

Review

Challenges and Opportunities for Extending Battery Pack Life Using New Algorithms and Techniques for Battery Electric Vehicles

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Abstract

The shift from Internal Combustion Engine Vehicles (ICEVs) to Battery Electric Vehicles (BEVs) has accelerated global efforts to decarbonize transportation. However, battery degradation, high costs, and limited lifespan remain critical barriers. This review synthesizes recent innovations to extend Li-ion battery life in BEVs by exploring advances in degradation modeling, adaptive Battery Management Systems (BMSs), electronic component simulations, and real-world usage profiling. The authors have systematically analyzed over 80 recent studies using a PRISMA-guided review protocol. A novel comparative framework highlights gaps in current literature, particularly regarding real-world driving impacts, ripple current effects, and second-life battery applications. This review article critically compares model-driven, data-driven, and hybrid model approaches, emphasizing trade-offs in interpretability, accuracy, and deployment feasibility. Finally, the review links battery life extension to broader sustainability metrics, including circular economy models and predictive maintenance algorithms. This review offers actionable insights for researchers, engineers, and policymakers aiming to design longer-lasting and more sustainable electric mobility systems.

Keywords: battery electric vehicle; extend battery life; adaptive battery management system



Academic Editor: Kan Akatsu

Received: 6 May 2025

Revised: 23 July 2025

Accepted: 24 July 2025

Published: 5 August 2025

Citation: Gonzalez-Rodriguez, P.S.; Lozoya-Santos, J.d.J.; Gonzalez-Hernandez, H.G.; Felix-Herran, L.C.; Tudon-Martinez, J.C. Challenges and Opportunities for Extending Battery Pack Life Using New Algorithms and Techniques for Battery Electric Vehicles. *World Electr. Veh. J.* **2025**, *16*, 442. <https://doi.org/10.3390/wevj16080442>

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1. Introduction

The escalating challenges of urban mobility necessitate the exploration of diverse transportation solutions. For decades, Internal Combustion Engine Vehicles (ICEVs) have dominated the market since their widespread adoption around 1920. However, the contemporary focus of smart cities increasingly emphasizes alternative transport methods, primarily to mitigate pollution. This shift positions electromobility as a crucial option for the future of urban environments [1].

The transition to Battery Electric Vehicles (BEVs) is propelled by several key factors: burgeoning market demand, international agreements like the Paris Agreement, and strategic decisions by Original Equipment Manufacturers (OEMs). Many OEMs, for instance, aim to phase out ICEVs production by 2030. Volkswagen, for example, has announced plans to cease manufacturing ICEVs starting in Europe, followed by the United States and China, all by 2030. The increasing global adoption of electric vehicles underscores a strong commitment to sustainability and reduction of carbon emissions, which is directly aligned with the objectives of the Paris Agreement [2].

Furthermore, the automotive industry is investing billions in the development of BEVs and their supporting technologies. This recognizes software's pivotal role in transitioning towards electrified and digitally integrated mobility. Such initiatives not only comply with environmental regulations but also aim to meet the growing consumer demand for cleaner and more efficient transportation options [2].

BEVs have gained significant prominence in recent years, largely due to the greenhouse gas emissions associated with ICEVs. It is reported that approximately 20.7% of global carbon dioxide (CO₂) emissions from transportation originate from ICEVs [3]. BEVs are designed to operate solely on electricity stored in a battery pack, eliminating the need for fossil fuels.

Beyond their environmental benefits, BEVs have seen improvements in areas enhancing user comfort, simplifying operation, and reducing driving noise [4]. Figure 1 illustrates the global sales of passenger BEVs from 2012 to 2024.

Despite their advantages, several challenges hinder BEVs from becoming the dominant commercial vehicles for future cities. The primary obstacle for electric vehicles lies in their energy storage system. Li-ion batteries, commonly used in BEVs, present four main issues: energy density, battery pack weight, safety technology, and their lifespan in automotive applications [5]. These problems are interconnected. Battery packs offer a lower energy density compared to an ICE, and recharging them takes significantly longer than refueling a gasoline tank.

Consequently, to achieve comparable energy output to an ICE vehicle, new techniques are developed that often require more batteries. This introduces a second challenge: the battery pack alone can account for approximately 40% of a BEV's total weight. This substantial weight negatively impacts vehicle efficiency and necessitates more advanced energy management and safety systems, further increasing manufacturing costs. As a result, a BEV's operational lifetime is significantly reduced by its performance, which is intrinsically linked to its discharge and charge cycles [6].

Ultimately, this often results in BEVs with a typical range of autonomy between 170 and 250 km, depending on usage. While their weight might be comparable to an ICE vehicle, their purchase price is higher, and they demand more drastic maintenance, often costing half the vehicle's price every 4 or 5 years. However, the current market is undergoing a significant transformation. By 2030, all major automotive companies are mandated to manufacture BEVs as their sole commercial vehicle. This establishes a critical deadline for electromobility to mature sufficiently, moving the ICE market into the past [7].

All these factors directly influence the needs of the final customer, whose goal is to seamlessly replace their ICE vehicle with a BEV. Key customer expectations include the widespread availability of charging centers, offering easy and fast charging comparable to gasoline refueling, and a similar total cost of ownership. Customers also expect equal or superior safety, enhanced passenger comfort, and reduced maintenance costs [8].

Recent innovations in battery chemistry, packaging, and simulation have reshaped EV design standards. A timeline of key battery milestones and a summary of dominant chemistries are provided in Section 3. The evolution of state-of-the-art BEV battery platforms—including 4680, Blade, and Ultium—is analyzed also in Section 3.

In light of these challenges, this article presents a comprehensive literature review on the current state of Li-ion batteries in BEVs. The review specifically addresses a critical concern: battery lifetime. This study explores both present limitations and future challenges associated with extending the operational life of Li-ion batteries in BEV applications [9].

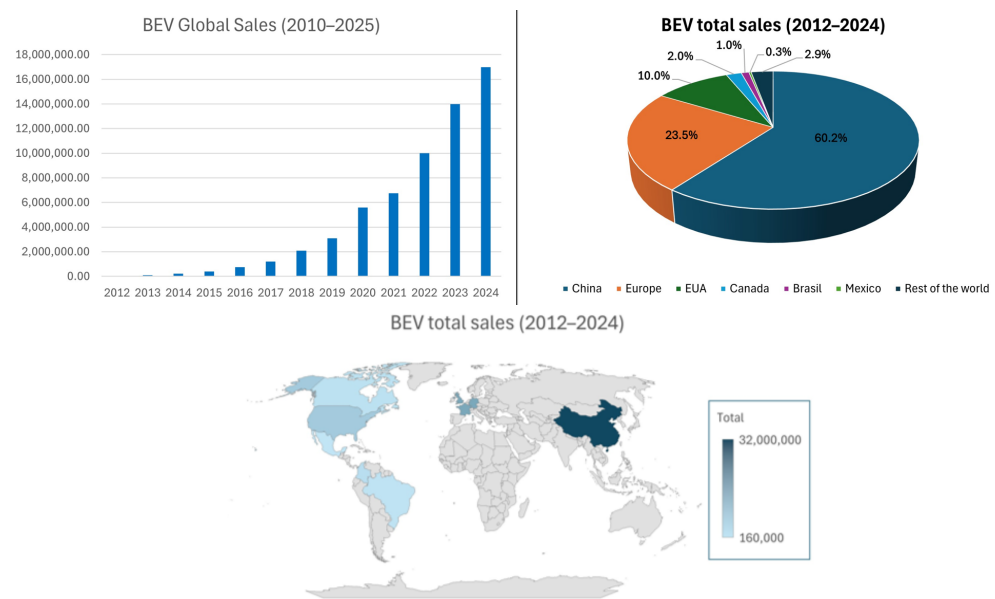


Figure 1. Global BEV sales between 2012 and 2024, according to [7].

Given the focus on the current landscape of Li-ion battery lifetime, this review seeks to answer the following overarching research question: **“What is the current performance and strategies for extending the lifetime of Li-ion batteries in BEV applications?”**, supported by several subquestions to delineate the scope:

- What are the key Battery Management System (BMS) functionalities or methodologies employed to monitor and predict Li-ion battery pack life in BEVs?
- What technologies and modeling approaches are utilized to simulate and study Li-ion battery pack behavior for lifetime assessment and prediction?
- What hardware and software components, and methodologies, contribute to extending the operational life of Li-ion batteries in BEV applications?

The main contributions of this work to the scientific community are as follows:

- Providing a comprehensive overview of Li-ion battery performance to enhance understanding of their life cycle in BEVs.
- Synthesizing existing literature on various techniques, methodologies, hardware, and software tools employed to assess and extend the lifetime of Li-ion batteries in BEVs.
- Identifying current challenges and highlighting significant research gaps in the field of BEV energy storage, specifically focusing on reducing costs and extending Li-ion battery lifetime.

The rapid global transition towards BEVs is driven by the urgent need to mitigate climate change and reduce reliance on fossil fuels, whose performance, range, and economic viability are intrinsically linked to the efficiency, lifespan, and degradation of their battery packs. Understanding and accurately predicting battery behavior under diverse real-world driving conditions, including the complex interplay with various electronic components, is therefore paramount for optimizing BEV design, operation, and maintenance.

While the academic literature boasts numerous valuable review papers on electric batteries and electric vehicles, a synthesized perspective that specifically links real-world driving conditions, detailed electronic component interactions, and their cumulative impact on battery degradation for BEVs remains less explored. Recent review efforts such as [10,11] provide extensive coverage of battery energy storage systems and lithium-ion commercialization in BEVs; however, they do not comprehensively explore the role of electronic subsystems or real-world degradation scenarios, which this review aims to address.

Table 1 provides an overview of recent and highly relevant review papers in this domain, highlighting their primary focus areas and identified limitations that are pertinent to our current scope.

Table 1. Overview of recent review papers on electric batteries and electric vehicles.

