencing, efficiency, and driving range. Optimizing these factors is key to improving battery durability and customer satisfaction. [9].

2.1.1. Calendar Aging Models and Investigations. Liu et al. [10] performed a comparative study on three types of calendar aging prediction models: the pseudo two-dimensional (P2D) electrochemical model, the semi-empirical Arrhenius law-based model, and a data-driven Gaussian Process Regression (GPR) model. Each model was trained using experimental data under various storage temperatures and SOC conditions. The study highlighted the strengths and limitations of each model type, advancing calendar aging prediction techniques and contributing to battery lifespan optimization.

In another study, Krupp et al. [11] explored the effect of periodic characterization measurements on calendar aging. They observed that characterization measurements, performed using small currents (below 1C), temporarily improved battery performance by increasing capacity and decreasing resistance. This effect was attributed to improved cell kinetics, such as faster ion transport and reduced resistance, which allowed the battery to discharge more fully and thus show an increase in capacity.

McBrayer et al. [12] investigated the reactivity of silicon in lithium-ion cells, revealing its contribution to accelerated aging. Silicon-based batteries face challenges with degradation, and further research is needed to develop effective mitigation strategies, improving energy storage technology. While much research has focused on mitigating volume changes in silicon anodes during cycling, little is known about time-dependent degradation (calendar aging). This Perspective highlights studies showing that silicon's reactivity accelerates calendar aging in lithium-ion cells. To maximize the potential of silicon-based batteries, future research should focus on assessing and mitigating this degradation issue.

Maures et al. [13] developed a calendar aging model for lithium-ion batteries that incorporates the effects of time and temperature on degradation mechanisms, specifically targeting Conductivity Loss (CL), Loss of Active Material (LAM), and Loss of Lithium Inventory (LLI). The model employs temperature parametrization based on the Arrhenius equation for LAM and LLI, while a new empirical model is applied for CL. Key aspects include temperature dependence, where LAM and LLI follow the Arrhenius law and CL utilizes a simpler empirical model; time dependence, indicating that degradation evolves over the square root of time (t^0.5), suggesting slower degradation as time progresses; and quantification methods, where Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA) are used to quantify LAM, LLI, and CL over time. The model was validated under a 95% state of charge (SoC) at temperatures ranging from −20°C to 55°C, successfully predicting aging behavior, with LAM and LLI fitting the Arrhenius law and CL aligning with the new empirical model.

Liu et al. [14] extended the calendar aging study by developing a data-driven model using Gaussian Process Regression (GPR) with an Automatic Relevance Determination (ARD) Matern32 (M32) kernel. The model reliably predicted aging for diverse storage conditions, showing great potential for multi-step predictions and accelerated aging scenarios.

2.1.2. Experimental Studies on Calendar Aging. Zilberman et al. [15] studied on 18650 nickel-rich/SiC cells and examined calendar aging and self-discharge rates, finding that after 10 months of storage at 70% SOC and 25°C, capacity variance doubled, while impedance remained stable. Self-discharge testing revealed minimal impact on voltage imbalance, with aging rate differences contributing more to voltage drift. The study highlights the importance of considering calendar aging in battery design for long-term performance. The design of the battery has a direct impact on aging processes like material degradation, lithium plating, and SEI layer development. The way these processes take place and the rate at which the battery degrades are directly impacted by choices made about the materials, electrode configuration, and electrolyte composition.

Zhu et al. [16] studied on the impact of solid electrolyte interphase (SEI) growth on calendar aging in lithium-ion batteries found that SEI growth is a key degradation mechanism during high-temperature storage. Increased resistance wastes energy as heat, which reduces battery efficiency and increases component stress. This can eventually lower the battery's power output and diminish its lifespan. The research showed that capacity loss over 210 days at 55°C was directly related to state of charge (SOC), with higher SOCs causing greater degradation. Post-mortem analysis revealed thickened SEI layers and increased resistance in batteries stored at 100% SOC, leading to performance issues. The study suggests optimizing SEI design and reducing storage temperatures to mitigate calendar aging and enhance battery longevity.

Geisbauer et al. [17] provided a comparative analysis of calendar aging across different lithium-ion cell chemistries. Their study introduced a novel metric for comparing degradation rates, revealing that elevated temperatures and voltages significantly accelerated capacity loss, prompting further research into cyclic aging to enhance battery life.