Author	Contribution/Scope	Primary Focus Area(s)	Research Gap/Limitation
[12]	Reviews recent advances in materials for improved electrochemical performance.	Li-ion battery materials	Focuses on material chemistry; limited on system-level degradation, real-world data, or electronic component impacts.
[13]	Systematically reviews models for degradation and Remaining Useful Life (RUL) prediction for Li-ion batteries.	Battery degradation modeling, RUL prediction	Focuses on model types; less on specific real-world driving impacts or auxiliary load effects.
[10]	Comprehensive review of BESS and advanced BMS for various applications (including BEVs), addressing challenges and recommendations.	BESS, advanced BMS, challenges	Broad scope across applications; less in-depth on specific BEV driving profiles and their component-level interactions.
[11]	Reviews battery materials, characteristics, and commercial values of Li-ion batteries in BEVs.	Li-ion batteries in BEVs, commercial application	Focuses on battery chemistry and market; limited on operational degradation or electronic influences.
[14]	Analyzes technical developments in BMS, power electronics, and charging techniques for BEVs.	Energy and Battery Management Systems for BEVs	Covers broad BMS aspects; less focus on fine-grained electronic component interactions with battery degradation.
[15]	Reviews combined effects of environmental and operational factors on Li-ion battery performance.	Li-ion battery performance, environmental and operational factors	Good on factors, but might not delve into specific electronic component behaviors within a BEV system.
[16]	Comprehensive review of algorithms for BMS in BEVs, covering estimation and optimization.	Advanced BMS algorithms for BEVs	Focuses on algorithms; less on empirical impact of diverse BEV electronic components on battery degradation.
[17]	EV battery reuse and recycling using ML strategies with privacy-preserving data	Li-ion second life	strong on reuse/recycle of retired batteries; sorting for profitable recycling; not oriented for studying service-life degradation.
[18]	Second-life batteries: from characterization to management	Li-ion second life	centers on second-life use; omits in-vehicle degradation and adaptive BMS focus.
[19]	Sustainability of EV batteries: life cycle assessment and recycling	Li-ion second life	Provides lifecycle insight; lacks degradation models and usage-cycle simulations.

As shown in Table 1, existing reviews often concentrate on specific aspects such as battery materials [12], general degradation models [13], or broad overviews of BMS and BESS applications [10,14]. While recent works have begun to explore the broader circular economy [17–19], there remains a discernible gap in comprehensive reviews that holistically integrate the interplay of dynamic real-world driving cycles, the energy consumption profiles of diverse electronic components, and their collective influence on battery aging and lifetime

extension strategies within the specific context of BEVs, explicitly linking these to overarching sustainability metrics. Furthermore, a unified critical comparison of the various modeling paradigms used for BEV battery characterization is often fragmented.

To clearly demonstrate the novelty and necessity of this review, Table 2 provides a comparative benchmarking of this review article against prior relevant reviews, highlighting what new perspectives or coverage this review offers over existing literature.

Table 2. Comparative benchmarking: proposed article review with respect to prior relevant reviews.

Coverage Area/Criteria	[13]	[10]	[16]	This Review Article
BEV Perspective (Vehicle + Battery + Electronics)	Partial	Moderate	Partial	Extensive
Impact of Real-World Driving Cycles on Battery Degradation	Low	Moderate	Moderate	High
Specific Electronic Component (HVAC, Ripple Current) Impact on Battery Aging	Limited	Limited	Limited	Comprehensive
Adaptive BMS Strategies for Degradation Management	Moderate (general models)	Moderate (BMS overview)	High (algorithm focus)	High (Degradation-aware and adaptive)
Battery Degradation Modeling (Physics-based, Data-driven, Hybrid)	High (model types)	Moderate	Moderate	High (Operational-data integration)
Fast Charging Impacts on Battery Life	Low	Moderate	Moderate	High (System-level and operational)
Heavy-Duty EV Specific Battery Challenges	No	No	No	Dedicated Analysis
Synthesis of Simulation Strategies for BEV Characterization	Limited	Moderate	Moderate	Core Focus
Second-Life Applications	No	Low	High (recycling focus)	Dedicated Section
Battery Recycling	No	Low	High (LCA focus)	Dedicated Section
Integrated Lifecycle Sustainability (Beyond Battery Performance)	Limited	Limited	High (general)	High (Algorithm-linked)

As further illustrated by the comparative analysis in Table 2, this review distinguishes itself from prior works by offering a uniquely integrated perspective. While existing literature often focuses on isolated aspects such as specific degradation mechanisms [13], broad BMS overviews [10,16], or general sustainability themes [19], our review provides a comprehensive synthesis that:

- Explicitly links the impact of dynamic real-world driving cycles and the energy demands of diverse electronic components (e.g., Heating, Ventilation, and Air Conditioning (HVAC), power electronics generating ripple currents, etc.) on battery aging;
- Provides a detailed examination of simulation strategies specifically tailored to capturing these complex, interdependent interactions for BEV characterization;
- Incorporates discussions on emerging adaptive BMS strategies with a direct focus on degradation-aware control and optimal charging;
- Dedicates attention to the specific and often underexplored challenges of heavy-duty BEVs, identifying critical gaps for future research in this vital segment;
- Critically examines the downstream lifecycle stages of BEV batteries, including second-life applications and recycling, and integrates these with in-service performance;
- Explicitly links battery life extension strategies and advanced algorithms to broader lifecycle sustainability metrics;
- Presents a unified and critical comparison of model-driven, data-driven, and hybrid modeling methodologies.

By bridging these interdisciplinary areas, this review offers a novel and essential resource for understanding and advancing battery lifetime extension and holistic sustainability in contemporary BEV applications.

This work is structured as follows: Section 2 outlines the methodology for literature acquisition, including its statistical overview and additional relevant information; Section 3 presents the synthesized results and key findings from the literature review; and finally, Section 4 offers conclusions and proposes future courses of action to address the identified challenges.

2. Literature Review

This study employed a rigorous systematic literature review methodology to comprehensively analyze existing scientific literature concerning Li-ion battery lifetime in BEV applications. The review aimed to identify current findings and challenges within electromobility, with a specific focus on strategies for extending battery lifespan.

To ensure a thorough and transparent search, a systematic search was conducted across multiple prominent scientific databases: **Web of Science, IEEE Xplore, Elsevier, MDPI, and SAE Digital Library**. The search strategy was meticulously designed to identify studies exploring tools or strategies aimed at extending the lifetime of Li-ion batteries in BEV applications.

The selection and screening process for the relevant papers adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology (PRISMA 2020 guidelines were followed) [20]. This framework guided the identification, screening, eligibility assessment, and inclusion of studies. The following specific inclusion and exclusion criteria were applied:

- **Inclusion Criteria:**
 - **Publication Period:** Papers published within a recent five-year period (2019–2024, inclusive) were prioritized to ensure a focus on the most current state-of-the-art strategies, technologies, and tools for optimizing and extending Li-ion battery life in BEVs.

- **Publication Type:** Peer-reviewed journal articles, conference papers, and comprehensive review articles.
- **Language:** Articles published in English.
- **Focus:** Studies specifically addressing Li-ion batteries in BEV applications.
- **Relevance:** Papers discussing battery lifetime, degradation mechanisms, BMS, predictive modeling, or technologies/strategies for lifetime extension.
- **Impact and Citations:** While not strict exclusion criteria, articles from high-impact journals (Q1 or Q2) were prioritized for more detailed review. Additionally, highly cited papers (both journal and conference articles) were given precedence to identify foundational work, significant advancements, or consensus on challenges. Review articles were specifically sought to identify milestones and current research gaps. Among these, refs. [10,11] were identified as two key recent reviews offering broad but non-specialized insights into battery systems and BEV commercialization, which helped contextualize the more targeted scope of the present work.
- **Methodological Approach:** Emphasis was placed on articles that implemented a simulation tool, specific strategy, physical prototype, digital twin, or laboratory tests to understand and extend the behavior and lifetime of Li-ion batteries in various BEV applications.
- **Exclusion Criteria:**
 - Studies focusing solely on other battery chemistries (solid-state, NiMH) unless directly compared to Li-ion in a relevant context.
 - Articles primarily on grid-scale energy storage, consumer electronics, or other applications not directly related to BEVs.
 - Non-peer-reviewed sources (blogs, general news articles, white papers without clear academic rigor).
 - Duplicate publications across databases.
 - Purely theoretical papers without practical implications or experimental/simulation validation for BEV batteries.

Search Strategy Details:

The search queries were meticulously formulated using a combination of keywords and Boolean operators to maximize relevance and coverage across the selected databases. The keywords were structured into four main sections, reflecting critical areas influencing battery performance and degradation:

1. **Driving degradation Profile:** (“Driving profile”, “Driving cycle”, “Battery aging”, “battery aging”, “battery degradation”, “battery life impact”, “BEV”, “Battery Electric Vehicle”, “Overview”, “Extend battery life”, “battery optimization”, and “low battery performance”)
2. **Driving Performance:** (“Eco-driving”, “Driving hard conditions”, “Driving cycle”, “Battery aging”, “battery degradation”, “battery life impact”, “Electric Vehicle”, “BEV”, “Battery Electric Vehicle”, “vehicle applications”, and “low battery performance”)
3. **Battery Management System (BMS):** (“BMS”, “Energy Management System”, “Electric Vehicle”, “BEV”, “Battery Electric Vehicle”, “vehicle applications”, “Overview”, “Extend battery life”, “battery optimization”, and “low battery performance”)
4. **Batteries Li-ion Performance:** (“Battery effects”, “battery degradation”, “Li-ion new components”, “Battery Electric Vehicle cycle test”, “Laboratory test”, “State-of-art”, “Extend battery life”, “battery optimization”, and “low battery performance”)

Data Extraction and Synthesis:

For each included study, relevant data were systematically extracted, including:

- Author(s), publication year, and journal/conference.
- Study design (experimental, simulation, review).
- Specific Li-ion battery chemistry.
- Key findings related to battery lifetime or degradation mechanisms.
- Identified challenges or limitations.
- Proposed solutions, methodologies, or technologies for lifetime extension (specific BMS algorithms, thermal management strategies, cell balancing techniques, simulation models, digital twin implementations, novel materials, charging protocols).
- Type of validation (simulation, laboratory test, field data).