2.1.3. Advanced Calendar Aging Prediction Techniques. Kashkooli et al. [18] employed artificial neural networks (ANNs) to address the hysteresis effect in lithium-ion batteries during charge and discharge cycles. Their models demonstrated high accuracy in estimating State of Health (SOH), with the SOH estimation model achieving an RMSE of 1.67%. This study highlights the value of integrating aging effects into state estimation techniques to improve battery management systems.

Table 1. Comparison between different research about Calendar Aging.

Key Findings	Ref
GPR model outperforms others for aging prediction.	[10]
Periodic measurements improve performance, <1C is best.	[11]
Silicon accelerates aging, needs mitigation.	[12]
Model includes time, temp, conductivity, and inventory loss.	[13]
GPR with ARD kernel improves aging prediction.	[14]
Capacity, impedance vary; minimal self-discharge impact.	[15]
SEI growth is key in high-temp aging; optimize SEI.	[16]
High temp, voltage lead to loss; varies by chemistry.	[17]
ANN models accurately estimate SOC/SOH in aged cells.	[18]

2.2. Cycle Aging

Cycle aging results from repeated charging and discharging, gradually depleting battery capacity and influenced by factors like temperature, current, and SOC range. While laboratory studies often focus on steady-state conditions, real-world dynamic factors, such as variable current and temperature, must be considered for a complete understanding of degradation and to improve mitigation strategies.

Spitthoff et al. [19] did a literature survey on lithium-ion battery degradation and found that temperature, especially during cycling, significantly accelerates aging. It highlighted the impact of state of charge (SOC) and charge rate, which vary by cell chemistry. Temperature was identified as the most influential factor above room temperature, with high charge rates and poor cooling reducing battery life. The study emphasized the need for accurate temperature measurements and reporting, as cooling strategies can cause significant deviations that affect degradation and performance analysis.

Xiong et al. [20] reviewed aging mechanisms and diagnosis methods for lithium-ion batteries. They discussed internal side reactions and external factors affecting degradation, while also examining methods like disassembly-based, curve-based, and model-based analysis. This review provided valuable insights for developing strategies to enhance battery performance and longevity.

Barcellona et al. [21] explored the impact of current rate on lithium-ion battery aging while maintaining constant temperature. They found that cycle aging was independent of current rate, challenging previous assumptions. Their work underscores the need for more precise aging models and contributes to better battery management strategies by highlighting the complex interaction between current rate and battery aging.

Atalay et al. [22] developed a dual-layer SEI formation model for lithium-ion batteries that accounts for lithium-plating aging and porosity changes. Their model accurately predicted voltage and capacity fade

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across cycling numbers and forecasted future degradation under new conditions. The model significantly improves the accuracy of capturing nonlinear capacity fade characteristics.

Braco et al. [23] conducted an experimental study on lithium-ion modules from Nissan Leaf electric vehicles, simulating second-life conditions. They proposed an end-of-life criterion based on capacity and internal resistance measurements and identified the aging knee point. The study revealed that the modules could withstand a minimum of 2033 equivalent full cycles before reaching the aging knee, emphasizing the importance of robust assessment methods for second-life battery potential.

2.2.1.Advanced Modeling and Temperature Effects. The materials in the battery expand in response to temperature changes. Over time, this repeated stress can cause protective layers to wear out and crack, decreasing capacity and raising resistance. Guo et al. [24] developed a transfer learning method to estimate parameters in the fractional-order model (FOM) of lithium-ion batteries using limited data. Validated by accelerated aging tests, the method enhances aging model accuracy for battery management. Using a backpropagation neural network (BPNN), it identifies FOM parameters with minimal data and adapts to different aging states. Key contributions include a model-based data generation method, a BPNN tool for parameter estimation, and transfer learning for accurate lifecycle parameter identification. Future work will improve generalization and expand the dataset. Ouyang et al. [25] studied on the impact of abusive-temperature cycling on aging lithium-ion cells and found significant degradation, including lithium inventory loss, anode material degradation, and electrode interface deterioration. High-temperature cycling improved thermal stability, while low-temperature cycling reduced safety, leading to lithium plating and SEI layer thickening. In contrast, the SEI layer becomes unstable at very high temperatures, continually dissolving and re-forming. Lithium plating can pose safety risks and decrease capacity. The chance of failure is increased when it occasionally produces dendrites, which are needle-like structures that can puncture the separator and result in short circuits.The performance of the battery is adversely affected by this process, which depletes lithium and raises resistance.

Thermal runaway tests showed that aged cells from high-temperature cycling experienced thermal runaway later than fresh cells, while low-temperature aged cells showed worse thermal runaway behaviors. The study highlights the need for careful monitoring of aged cells to mitigate thermal risks during operation, transportation, storage, and recycling. Redondo-Iglesias et al. [26] proposed a novel method for modeling capacity degradation in lithium-ion batteries using a system of differential equations. The model, based on a two-step reaction rate formulation with only two differential equations and seven parameters, accurately predicts capacity fade in electric vehicle batteries. It captures the complex non-linear interactions between cycling and calendar aging, addressing limitations in conventional models. The approach is useful for battery use assessment, optimal charge scheduling, and energy management in plug-in hybrid electric vehicles, offering a significant advancement for improving battery performance and longevity in e-mobility.

Xie et al. [27] studied the thermal safety of lithium-ion batteries under flight conditions. They found that cycling aging and ambient pressure greatly influence battery safety, with an increased number of cycles or reduced external pressure accelerating the onset of thermal runaway. Their research identified factors like cathode material loss and structural damage that further reduce battery safety, particularly in aircraft applications.

Table 2. Comparison between different research about Cycle Aging

Focus	Key Findings	Significance	Ref
Temp & SOC impact	Temp impacts aging; SOC and C rate vary by chemistry.	Emphasizes thermal management.	[19]
Aging mechanisms & diagnosis	Reviews internal/external factors, diagnostics.	Insights into aging mechanisms and diagnostic tools.	[20]
Current rate on aging	Aging independent of current rate.	Highlights need for current rate control.	[21]

Aging model	Model predicts voltage/capacity fade.	Improves aging behavior prediction.	[22]
Second-life module aging	2000+ cycles before aging knee.	Supports second-life battery use.	[23]
Transfer learning for aging	Limited data for aging model estimation.	Introduces transfer learning for aging models.	[24]
Temp cycling effects	Extreme weather causes lithium loss, safety risks.	Highlights need for temperature control.	[25]
EV capacity degradation	Model predicts capacity fade based on usage.	Aids EV battery management.	[26]
Thermal safety in aviation	Aging and low pressure reduce safety.	Stresses importance of cycling and pressure in battery safety.	[27]

2.3. Temperature-Related Aging

2.3.1. High-Temperature Aging. High-temperature aging of lithium-ion batteries has been extensively studied, revealing several key degradation mechanisms and performance impacts. Research summarized in Table 3 demonstrates that temperatures above 25°C (specifically from 25°C to 80°C) lead to significant changes in battery performance over cycling. At 60°C, the formation of thicker solid electrolyte interphase (SEI) layers was observed, along with an increased risk of thermal runaway. Temperatures reaching 80°C caused SEI decomposition and transformation into loosely structured particles, prolonging thermal runaway and lowering peak temperatures [28]. This indicates that high temperatures exacerbate thermal safety risks, similar to the effects seen with cyclic and calendar aging.

Further studies have shown that elevated temperatures amplify these risks through several mechanisms. Lithium plating, a common issue at higher temperatures, lowers the self-heating initiation temperature and accelerates thermal runaway by weakening the cathode due to the dissolution of transition metals [29]. As lithium plating progresses, the battery exhibits increased DC resistance and AC impedance, correlating with higher temperature rises during degradation, despite an overall capacity fade [30]. The performance of Li(Ni,Mn,Co)O2/carbon cathodes at temperatures up to 120°C illustrates these issues; PVdF binder migration and changes in SEI composition impact battery performance, though the material is found suitable for high-temperature applications [31]. Moreover, extended low-temperature cycling followed by high-temperature exposure demonstrates a two-stage aging process: initial capacity loss due to "dead lithium," followed by SEI growth and accelerated aging from lithium plating [32]. Impedance rise, driven by low-frequency diffusion, provides new insights into battery lifetime and highlights the need for adaptive methodologies based on chemistry [33].