With these defined parameters and the methodology implemented for the literature, 85 articles were reviewed in detail, 60 of which were analyzed. From Figures 2–5, the scientometrics of the literature review is illustrated according to the particular domain of interest studied in this paper.



Figure 2. Data publications of driving profile degradation in Scopus.

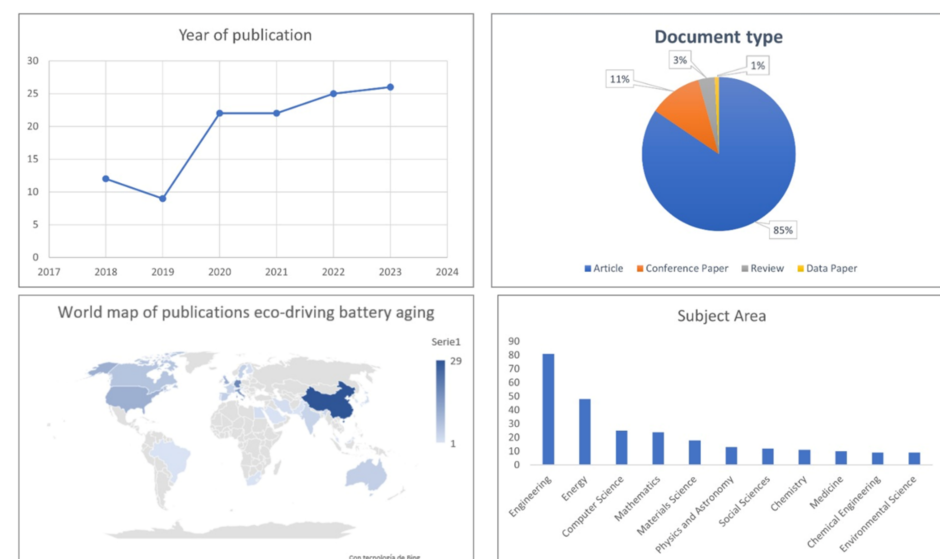


Figure 3. Data publications of driving performance in Scopus.

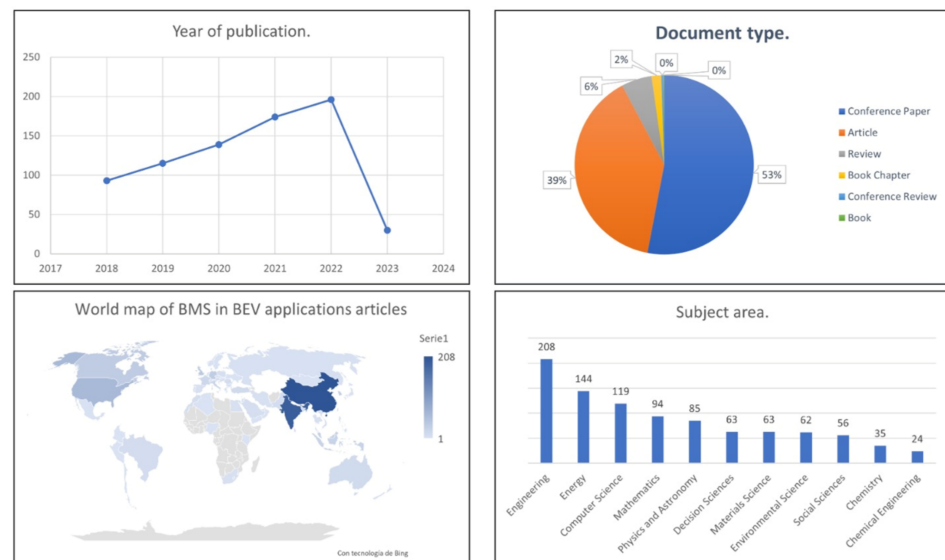


Figure 4. Data publications of Battery Management System in Scopus.



Figure 5. Data publications of Li-ion batteries in Scopus.

Figure 2 shows the volume of related publications over time, indicating a consistent increase in research activity and the growing relevance of driving degradation profiles. Figure 3 identifies the contributions most significant to the literature, focusing on global research on driving performance. Figure 4 presents the most relevant keyword searches related to this paper, highlighting the primary areas of interest in BMS. Finally, Figure 5 maps the distribution of scientific contributions, revealing key regions leading in this area of study of Li-ion batteries.

The extracted data were then synthesized thematically to address the research questions and objectives outlined in the introduction. A descriptive analysis of the included studies, including publication trends and geographical distribution, is presented in Section 3.

3. Results

This section presents the key findings extracted from the systematic literature review, offering a clear understanding of the primary factors that significantly impact Li-ion battery behavior and lifespan in BEVs. Furthermore, it highlights various solutions and strategies implemented in the literature to address these identified challenges.

The review reveals that battery behavior and lifespan are influenced by a complex interplay of factors, including operational conditions (charge/discharge rates, temperature, depth of discharge), environmental factors, and the effectiveness of the BMS. As an illustrative example, Figure 6 demonstrates the dynamic behavior of a BEV battery pack under varying load conditions. Such fluctuations directly influence the vehicle's performance and overall energy efficiency.

For instance, rapid discharge during high acceleration phases can significantly impact voltage stability and battery internal resistance, while efficient regenerative braking directly affects charge recovery efficiency. Comprehending these intricate behaviors is essential for optimizing the energy management system and, consequently, extending the operational lifespan of BEV batteries.

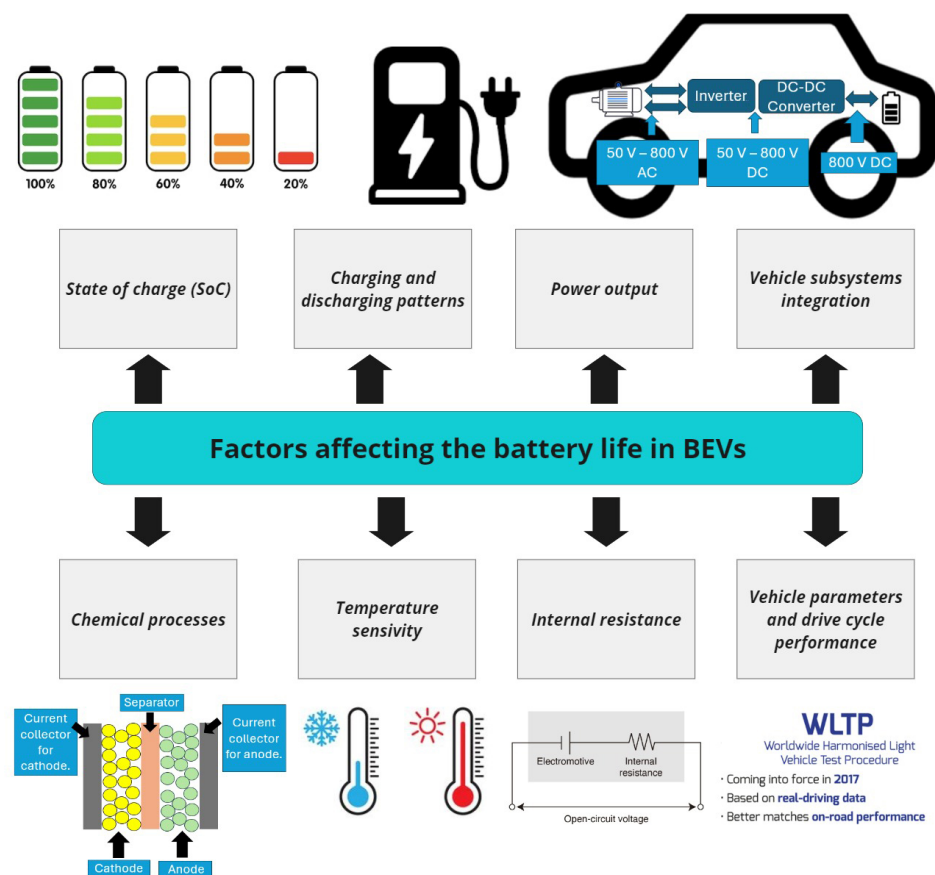


Figure 6. Diagram of factors that affect battery life in BEVs.

3.1. Li-Ion Battery Behavior in BEV Applications

Battery packs constitute the primary energy storage unit in BEVs, fundamentally determining driving range, acceleration, and overall vehicle performance. Key aspects of battery performance analysis include the State of Charge (SoC), electrochemical reactions during charging and discharging, thermal behavior under varying operating conditions, power output stability, and internal resistance fluctuations.

Understanding how these factors interact with vehicle-level parameters such as speed, load, and driving mode is crucial. Additionally, the seamless integration of the battery with subsystems like the powertrain, regenerative braking, and thermal management systems plays a pivotal role in determining overall efficiency and durability.

3.1.1. State of Charge (SoC)

The State of Charge (SoC) is a critical parameter that quantifies the remaining available energy in the battery pack, providing essential information to drivers regarding available driving range, much like a fuel gauge in ICE vehicles. Effective SoC management is vital for ensuring the vehicle reaches its destination and for optimizing energy consumption. Vehicle control systems leverage SoC data to prevent deep discharge, which can be detrimental to battery life.

Furthermore, SoC plays a role in determining optimal activation of regenerative braking for energy recovery during deceleration. The dynamic effects of SoC are particularly evident during charging and discharging cycles, whether from regenerative braking, connection to a charging station, or normal vehicle operation. The rate of these processes significantly influences acceleration and overall vehicle dynamics.

3.1.2. Chemical Processes

As shown in Figure 7, a BEV battery pack comprises multiple Li-ion cells, each containing an anode, a cathode, and an electrolyte. These components facilitate the electrochemical reactions essential for energy storage and release during charging and discharging cycles [21].

The specific arrangement and chemical composition of these cells directly impact the battery's energy density, cycle life, and thermal performance. During charging, lithium ions intercalate from the cathode to the anode; conversely, during discharging, they deintercalate from the anode back to the cathode, releasing electrical energy.

The behavior of these batteries is highly dependent on the manufacturer's chosen chemistry and materials, which in turn influence critical factors such as energy density, thermal performance, and cycle life [22].