2.3.2. Low-Temperature Aging. Low-temperature aging significantly affects lithium-ion battery lifespan, particularly in 100Ah LiFeMnPO4 batteries. Aging studies emphasize the importance of effective thermal management to prevent performance degradation. At low temperatures, processes like lithium plating occur, reducing capacity, power efficiency, and increasing impedance, especially during high charging rates. Lithium ions move more slowly at low temperatures, which might cause transient problems like increased resistance and lithium plating. A portion of this capacity loss can be restored when the battery warms up. Proper thermal strategies are essential to maintain optimal operating conditions, prevent degradation, improve charge acceptance, extend cycle life, and enhance safety in hybrid electric vehicles (HEVs) and electric vehicles (EVs) [34].

Performance analysis reveals that cold temperatures exacerbate internal resistance and reversible capacity loss, with lithium plating emerging as a primary aging mechanism leading to anode deterioration and capacity fade [35]. Notably, low-temperature cycling with varying discharge rates showed more significant capacity degradation at lower discharge rates, challenging the assumption that lower temperatures always lead to reduced aging [36].

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Further, research on low-temperature charging aging indicates that both lower temperatures and higher charging currents exacerbate capacity decay due to lithium deposition [37]. Analysis of 18650 batteries revealed that charging rates significantly impact capacity degradation and internal resistance, highlighting risks associated with low-temperature aging and the importance of managing charging conditions [38]. Insights from cycle life tests on LiFePO4 batteries at -10°C confirm that higher charging currents and cut-off voltages accelerate capacity degradation, primarily due to lithium deposition [39]. Performance analysis also shows that increased impedance and loss of active material at low temperatures necessitate improved battery design and management [40]. A study on 18650 batteries under different temperatures and charge/discharge rates offers guidance on designing batteries for low-temperature and fast-charging scenarios [41]. Finally, the impact of lithium precipitation at low temperatures significantly increases impedance, contributing to capacity degradation and enhancing understanding of battery aging mechanisms [42].

2.4. Charge/Discharge Efficiency Aging

2.4.1. Overcharge/Overdischarge Aging. Overcharge and overdischarge aging degrade lithium-ion batteries by causing issues like lithium plating, electrolyte breakdown, and irreversible capacity loss. Understanding these mechanisms is vital for improving battery management systems and optimizing charging/discharging protocols to enhance battery longevity and performance. While over discharging degrades electrodes and drains the electrolyte, overcharging harms the battery by generating edema and gas accumulation. Both situations degrade the battery's lifespan by accelerating wear and tear.

Ref [43] studied on overcharge and overdischarge in lithium-ion phosphate batteries and identified early failure signs, including increased temperature, impedance, and visual deformation during overcharge, and capacity loss, degradation, and impedance rise during overdischarge. These changes serve as precursors to failure, emphasizing the need for fault diagnosis systems. Future research will focus on electrochemical analysis, temperature estimation, and fault feature extraction to enhance battery safety and performance.

Ref [44] has summarized the aging mechanisms of LIB components and the degradation processes under stress-accelerated conditions, providing a reference for evaluating the consistency of aging mechanisms. Furthermore, the introduction of accelerated aging-based lifetime prediction models offers valuable tools for researchers aiming to enhance the reliability of lifetime forecasts.

To improve battery lifetime predictions, it is essential to increase stress levels in aging studies, explore multi-stress effects, and validate models in real-world conditions. This will enhance the accuracy of predictions and support the development of more efficient and reliable energy storage solutions.

2.4.2. Coulombic Efficiency Aging. Studies on coulombic efficiency (CE) and capacity degradation reveal critical insights into battery performance under various conditions. One study used incremental capacity (IC) analysis to show that both lithium inventory loss and active material loss significantly affect CE, providing a basis for developing degradation models and early failure warnings [45]. Another investigation into CE across different current rates found that higher current rates result in lower capacity loss per cycle, indicating efficient charge extraction even at elevated currents [46]. A semi-empirical model linking CE to capacity degradation demonstrated improved accuracy over traditional models and offers a framework for online battery health estimation and remaining useful life prediction [47]. Further, a quantitative approach to characterize side reactions using constant-voltage charging and precise current measurement provided a novel method for predicting battery lifespan based on CE evolution under various conditions [48]. Additionally, an analysis of lithiation in the graphite anode overhang, coupled with CE measurements, revealed significant impacts of storage conditions on CE and capacity degradation, highlighting the importance of considering storage parameters in health assessments [49]. Finally, a model for LiFePO4 batteries, incorporating electrochemical principles and neural networks, achieved high accuracy in state of charge estimation, emphasizing its effectiveness for reliable capacity predictions [50].