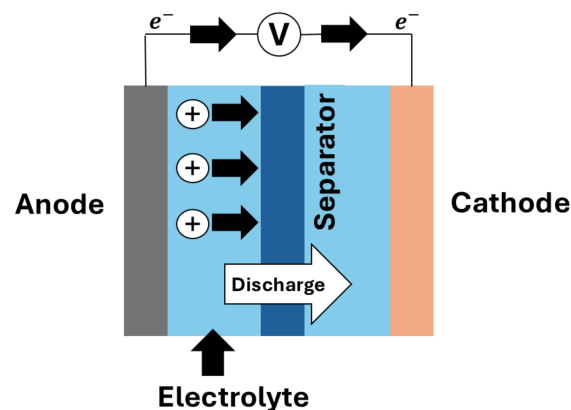


Figure 7. Schematic illustration of rechargeable battery chemistry.

3.1.3. Charging and Discharging Patterns

Charging and discharging processes are fundamental to a BEV's operation. When connected to a charging station, electrical energy is transferred to the battery pack, initiating chemical reactions that store energy. Conversely, during vehicle operation, the battery discharges, supplying energy to power the electric motor and propel the vehicle. The rate of these charging and discharging cycles significantly impacts a BEV's performance and battery longevity.

The increasing prevalence of fast-charging stations enables rapid BEV recharging, crucial for extended travel. However, rapid energy transfer inherently generates substantial heat within the battery cells. Effective thermal management of this heat buildup is paramount for ensuring both safety and the long-term health of the battery.

This challenge necessitates advanced cooling strategies to prevent overheating and accelerated degradation during fast charging cycles. Manufacturers are continuously developing more robust battery chemistries and enhanced thermal management systems to ensure fast charging is both safe and efficient.

3.1.4. Temperature Sensitivity

Temperature is a critical environmental factor significantly influencing the lifetime and overall performance of Li-ion batteries in BEV applications. These batteries exhibit high sensitivity to temperature fluctuations, making the maintenance of an optimal operating temperature range essential for maximizing their longevity and ensuring safety.

One primary consequence of suboptimal temperatures is capacity fade, which is the gradual reduction in a battery's ability to hold charge over time. Elevated temperatures, particularly sustained high temperatures, accelerate this process. Prolonged exposure to high temperatures promotes increased parasitic side reactions within the battery. These reactions can lead to the irreversible consumption of lithium ions, often through the accelerated formation of Solid-Electrolyte Interphase (SEI) layer components. This permanent loss of active lithium directly reduces the battery's usable capacity, thereby diminishing the BEV's driving range.

Beyond capacity fade, Li-ion batteries are highly susceptible to safety risks at elevated temperatures. Extreme heat can lead to **thermal runaway**, an uncontrolled chemical reaction within the battery that generates further heat, potentially resulting in fire or explosion. This poses a significant safety hazard to the BEV and its occupants.

Temperature-induced degradation also affects the battery's electrolyte. At elevated temperatures, the electrolyte can decompose, leading to the release of volatile and flammable gases. This decomposition not only impairs the electrolyte's effectiveness but also contributes to thermal runaway events by increasing internal pressure within the battery cells.

3.1.5. Power Output

Power output refers to a battery's capability to deliver electrical energy at the rate required for vehicle propulsion, acceleration, and overall dynamic performance in BEV applications. This output is directly linked to the battery's ability to provide high power levels on demand.

Li-ion batteries experience wear and tear throughout their operational life, with high-power discharges being a significant contributing factor. Such discharges generate heat and induce chemical reactions within the cells, accelerating SEI layer formation and degrading electrode materials. Consequently, the battery's internal resistance increases, leading to reduced power output and overall capacity over time.

Inadequate thermal design in response to power demands, especially during rapid charging or discharging, can lead to detrimental thermal effects. High-power operations inherently generate heat within the battery. Excessive heat accelerates degradation and thermal stress. To mitigate these effects, BEVs are equipped with sophisticated thermal management systems that regulate cell temperatures. Should temperatures exceed safe limits, both immediate power output and long-term battery health are negatively impacted.

Power demand is also intricately linked to capacity loss. As a battery ages and experiences capacity fade, its inherent ability to deliver high power diminishes. This reduction in power output directly affects the driving performance perceived by BEV owners as the battery ages. Effective management of power output is therefore crucial for extending the useful life of the battery and maintaining satisfactory vehicle performance throughout its operational lifespan.

3.1.6. Internal Resistance

Internal resistance represents the opposition to the flow of electric current within a battery and is pivotal in determining its energy storage and delivery efficiency. During both charging and discharging, Li-ion batteries incur energy losses primarily as heat due to this internal resistance. This resistance originates from several factors, including electrolyte resistivity, electrode material properties, and interface resistances between different battery components.

A battery's internal resistance significantly impairs its overall efficiency by converting usable electrical energy into waste heat. As current traverses the battery, voltage drops occur across the internal resistance, leading to reduced usable power output. This generated heat not only diminishes energy efficiency but can also accelerate battery degradation if not adequately managed. Maximizing efficiency is critical in BEV applications to extend driving range and enhance overall vehicle performance.

During high-power demand scenarios in a BEV, such as rapid acceleration or climbing steep inclines, the battery's internal resistance can cause **voltage sag**. This phenomenon occurs when the battery's voltage output temporarily drops below its nominal level due to internal resistive losses [23]. Voltage sag critically impacts vehicle performance: a reduced voltage means the electric motor receives less power, leading to diminished acceleration and overall responsiveness. This effect is particularly pronounced in BEVs with smaller or older battery packs, where internal resistance tends to be higher.

The escalation of internal resistance is often exacerbated by battery heating during operation. As current flows through the battery's internal components, energy dissipates as heat. This heat generation is particularly significant during high-power operations like fast charging or rapid acceleration. Effective thermal management is thus crucial for maintaining battery health and longevity.

Excessive heat accelerates the degradation of electrode materials and other components, leading to a reduction in capacity and power output over time. BEVs employ advanced thermal management systems, such as liquid or air cooling, to regulate battery temperature and counteract the detrimental effects of internal resistance-induced heat.

Furthermore, internal resistance contributes to cycle aging, a process where the battery's capacity gradually diminishes with each charge-discharge cycle. Energy lost as heat during cycling imposes increased stress on battery components. Over repeated cycles, this cumulative effect can accelerate the formation of the SEI layer on electrode surfaces.

An expanding SEI layer reduces the availability of lithium ions for electrochemical reactions, ultimately leading to a decline in battery capacity and overall performance. Therefore, minimizing internal resistance is essential to mitigate cycle aging and capacity fade, thereby extending the battery's useful lifetime.

3.1.7. Vehicle Parameters and Drive Cycle Performance

The design of a BEV, encompassing its weight, aerodynamics, and powertrain, profoundly influences the behavior and operational lifespan of Li-ion batteries. A BEV's weight directly dictates battery utilization. Heavier vehicles necessitate larger battery packs to achieve a desired driving range; these packs typically involve more cells in parallel to supply the required energy. However, increased vehicle weight can subject battery cells to higher mechanical stress, potentially accelerating wear and degradation.

Vehicle aerodynamics play a significant role in energy consumption. Improved aerodynamics reduce the energy needed to overcome air resistance at higher speeds, thereby extending the driving range. When the battery operates under lower power demands due to better aerodynamics, it experiences less stress and heat generation, which contributes to a longer lifespan. Similarly, the efficiency of the electric powertrain dictates how ef-

fectively the battery's stored energy is converted into vehicle motion. A more efficient powertrain translates to less energy loss during propulsion, leading to reduced battery heating and wear. Thus, efficient powertrains maximize overall BEV efficiency and contribute to extended battery life.

Drive cycle performance refers to how a BEV operates under real-world driving conditions, including various patterns of acceleration, deceleration, and steady-state cruising. Different drive cycle parameters significantly impact Li-ion battery lifespan. Frequent speed changes and variations, common in stop-and-go traffic, result in more frequent battery cycling and higher peak power demands, potentially accelerating aging. In contrast, consistent, steady-speed driving generally imposes less stress on the battery.

The type of drive cycle, whether highway or city driving, affects the battery distinctively. Highway driving typically involves sustained higher speeds and greater continuous energy consumption, while city driving is characterized by more frequent stops and starts with intermittent high-power demands. BEVs experience varying degrees of battery stress depending on the dominant driving environment.

Ultimately, user driving patterns critically influence Li-ion battery lifespan. Drivers who frequently engage in aggressive behaviors, such as rapid acceleration and hard braking, subject the battery to greater mechanical and thermal stress. Conversely, more efficient and gentle driving habits can significantly help prolong battery life.

3.1.8. Vehicle Subsystem Integration

Figure 8 illustrates the intricate integration of the battery pack with key BEV subsystems, including the electric motor, power electronics, regenerative braking system, and the BMS. This integration ensures coordinated energy flow, efficient power delivery, and real-time monitoring of battery health and safety, all of which are paramount for optimal and reliable BEV performance.

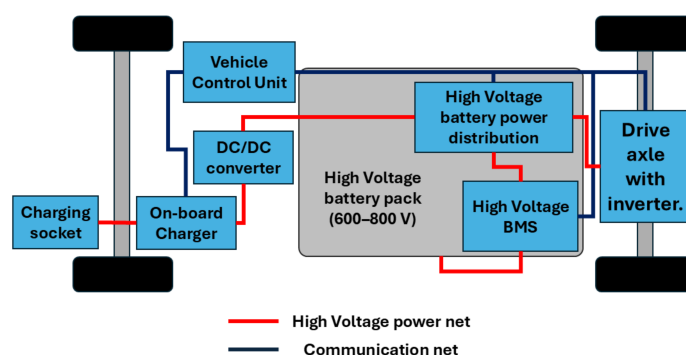


Figure 8. Subsystems with essential components in a BEV.

The electric motor receives power from the battery pack and converts it into mechanical energy for vehicle propulsion. Power electronics control the precise flow of energy between the battery pack and the motor. The BMS, as a central component, is responsible for continuous monitoring and active management of the battery's health, ensuring operation within safe parameters and optimizing performance. Efficient integration and seamless coordination among these systems are essential for maximizing energy efficiency and overall vehicle performance.

One of the distinctive features of BEVs is regenerative braking. During deceleration and braking, electric motors can function as generators, converting kinetic energy back into electrical energy. This recovered energy is then efficiently returned to the battery pack for storage and subsequent use. The efficient capture and release of regenerated energy

are crucial for maximizing overall energy efficiency and reducing wear on conventional friction brake systems, thereby decreasing maintenance costs.

3.1.9. Battery Technology Evolution

Battery technology for electric vehicles has undergone major evolution in the past 15 years, moving from early adoption of NCA-based Li-ion cells to large-format pouch and tabless cylindrical cells, and toward promising breakthroughs in solid-state chemistries. Table 3 presents a timeline of selected milestones between 2010 and 2025 that have significantly impacted the performance, manufacturing, and packaging of BEV battery systems.

Table 3. Timeline of BEV battery technology evolution (2010–2025).

Year	Technological Milestone or Innovation
2010	Nissan Leaf launched with air-cooled pouch-cell Li-ion batteries (NMC, 24 kWh) [24].
2013	Tesla Model S popularizes NCA chemistry and large cylindrical 18,650 cells with liquid cooling [25].
2016	Introduction of NCM811 cells for higher energy density and reduced cobalt usage [26].
2018	CATL introduces cell-to-pack (CTP) technology, improving volumetric efficiency and thermal management [27].
2020	BYD launches “Blade Battery” using LFP chemistry in prismatic format with high safety and cycle life [28].
2021	Tesla unveils 4680 tabless cylindrical cell offering higher energy, power, and simplified manufacturing [29].
2022	Toyota announces solid-state battery prototypes with 1200 Wh/L energy density and 80% charge in 10 min [30].
2024	QuantumScape and Solid Power report progress on lithium-metal and solid-state batteries targeting commercial deployment [31].

To complement these milestones, Table 4 summarizes key commercial Li-ion chemistries currently deployed in BEVs, highlighting trade-offs across safety, performance, and energy metrics.

Table 4. Dominant BEV battery chemistries and performance metrics (2024).

Chemistry	Energy Density (Wh/kg)	Cycle Life (to 80%)	Thermal Stability	Commercial Use
NCA (LiNiCoAlO ₂)	250–300	1000–1200	Moderate	Tesla (18,650, 2170)
NMC811	230–280	1200–1500	Moderate	Hyundai, BMW
LFP (LiFePO ₄)	160–200	2000–3000	High	BYD, Tesla (China)
LMFP (LiMnFePO ₄)	190–230	1500–2500	High	Emerging in 2025 models
Solid-State (Li-metal)	350–500 (theoretical)	TBD	Very High	Toyota, QuantumScape (R&D)

These developments illustrate the trajectory of BEV battery design toward safer, more energy-dense, and cost-effective solutions. The evolution toward solid-state technologies promises a potential paradigm shift, though commercial scalability remains a challenge.

3.2. Findings in Literature Review: Strategies for Lifetime Extension

Building upon the comprehensive understanding of the intrinsic factors and components that influence the lifetime of Li-ion batteries in BEV applications, this literature review now presents a synthesis of various strategies employed in the scientific literature to extend battery operational life.

Rather than merely summarizing individual contributions, this section aims to identify overarching trends, compare methodological approaches, and highlight common challenges and emerging solutions in battery lifetime extension. These strategies are systematically grouped into thematic categories to facilitate a clearer comprehension of current advancements, their practical implementation, and critical areas for future investigation.

3.2.1. Simulation Strategies for Characterizing BEV Battery Behavior in Road Conditions

Simulation plays a pivotal role in the development and evaluation of BEVs, enabling the assessment of battery behavior under diverse operational conditions encountered during real-world road use. While standardized driving cycles are fundamental for initial design validation and energy consumption evaluation based on vehicle dynamics and speed, their representativeness of complex, actual driving patterns can be limited. Addressing this gap requires more sophisticated simulation strategies that can accurately capture the nuances of real-world usage and their impact on battery degradation.

The literature extensively demonstrates the application of various simulation strategies to understand and predict BEV battery performance and degradation. Collective findings from these studies, which are detailed across Tables 5 and 6, provide comprehensive insights into how road conditions and driving styles influence energy consumption and, consequently, battery stress.

A primary focus of simulation studies involves analyzing the impact of different road types on the energy consumption of BEVs using real-world data [32]. This addresses a noted research gap regarding studies exploring such impacts under realistic conditions. These analyses go beyond basic vehicle dynamics, identifying key factors that significantly influence BEV efficiency during specific driving cycles, including average speed, stop-and-go frequency, road gradient, and acceleration patterns. Furthermore, methodologies are employed to synthesize representative real-world cell aging tests for battery packs. This involves meticulously characterizing cell duty cycles and synthesizing driving cycle profiles through advanced techniques such as Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Power Spectral Density (PSD), and Welch's method, as demonstrated by [33]. Such approaches aim to ensure that simulated test conditions accurately reflect the complex electrical and thermal stresses batteries experience in diverse real-world driving environments.

Table 5. Data findings about contribution and research gap in simulation strategies for characterizing BEVs.

Author	Contribution	Algorithms or Mathematical Model	Research Gap
[34]	Performance constraints and needs of electric semi-trucks, including a comparison of their cost, range, payload capacity, and energy usage.	Standard dynamic vehicle model and a Monte Carlo simulation to estimate truck parameters	Analysis of performance and needs of electric semi-trucks, focusing on battery metrics and vehicle design parameters in the trucking sector.
[32]	Impact of different road types on the energy consumption of BEVs using real-world data.	Linear regression models, stepwise selection, ANOVA, Grubbs' test, and the Jarque-Bera test	Lack of studies exploring the impact of road types on the energy consumption of BEVs in real-world conditions.
[33]	Test methodology to characterize and synthesize battery duty cycles from real-world driving data	Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Power Spectral Density (PSD), and Welch's method.	Apply the framework in new datasets of real-world driving data and different battery chemistries.
[35]	Evaluates different driving cycles electric vehicle battery degradation using different methods.	The degradation model results are interpolated in the Hermite Cubic Interpolation Polynomial (PCHIP).	Studies applied in electric heavy-duty trucks' battery degradation and data-driven strategies for real-time monitoring.

Table 5. Cont.

Author	Contribution	Algorithms or Mathematical Model	Research Gap
[36]	Predict in-vehicle performance degradation of batteries using real-world driving data.	Performance-based models of NCM-LMO Li-ion variant batteries.	Thorough and practical evaluation of battery degradation in BEVs under different usage scenarios.
[37]	Twin framework predicts Li-ion cell degradation using a comprehensive lab dataset and validates its effectiveness against other models.	Specific mathematical equations, Rainflow counting algorithm, and Root-mean-squared error metric.	Need for a practical lifetime modeling approach for Li-ion cells, considering analysis of aging factors, and model validation with real data.
[38]	Performance and degradation of a LiFePO4 Li-ion battery cell are influenced by climate control loads and battery thermal preconditioning.	Equivalent circuit model, a modified version of Ning's model for battery degradation, and a thermal model of the vehicle cabin.	Lack of real-life vehicle operation data for modeling battery degradation in BEVs.
[39]	Experimental testing and analysis of a Li-ion battery for BEVs leads to develop a lifetime model that calculates total capacity loss under different scenarios.	Dynamic model of a BEV, an AC motor model, incremental capacity, differential voltage analysis, and a lifetime model.	There is a gap in studies on real-world aging mechanisms of Li-ion batteries, and lifetime models to estimate capacity loss under different scenarios.
[40]	Experimental study on battery aging in BEVs, focusing on the impact of regenerative braking at different conditions.	Electrochemical impedance spectroscopy (EIS) and Coulomb tracking are used to study battery aging in BEVs.	Insufficient experimental studies on how dynamic driving loads and regenerative braking impact battery aging in BEVs.
[41]	Dataset of Li-ion battery cells, tested over 23 months under real BEV discharge scenarios, supports the development of models and management strategies for electric vehicles.	An electrochemical model-based adaptive interconnected observer is used for data collection and battery degradation evaluation.	Lack of experimental data on Li-ion battery aging under real-driving scenarios for BEVs, and existing datasets fail to capture the complexity of real-world operation.

Table 6. Data findings about experimentation, tools, and results in simulation strategies for characterizing BEVs.

Author	Simulation or Experimentation	Object of Study	Measurement and Analysis Tools	Results
[34]	Simulation	Performance limitations and requirements of electric semi-trucks based on battery metrics and vehicle design parameters.	DriveCAT	Li-ion batteries, currently unsuitable for electric trucks, could potentially be used if they attain over 400 Wh/kg specific energy and cost under USD 100/kWh.
[32]	Simulation and Experimental test	Impact of road types on the energy consumption of a 2017 Volkswagen eGolf in real-world conditions.	Controller area network (CAN) bus gateway with a data logger.	Energy consumption of BEVs is influenced by road types, with medium speed and low variation roads being the most efficient.

Table 6. Cont.