The comparison of charge/discharge efficiency studies highlights the importance of monitoring overcharge/overdischarge conditions and coulombic efficiency degradation to understand battery performance and longevity. Developing semi-empirical models and effective monitoring systems is crucial for enhancing battery safety, performance, and lifespan.

Table 3. Comparison between different research about about battery Aging

Appearance	Findings	Techniques Used	Battery Types	Key Contribution	Ref
Overcharge/Overdischarge	Gas release (overcharge), failure (overdischarge)	Electrochemical, impedance	Lithium-ion phosphate	Early warning systems	43
Accelerated Aging	Predicts lifespan through stress-accelerated aging	Aging models	Lithium-ion (general)	Review of aging models	44
Coulombic Efficiency	Lithium loss reduces CE	IC analysis, CE tracking	Commercial lithium-ion	Links CE decline to capacity loss	45
CE & Current Rate Cycling	Higher rates increase capacity loss	Charge cycling, CE comparison	Commercial lithium-ion	CE stability, capacity fade	46
CE-based Model	CE-based model predicts degradation	Cycle tests, CE model	Lithium iron phosphate	Proposed CE-based prediction model	47
Side Reaction Quantification	Measures side reactions and CE evolution	Precision charger, SOC analysis	Lithium-ion	New approach for side reaction measurement	48
Lithiation & Storage	High SoC lithiation affects CE and capacity	XRD, CE measurements	Lithium-ion	Anode lithiation impact on CE	49
LiFePO4 Modeling	Models estimate SoC and capacity	Thévenin, BPNN, models	LiFePO4	Accurate SoC and capacity estimation	50

3. Battery aging tests

Battery aging tests, including cycle life, calendar life, temperature stress, and mechanical stress tests, are crucial for evaluating long-term battery performance and reliability. Techniques like EIS, ICA, and accelerated aging help understand degradation mechanisms and improve battery designs for enhanced durability and lifespan.

3.1. Accelerated Life Tests

Figure 3 illustrates a characterization method for lithium-ion batteries. Characterization tests are vital for evaluating lithium-ion battery performance, durability, safety, and aging behavior. These tests provide crucial insights that guide the development of better battery designs and optimized management systems, driving advancements in battery technology and energy storage solutions.

An accelerated life test (ALT) matrix for lithium-ion batteries evaluates lifespan and reliability under stress conditions, using methods like EIS, capacity tests, and thermal imaging. Accurate lifetime predictions for EV batteries require designing tests that mimic real-world conditions, as existing methods often rely on static offline data, which may not reflect dynamic operating environments. An accelerated life test matrix for lithium-ion batteries is demonstrated in Figure 4.

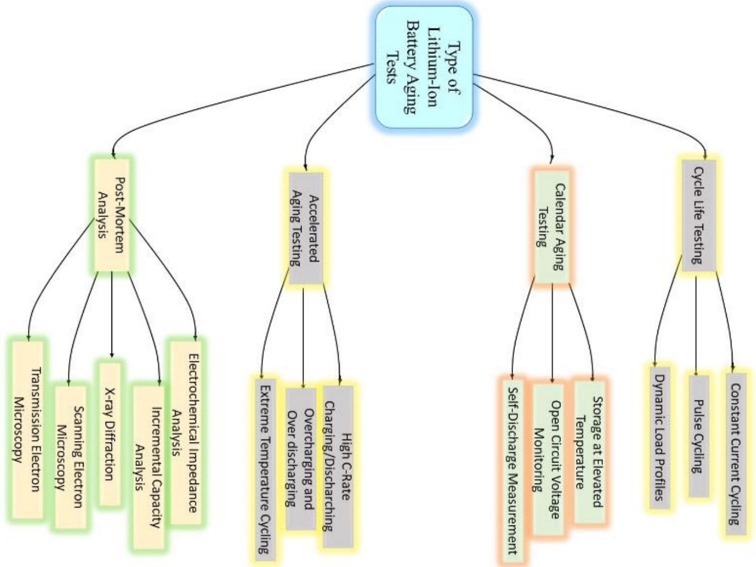

Figure 2. Different battery aging tests.