Author	Simulation or Experimentation	Object of Study	Measurement and Analysis Tools	Results
[33]	Simulation and Experimental test	NMC batteries in a 48 V hybrid vehicle	MATLAB, Arbin BT-2000 battery cyclers and MITS Pro data acquisition software	Temperature and driving style have significant impacts on the cell capacity loss.
[35]	Simulation	NMC battery cells in electric heavy-duty trucks	Alawa toolbox (developed by the authors and was not publicly available).	Real driving conditions affect battery degradation, with irreversible lithium plating being the primary factor.
[36]	Simulation	NCM-LMO Li-ion batteries.	Transport Technology and Mobility Assessment (TEMA) platform.	Battery aging is affected by factors such as temperature, recharging, and driving distance.
[37]	Experimental test	48 commercial NMC Li-ion cells with a rated capacity of 43 Ah and a nominal voltage of 3.6 V.	Battery cyclers, climate chambers, and the Hybrid Pulse Power Characterization test procedure.	The model can predict the capacity fade and the resistance growth with an error of 1.31% and 0.56%.
[38]	Simulation and experimental results	LiFePO ₄ battery in a plug-in hybrid electric vehicle.	Autonomy software, MATLAB, a powertrain test stand, and a converted EV are used.	Usage scenarios, climate control loads, and battery thermal preconditioning impact vehicle performance, range, and battery life degradation.
[39]	Simulation and experimental test	Li-ion battery for BEVs, focusing on its capacity loss, internal impedance variation, and degradation mechanisms.	Bitrode cycler, a climate chamber, the WLTP CLASS 3B driving cycle, a dynamic model of a BEV, and an AC motor model are employed.	The experimental tests revealed a 10% capacity loss and a 50% increase in internal impedance in the Li-ion battery.
[40]	Experimental test	The Li-ion batteries Panasonic NCR18650PD and the driving load profile US06 highway.	32-channel BaSyTec CTS battery test system, a GAMRY G750 galvanostat/potentiostat, and a coulometry method.	Regenerative braking and optimal operating temperatures around 25°C are key factors influencing the performance and aging of Li-ion batteries in BEVs.
[41]	Experimental test	INR21700-M50T Li-ion battery cells. These cells are tested over 23 months under a BEV discharge profile.	Arbin LBT21024, Amerex IC500R thermal chamber, Gamry EIS 1010E, T-type thermocouple sensor, and MITS Pro software.	Dataset of Li-ion battery cells tested under real BEV scenarios, enabling the development of models and management strategies.

Beyond these foundational analyses of driving cycles, simulation enables the development of advanced battery models crucial for comprehensive lifetime prediction. For instance, studies focus on constructing comprehensive aging models that account for multiple

relevant degradation factors, with frameworks like the “twin framework” proposed by [37] demonstrating high accuracy in predicting capacity fade and resistance growth through robust validation against comprehensive laboratory datasets. Such sophisticated models, often leveraging mathematical equations, Rainflow counting algorithms, and error metrics, serve as invaluable tools for forecasting battery lifetime based on dynamic operational profiles, addressing the critical need for robust lifetime modeling and detailed analysis of aging factors.

3.2.2. Impact of Real-World Driving Cycles and Usage Profiles

The performance and degradation of BEV batteries are profoundly affected by the specific driving cycles and usage profiles encountered in real-world operation. While standardized driving cycles (e.g., WLTP, US06) provide a valuable benchmark for regulatory compliance and vehicle comparison, they often fail to capture the full complexity and variability of actual driving conditions that significantly impact battery life.

Real-world variability introduces numerous factors that accelerate or decelerate degradation:

- **Geographic and Climatic Zones:** Extreme ambient temperatures are critical stressors. Cold climates increase internal resistance, reduce usable capacity, and can promote lithium plating during charging, especially at high C-rates. Conversely, hot climates accelerate undesirable side reactions (e.g., SEI layer growth), leading to faster capacity fade and impedance rise [42]. Fleet-level telemetry data from different regions consistently reveal distinct degradation patterns influenced by prevailing climate conditions.
- **Urban vs. Rural Driving Patterns:** These distinct environments impose different stress profiles. Urban driving is characterized by frequent stop-and-go maneuvers, lower average speeds, and high regenerative braking events. While regenerative braking can recover energy, the repeated high-current pulses and rapid voltage fluctuations can contribute to mechanical stress and accelerated degradation through mechanisms like particle cracking and active material delamination [40]. In contrast, rural or highway driving typically involves higher sustained speeds and fewer acceleration/deceleration cycles, potentially leading to more stable thermal conditions but also prolonged periods at high power output.
- **Driver Behavior (Aggressiveness):** An aggressive driving style, marked by rapid accelerations and decelerations, results in higher peak currents and more pronounced temperature excursions within the battery pack. These conditions exacerbate both cycle and calendar aging, promoting lithium plating, increased SEI layer growth, and structural degradation of active materials due to intensified thermal and mechanical stresses.
- **Seasonal and Long-Term Storage:** Prolonged periods of vehicle inactivity, especially under suboptimal SoC and extreme ambient temperatures (e.g., a vehicle parked in a hot garage or freezing outdoors), can lead to significant calendar aging. This highlights the importance of intelligent parking and storage recommendations from the BMS.
- **Auxiliary Load Profiles:** Beyond powertrain demands, the continuous or intermittent use of auxiliary systems like HVAC, infotainment, and lighting significantly impacts the total energy drawn from the battery. In extreme weather, prolonged HVAC operation can create substantial parasitic loads, reducing effective driving range and imposing additional stress on the battery, especially if it leads to deeper discharge cycles.

To accurately capture and model these complex real-world variabilities, researchers increasingly rely on:

- **Fleet-Level Telemetry Data:** Large-scale data collected directly from operational vehicle fleets provides invaluable insights into actual usage patterns and battery

degradation trends under diverse conditions [43]. This empirical approach allows for statistical analysis and identification of the most impactful operational factors.

- **Stochastic Modeling Approaches:** Incorporating uncertainties and variabilities inherent in real-world driving (e.g., traffic congestion, unexpected stops, dynamic environmental changes) through stochastic models or probabilistic frameworks offers more robust and realistic degradation predictions compared to deterministic models based on simplified cycles.
- **Advanced Data-Driven Techniques:** Machine learning and AI-driven methods are particularly well-suited to identifying complex, non-linear relationships between various real-world driving inputs and multi-faceted battery degradation outputs from large datasets [44].

These advanced approaches, coupled with detailed experimental validation using real-world data [45], are crucial for developing more accurate battery lifetime models and optimizing BEV performance for true operational longevity.

Research endeavors leverage both simulation and experimental approaches to enhance the realism and accuracy of battery performance assessments. This includes applying rigorous experimental tests to Li-ion batteries under specific driving cycles to quantify capacity loss percentages and validate simulation models. For instance, ref. [39] conducted experimental testing and analysis of Li-ion batteries for BEVs, leading to the development of a lifetime model that calculates total capacity loss under different scenarios, revealing significant capacity loss and impedance increase. Additionally, the durability of Li-ion batteries in BEVs has been extensively investigated using real-world driving data collected from various cities [36]. These studies critically evaluated the combined impact of calendar and cycling-induced capacity decay, considering a wide array of variables such as actual driving patterns, environmental and battery temperatures, frequency and speed of charging, and idle time. The absence of comprehensive real-world degradation data is a recurring gap, as highlighted by [38,39].

Another form of analysis involves utilizing detailed thermal models to evaluate battery performance, heat generation, and degradation, specifically considering the impact of climate control loads and their associated thermal effects within simulations. In [38], it has been demonstrated how usage scenarios, climate control loads, and battery thermal preconditioning significantly impact vehicle performance, range, and battery life degradation. These models are typically calibrated and validated with experimental datasets from Li-ion battery cells subjected to standard BEV discharge profiles derived from specific driving cycles. Periodical diagnostic examinations are then used to assess and quantify capacity loss. More recent experimental studies have directly investigated battery aging in BEVs by applying representative driving load profiles, moving beyond theoretical models. The authors in [40] have conducted an experimental study focusing on the impact of regenerative braking under different environmental conditions, revealing its significant influence on battery performance and aging, along with optimal operating temperatures around 25 °C. The compilation of extensive datasets from Li-ion battery cells tested under real BEV discharge scenarios over long periods, as exemplified by [41], is crucial for supporting the development of robust models and management strategies for electric vehicles, addressing the lack of comprehensive real-world aging data.

While the majority of existing research on BEV battery degradation and simulation focuses on passenger vehicles, a critical and underexplored area requiring significantly more attention is **electric heavy-duty trucks**. The challenges for this segment are distinct and more formidable due to their higher power requirements, larger battery pack sizes, and more demanding duty cycles. As highlighted by [34], electric semi-trucks face severe limitations in achieving practical driving ranges, coupled with restricted payload capacity

and high costs, suggesting current Li-ion battery technology is often unsuitable. Furthermore, ref. [35] specifically calls for more studies on electric heavy-duty trucks' battery degradation. This underscores a pressing need to re-evaluate current battery and vehicle design standards within the trucking industry. Future research must explore not only optimized Li-ion battery technologies but also potentially alternative battery chemistries and advanced energy management strategies specifically tailored for heavy-duty applications to facilitate the necessary transition in this vital sector.

3.2.3. Electronic Simulation Components in BEV Behavior

This subsection synthesizes findings from the literature concerning the pivotal role of electronic simulation components in understanding and optimizing BEV behavior, particularly as it relates to battery performance and lifespan. Electronic simulation is critical for analyzing complex interactions within the BEV's electrical architecture and its impact on the battery, offering a cost-effective and flexible environment for design and validation.

Tables 7 and 8 present key findings regarding specific electronic simulation components and their applications in modeling various aspects of BEV behavior. These simulations are instrumental in evaluating how different electronic designs, control strategies, and component interactions influence energy flow, power delivery, and ultimately, battery degradation. The identified research gaps in Table 7 underscore the ongoing need for more comprehensive models and datasets to capture the full complexity of real-world operational effects.

Electronic simulations are widely leveraged to optimize individual BEV components and their interactions, directly impacting battery longevity.

- **Power Electronics Design:** Simulating converters (DC-DC, inverters) is crucial for optimizing efficiency and reducing detrimental ripple currents that can accelerate battery aging. The SiCWell project, as exemplified by [46], meticulously investigates the effects of overlapping ripple currents on battery aging. This undertaking involves measuring actual ripple currents, developing sophisticated simulation models (e.g., using Discrete Fourier Transformation and Space Vector Pulse Width Modulation) to predict their impact, and creating specialized high-resolution battery testers for experimental validation. This addresses a noted research gap concerning comprehensive datasets on ripple currents' influence on battery aging.
- **Electric Motor and Drivetrain Interactions:** Understanding how motor control strategies and torque demands affect battery discharge patterns and instantaneous power delivery is critical. While not explicitly detailed in the provided tables for this section, this area typically involves complex electromechanical simulations to balance performance with energy efficiency.
- **Battery Management System (BMS) Algorithms:** Electronic simulation is vital for developing and validating BMS functionalities such as State of Health (SoH) estimation, cell balancing, and fault detection. These simulations assess algorithm effectiveness in various real-world scenarios without the need for physical prototypes, enabling evaluation of algorithm precision for predicting battery life and managing cell variations.
- **Auxiliary Electrical Load Profiles:** Simulating the impact of auxiliary loads, such as HVAC and infotainment systems, on overall battery discharge and energy consumption is crucial. Ref. [47] highlighted the significant impact of the HVAC system on battery size and driving ranges, noting a research gap in suitable, scalable HVAC models. These simulations inform optimal design to minimize effective driving range reduction and battery stress.