Temperature level 1 SOC level 1 Cycle Depth level 1	Temperature level 1 SOC level 2 Cycle Depth level 1	Temperature level 1 SOC level 3 Cycle Depth level 1
Temperature level 2 SOC level 1 Cycle Depth level 1	Temperature level 2 SOC level 2 Cycle Depth level 1	Temperature level 2 SOC level 3 Cycle Depth level 1
Temperature level 3 SOC level 1 Cycle Depth level 1	Temperature level 3 SOC level 2 Cycle Depth level 2	Temperature level 3 SOC level 3 Cycle Depth level 1

Figure 3. A characterization method for lithium-ion batteries and aging test matrix.

4. Aging of Lithium-Ion Batteries: Mechanisms, Diagnostics, and Emerging Solutions

Various types of battery aging mechanisms are illustrated in Figure 5. This section explores different modeling approaches and diagnostic methods used to understand and predict the aging of lithium-ion batteries.

Empirical and Semi-Empirical Modeling Methods:

Lithium-ion battery (LIB) aging is influenced by multiple stress factors, with solid electrolyte interphase (SEI) growth playing a significant role. Challenges in empirical modeling, including temperature dependence and inaccuracies in C-rate and depth of discharge (DoD) interactions, are acknowledged. Improved experimental designs and a cautious approach to current models are recommended to enhance predictions and support the electrification of transport [51].

Comprehensive Aging Mechanisms and Diagnostics:

The complexity of lithium-ion battery aging mechanisms is acknowledged, with a call for innovative approaches to improve battery health management. Advanced methods for online aging diagnosis, such as cloud computing and machine learning, are recommended. Implementation challenges related to data integration and compatibility with various applications are recognized. [52].

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Recent Research on Estimation Techniques:
Aging of lithium-ion batteries is driven by interrelated factors, resulting in capacity fade and increased resistance. Current estimation methods are deemed insufficient for capturing complex aging interactions. Development of real-time techniques is recommended to reflect all aging factors and improve diagnostics. [53].

Broader Examination of Battery Degradation:
Lithium-ion battery degradation is influenced by internal aging mechanisms, design, and usage conditions. Further research into high-energy-density chemistries and model-based optimization is recommended to mitigate degradation and extend battery lifespan. [54].

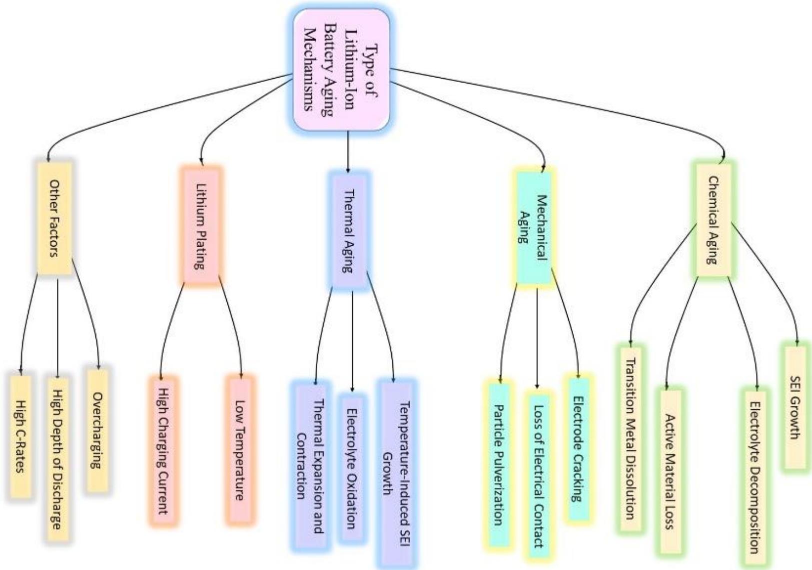

Figure 4. different types of Battery aging mechanism

Table 4. summary of battery aging.

Appearance	Key Findings	Research Directions	Ref
CEI Evolution	NCA interface evolution linked to H2-H3 phase.	Develop stable electrolytes and additives.	[55]
Volumetric Stresses	H2-H3 phase causes microcracks, worsening aging.	Study cathode/electrolyte degradation for optimization.	[56]
Capacity Decay	Degradation from side reactions, not H2-H3 phase.	Profile safety of Ni-rich cathodes.	[57]
Rock Salt Phase	Rock salt formation reduces NCA performance.	Use advanced methods to improve material performance.	[58]
Temperature Effects	High time accelerates aging and resistance.	Optimize thermal management strategies.	[58]
Storage Conditions	High charge and temperature worsen degradation; LFP better than NMC.		[58]

5. Summary
Electric vehicles rely heavily on lithium-ion batteries, but it is currently very difficult to forecast how these batteries will age. The complicated interactions between variables including temperature, charging rates, and the battery's state of charge (SOC) are often not adequately taken into consideration by current

approaches. It can be challenging to predict aging because of these interactions, which might have unpredictable and nonlinear impacts on battery performance.

A lithium-ion battery's internal aging process is influenced by several important aspects. These include lithium plating, electrode cracking, and the development of the solid electrolyte interphase (SEI). The design of the battery, including the selection of materials and electrode thickness, influences the course of these processes. External variables that affect capacity loss include temperature, battery charging speed, and discharge depth. When these elements combine, the effects of aging may be exacerbated, resulting in decreased performance and quicker deterioration.

Accelerated aging studies are necessary to replicate real-world circumstances and forecast the lifespan of electric car batteries. A major factor is temperature variations: high temperatures can cause the SEI to collapse, which accelerates degradation, and thermal runaway can result in a hazardous reduction in lifespan and efficiency. On the other hand, low temperatures have the potential to encourage lithium plating, which poses a major safety risk, as well as temporarily reduce capacity and raise internal resistance. Furthermore, either overcharging or undercharging upsets the battery's internal chemical equilibrium, hastening wear and tear and jeopardizing safety.

Battery aging can be effectively combated with a few tools. Smart algorithms and artificial intelligence are used by battery management systems to adapt to the battery's changing condition and assist slow down the aging process. It is possible to forecast degradation in real time with greater accuracy by utilizing models grounded in the physics of battery aging and integrating machine learning.

Current techniques of estimating the aging of lithium-ion batteries are inadequate because they fail to take into consideration the intricate relationships between several stressors, such as internal degradation mechanisms, charge/discharge cycles, and temperature changes. The instability of the SEI layer at high temperatures, lithium plating during low-temperature aging, and the effects of overcharge/overdischarge situations are some of the factors that lead to performance loss. Long-term stress exposure is associated with increased resistance and capacity loss, whereas temperature variations can hasten chemical deterioration. The risks of thermal runaway are reduced by thermal management systems and sophisticated safety features. Effective battery management strategies, such as machine learning and real-time monitoring, can extend battery life by modifying operations to lessen the impacts of aging.

6. Conclusion

In conclusion, lithium-ion battery degradation is influenced by various factors such as calendar aging, cycle aging, temperature, and charge/discharge efficiency. Calendar aging, which occurs even when the battery is not in use, is affected by temperature, state of charge, and electrode materials. Research is focused on mitigating this through improved designs and advanced modeling techniques like artificial neural networks. Cycle aging, caused by repeated charging and discharging, impacts capacity and internal resistance, with factors like temperature, current rates, and state of charge playing significant roles. Advanced models help predict and manage aging, especially under extreme conditions, to ensure safety and extend lifespan.

Temperature-related aging significantly impacts battery performance, with high temperatures accelerating degradation through SEI thickening and gas generation, while low temperatures cause capacity and power degradation. Effective thermal management is crucial for battery safety and performance. Charge/discharge efficiency aging, linked to overcharge/overdischarge conditions and Coulombic efficiency degradation, affects overall battery performance. Understanding these degradation patterns through accurate models is vital for improving battery management systems and enhancing battery safety and longevity.

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