- **Charging Infrastructure Interaction:** Electronically modeling the interaction between the BEV's battery system and various charging station types (AC, DC fast charging) is essential to understand thermal stresses and current profiles during charging. Ref. [48] analyzed the impact of fast charging on Li-ion battery degradation in electric buses through simulation, pointing out the need for more degradation models under real operation profiles and considering the negative effects of charging stations.

Table 7. Data findings about contribution and research gap in electronic simulation components in BEV behavior.

Author	Contribution	Algorithms or Mathematical Model	Research Gap
[47]	Heating ventilation and air conditioning model used for efficient BEV design and analysis.	F-chart method, lumped parameter model, regression model, and optimization model for HVAC system analysis.	Lack of a suitable HVAC model for BEVs, with existing models being simplified and not scalable.
[49]	Methodology for reducing energy consumption in BEVs, including simulation models, optimization methods, and verification tests.	Computational fluid dynamics, a reverse simulation model, and an algorithm for velocity trajectory optimization.	Lack of a comprehensive methodology for designing and testing BEVs and a need for advanced control methods to reduce energy consumption.
[46]	Dataset on battery aging in BEVs, an approach to model the influence of ripple currents on battery life, and a high-resolution battery tester.	Discrete Fourier Transformation, Space Vector Pulse Width Modulation, and an incremental measurement method.	Lack of datasets on ripple currents' influence on battery aging in BEVs and studies of ripple current parameters' impact on battery life.
[50]	Real-time model used for planning energy-efficient speed trajectories of electric trucks, assessing the impact on battery degradation.	State-space model, energy minimization problem, alternating direction method of multipliers, model predictive control framework, and aging model.	Need for real-time eco-driving control techniques for battery electric heavy-duty trucks that can reduce energy consumption by considering road topography and traffic information.
[48]	Analysis of fast charging's impact on Li-ion battery degradation in electric buses.	MATLAB/Simulink model and a comprehensive battery model.	Lack of battery degradation models under real operation profiles and negative effects of charging stations.
[51]	Physics-based battery degradation model to assess and improve the energy efficiency and performance of automated BEVs.	Model Predictive Control, a two-track vehicle model, ACADOS software, and Spline functions for optimal control.	Need for a thorough evaluation of automated BEVs' energy efficiency and performance.
[52]	Proposes a circular economy model for BEVs to minimize environmental effects by recycling materials throughout the vehicle's lifespan.	Life cycle assessment, Sankey diagrams, and the GREET model.	Lack of a circular economy framework in the automotive industry, hindering the reduction of non-renewable materials.
[53]	High-resolution traffic sensing framework employs vehicle data, incorporating a two-step estimation method.	Two-step framework for traffic sensing, employing mathematical models like Lebesgue measure and harmonic mean.	The absence of a thorough evaluation of factors affecting BEVs' energy use and performance.
[54]	The impact of vehicle electrification on the European maintenance and repair sector.	Qualitative approach, literature review, and expert interviews to estimate the impact of BEVs on the maintenance sector.	The impact of BEVs on the maintenance and repair sector needs to work on regulations and non-insurable risks.

Table 8. Data findings about experimentation tools and results in electronic simulation components.

Author	Simulation or Experimentation	Object of Study	Measurement and Analysis Tools	Results
[47]	Simulation and experimental test	The HVAC model for BEVs results.	AMESim, ADVISOR, Matlab/Simulink, IMST-ART, e-Thermal, SINDA/FLUINT, and CFD simulations.	The HVAC system significantly impacts battery size and driving ranges of BEVs.
[49]	Simulation and experimental test	The simulation model of BEVs, verification tests of the simulation in specific conditions.	MATLAB, CFD software, bench test, and a wind tunnel.	The optimal strategy developed using the model resulted in a score of 487.3 km/kWh, twice as good as the strategy determined by drivers themselves.
[46]	Simulation and experimental test	Impact of ripple currents, generated by the power electronics in BEVs, on the aging in Li-ion cells.	MATLAB/Simulink, battery tester, impedance analyzer, and pulse measurement device.	Ripple currents negatively impact the capacity and lifetime of Li-ion cells.
[50]	Simulation and experimental test	Performance of an eco-driving control algorithm for electric trucks.	MATLAB/Simulink.	The eco-driving algorithm reduces energy consumption (17.5%) and battery degradation (9.8%) in electric trucks.
[48]	Simulation	Impact of fast charging on the battery lifetime under different scenarios and parameters.	MATLAB/Simulink.	Fast charging impacts the degradation of Li-ion batteries in electric buses.
[51]	Simulation	Energy use and performance of BEVs and BEVs.	MATLAB/Simulink and ACADOS software.	BEVs have a minor impact on range and battery life.
[52]	Simulation	Circular economy framework for vehicles, focusing on recycled materials in vehicles.	GREET model and the Transportation Energy Data.	First circular economy framework for the automotive industry, focusing on reducing non-renewable materials.
[53]	Simulation and experimental test	Energy use and performance of BEVs by electric components.	NGSIM and Waymo data, using Python and TensorFlow for a data-driven approach.	Data-driven framework for traffic sensing, validated using real-world data.
[54]	Simulation	Impact of vehicle electrification on maintenance and repair.	Literature review and average value estimation.	BEVs have lower maintenance and repair costs than ICE Vehicles, with an average cost reduction of 30%.

Beyond specific component analyses, electronic simulation components are increasingly extended to evaluate broader operational and systemic strategies, often integrating multiple BEV elements.

- **Eco-Driving Strategies for Heavy-Duty Trucks:** Simulations are a crucial tool for developing and validating eco-driving strategies for battery electric heavy-duty trucks. Research by [50] demonstrated that real-time models can plan energy-efficient speed trajectories for electric trucks, leading to significant reductions in energy consumption (17.5%) and battery degradation (9.8%). This directly addresses the research gap for real-time eco-driving control techniques considering road topography and traffic information.
- **Data-Driven Strategies for Autonomous Battery Electric Vehicles (ABEVs):** Research on intelligent transportation systems increasingly investigates data-driven strategies for predicting traffic conditions. ABEVs leverage their capabilities to improve real-time monitoring, safety, and infrastructure management through electronic simulation of complex traffic scenarios and autonomous driving algorithms [53]. While ABEVs offer advantages, their integration introduces new challenges, including increased complexity in hardware and software integration. Furthermore, the continuous operation of sensors, frequent data processing, and automated driving behaviors (which may differ from human operation) can lead to higher rates of wear and tear on electrical and mechanical components [51,54], necessitating advanced simulation models for predictive maintenance. This highlights the need for a thorough evaluation of factors affecting ABEV energy use and performance, as noted by [53].
- **Circular Economy and Sustainability:** As the automotive industry shifts towards sustainability, the automotive circular economy has emerged as a central focus. Electronic simulations are used to model the lifecycle impacts of BEVs versus ICEVs, incorporating metrics related to renewable energy utilization and the integration of recycled materials [52]. Such analyses, often leveraging life cycle assessment and GREET models, challenge traditional perceptions of environmental impact across the vehicle's entire lifespan and address the noted lack of comprehensive circular economy frameworks in the automotive industry.

In the constantly evolving landscape of automotive design, these complex considerations—spanning innovation in electronic components and their simulation, stringent regulation, and overarching sustainability goals—merge into a dynamic framework that defines the path forward for BEVs.

3.2.4. Adaptive Battery Management Systems (ABMSs) in BEVs

The advent of Adaptive Battery Management Systems (ABMSs) marks a significant advancement in the electric vehicle industry, offering substantial advantages that redefine BEV ownership. Critically, ABMS plays a pivotal role in extending battery life, thereby contributing to the development of more durable and cost-effective BEVs.

Table 9 synthesizes key contributions from the literature regarding ABMS, highlighting the algorithms and models employed, as well as identified research gaps in the field. These findings demonstrate how ABMS can lead to reductions in degradation rates and enhanced charging efficiency. Complementing this, Table 10 provides a comparative analysis of the experimental setups, tools, and results from various studies focused on extending battery lifespan through advanced BMS functionalities.

ABMS-equipped BEVs exhibit enhanced performance across all operational areas, from acceleration to handling, as intelligent systems precisely manage power output and distribution. This goes beyond mere longevity, embodying a commitment to maximizing energy efficiency by optimizing every joule and minimizing waste.

This comprehensive energy management approach boosts the overall efficiency of BEVs, leading to both financial savings and a reduced carbon footprint. Furthermore, the sustainability principles inherent in ABMS are evident in its capacity to decrease

the frequency of battery replacements, making a crucial contribution to environmental preservation by lowering manufacturing and recycling demands.

To enhance BEV efficiency and extend battery life, particularly on diverse highway terrains, a sophisticated hierarchical control strategy is identified as a linchpin in ABMS. This strategy dynamically optimizes the vehicle's speed profile and torque allocation between axles, skillfully managing energy resources over varying road slopes [5,55]. Its success, however, hinges on a deep understanding of battery aging, necessitating the identification of influential factors under various storage and cycling conditions. This knowledge fuels the development of simplified yet highly accurate battery health estimation models for implementation across all ABMS operational scenarios [56,57].

Table 9. Data findings about contributions and research gaps in Battery Management Systems in BEVs.

Author	Contribution	Algorithms or Mathematical Model	Research Gap
[5]	Energy-oriented cruising control strategy for BEVs, which optimizes speed and torque considering energy efficiency.	Dynamic programming and indirect optimal control methods, along with equivalent circuit and semi-empirical models.	Lack of eco-cruising control strategies for BEVs by energy consumption.
[56]	Optimized semi-empirical model for estimating the health of LiFePO ₄ batteries, validated with driving profiles.	Optimized semi-empirical model, window-based approach, and curve fitting technique.	Absence of an efficient and accurate aging model for LiFePO ₄ batteries for use in BMS.
[57]	Method for estimating the SoH of Li-ion batteries for BEVs.	Fractional-order model, co-estimation scheme, PI controller, and Oustaloup's recursive approximation.	The methods for estimating the SoH of Li-ion batteries are too complex, inaccurate, or overly reliant on electrochemical parameters.
[58]	Comprehensive review and comparison of battery modeling and state estimation methods.	Physics-based electrochemical models, electrical equivalent circuit models, data-driven models, filter-based methods, and observer-based methods.	Lack of a comprehensive review of battery modeling and state estimation approaches.
[59]	New battery aging model, a vehicle energy consumption model, and the importance of user patterns for optimizing battery size.	Second-order exponential function, a linear and non-linear relation for parameters, and an energy consumption model.	The absence of an empirical model to quantify the impact of SoC, DOD, and C-rate on battery aging for battery management strategies.
[55]	Deep-reinforcement-learning-based eco-cruising strategy for BEVs.	Deep reinforcement learning with the Deep Deterministic Policy Gradient algorithm and Pontryagin's Minimum Principle.	The lack of existing eco-cruising strategies considering road slope and the absence of strategies using deep reinforcement learning.
[60]	A hybrid solution with staggered cylindrical cells cooled by a fluid that flows in wavy channels to prevent or mitigate thermal runaway.	RANS equations, conjugate heat transfer, and CFD simulation.	The need for an efficient BTMS for cylindrical cells and the scarcity of CFD-based optimization approaches to find the best performance.
[61]	Developing life predictive models for Li-ion batteries, evaluating the effects of ambient and operating conditions on battery life.	NREL Electrochemical/Thermal/Life Models, Multi-Scale Multi-Domain (MSMD), Macro-scale Stress and Degradation Model.	The need for physics lifetime models, understanding of mechanical coupled stress, and cell-to-cell degradation.

Table 10. Data findings about experimentation, tools, and results in Battery Management Systems.

Author	Simulation or Experimentation	Object of Study	Measurement and Analysis Tools	Results
[5]	Simulation	Energy-oriented cruising control strategy for BEVs on highways with varying slopes.	Software tool not mentioned	The control strategy increases the battery life. It was evaluated through real-world simulations.
[56]	Experimental test	The aging behavior of 8 Ah lithium iron phosphate cylindrical cells under different cycling conditions	Accelerated aging tests, a temperature chamber, and data acquisition system.	Their model is accurate, efficient, and adaptable for different operating conditions.
[57]	Simulation and Experimental test	State-of-health estimation of Li-ion batteries for BEVs.	Battery tester, a climate chamber, a control computer, and a fractional-order electrochemical model.	The SoH estimation scheme is accurate and robust, making it suitable for real Battery Management Systems.
[58]	Experimental test	Battery modeling and state estimation for advanced Battery Management Systems.	Electrochemical Impedance Spectroscopy, Genetic Algorithm, Neural Network, and Kalman Filter.	Compares various battery modeling, highlighting their strengths and weaknesses.
[59]	Experimental test	26 Ah commercial pouch battery cell.	Battery test equipment: MACCOR Series 4000, PEC SBT0550, and Digatron MCT 100-05-08 ME.	Avoiding high SoC levels, the lifetime of Li-ion battery cells can be significantly extended.
[55]	Simulation	The eco-cruising control of BEVs on slopes using deep reinforcement learning	Python 3.7, TensorFlow 1.15, and deep learning.	The deep-reinforcement-learning-based eco-cruising strategy for BEVs can save energy and adapt to different driving environments.
[60]	Simulation	Simulation with cylindrical cells that optimize the distance between two cells and the width of the channels for different materials and coolants.	STAR-CCM+, thermocouples, and spray cooling system.	The materials with additives and water cooling improve the BTMS performance and suitability for BEVs.
[61]	Simulation	Predictive models of Li-ion battery lifetime	Physics-based, semi-empirical, and multi-scale models.	The semi-empirical and physics-based models to predict the degradation of Li-ion help to extend battery life by up to 50%.

Advancing the state of BMS further requires a thorough evaluation of SoH and SoC estimation techniques, illuminating current research landscapes and prospects for future exploration [58]. This extends to the broader realm of battery modeling and state estimation within advanced Battery Management Systems, where challenges such as sensing, thermal management, and fault diagnosis demand innovative solutions.

The literature highlights the ongoing drive for eco-conscious travel through the implementation of learning-based eco-cruising control strategies, meticulously fine-tuning motor torque and maximizing efficiency during journeys under speed constraints to minimize electricity consumption across the BEV's entire route [55].

On a parallel track, the choice of Li-ion battery pack cooling methods is under scrutiny. Comprehensive assessments unveil the temperature ranges and performance attributes of air-cooling and liquid-cooling systems, providing vital insights for BEV designers and for optimizing battery thermal management within ABMS [60].

The development of accurate battery lifetime models also emerges as a critical area, encompassing semi-empirical models suitable for system design (though in need of long-term validation, standardization, and extensive cell aging experiments) and physics-based lifetime models aimed at reducing testing time and guiding future cell design, thereby pushing the boundaries of battery innovation [61].

In summary, the literature presents innovative battery models sculpted from degradation trajectories and real-world BEV data. These models offer a pathway to unravel the intricate dynamics of battery aging and performance enhancement, directly informing ABMS design. Addressing these interconnected technical challenges through advances in battery management and energy optimization is critical to improving the performance, safety, and sustainability of BEVs, thereby supporting the global transition to cleaner and more efficient transportation.

3.2.5. Simulation Tools for Battery Degradation

Understanding and predicting Li-ion battery degradation is paramount for optimizing their lifespan in BEV applications. The literature review highlights a multi-faceted approach involving various simulation tools and analytical techniques to characterize battery degradation processes. Tables 11 and 12 summarize key findings in this area, outlining research contributions, methodologies, and identified gaps.

Studies extensively use simulation to investigate the complex realm of capacity fade and End-of-Life (EoL) predictions. Researchers often blend diverse models with real-world driving data to unravel the intricate tapestry of battery degradation [62]. For instance, performance-based models, often combined with the Arrhenius or power law, are utilized to predict and compare capacity fade in BEV batteries using real-world operational data [62].

A fundamental aspect explored in the literature is the understanding of degradation mechanisms themselves. Studies employ various characterization techniques such as Atomic Force Microscopy, X-ray Diffraction, Raman spectroscopy, X-ray Photoelectron Spectroscopy, and Scanning Electron Microscopy to delve into these mechanisms, aiming to improve battery performance and longevity [63]. The aging behavior of Li-ion batteries during charging, standby, and driving is systematically described and analyzed, providing insights into how different stress factors contribute to degradation [64].

In the impact of operational conditions, simulation tools are critical for evaluating how various operational conditions influence battery degradation:

- **Driving Profiles:** Studies analyze how different road types (urban, rural, highway) and their associated driving profiles (average speed, stop-and-go frequency, road gradient, acceleration patterns) affect battery stress and energy consumption, leading to degradation [64].
- **Regenerative Braking:** Experimental investigations, often complemented by simulations, scrutinize the impact of regenerative braking on battery aging across diverse driving conditions, considering parameters such as temperature, SoC, and braking intensity [65]. These studies aim to identify optimized operating conditions to minimize battery aging induced by regenerative braking.

- **Stress Factors and Sensitivity Analysis:** Accelerated sensitivity analyses are conducted to optimize the trade-off between testing costs and model accuracy, while evaluating the impact of various stress factors on battery aging. Semi-empirical aging models, often derived from empirical observations and described by fit functions, are widely used for this purpose [66].

Table 11. Data findings about contributions and research gaps in battery degradation.

Author	Contribution	Algorithms or Mathematical Model	Research Gap
[63]	Shows degradation mechanisms in Li-ion batteries and the understanding of these mechanisms to improve battery performance.	Atomic Force Microscopy, X-ray Diffraction, Raman spectroscopy, X-ray Photoelectron Spectroscopy, and Scanning Electron Microscopy.	The lack of characterization techniques used to study degradation in Li-ion batteries.
[64]	Reviews the aging behavior of Li-ion batteries during charging, standby, and driving.	Systematic description and analysis of the aging mechanisms of Li-ion batteries in BEVs applications	Lack of comprehensive studies on the impact of different charging parameters, and temperature on battery aging.
[62]	Predict and compare the capacity fade of BEV batteries using real-world data and models.	Performance-based models, Arrhenius law, and power law.	There is a lack of models, data, regulation, and validation for battery durability in real-world scenarios.
[65]	A cycle life study of Li-ion batteries with different levels of regenerative braking, temperature, and SoC.	Simplified vehicle model, a numerical fixed-step solver, and an electrochemical model.	Lack of experimental data on the effects of regenerative braking on Li-ion batteries in BEVs, and the need for optimized operating conditions to minimize battery aging.
[67]	Comparison and evaluation of three different algorithms for estimating the SoC in Li-ion batteries in terms of accuracy, convergence speed, and robustness.	Extended Kalman Filter, Unscented Kalman Filter, and Particle Filter.	The lack of investigation into the influence of battery degradation and the development of hybrid algorithms for SoC estimation.
[68]	Provide a comprehensive review of data-driven methods for estimating the SoC of Li-ion batteries.	Model-based methods with the data-driven.	Providing a detailed survey of data-driven SoC estimation methods, highlighting their algorithms, features, strengths, weaknesses, errors, limitations, and future directions.
[69]	A nature-inspired algorithm to optimize the scheduling of charging requests for a fleet of carsharing BEVs participating in the Ancillary Service Market.	Hybridized Artificial Bee Colony (h-ABC) algorithm.	Need for an effective scheduling approach to optimize the charging requests for a fleet of carsharing BEVs in the Ancillary Service Market.
[66]	The sensitivity of Li-ion cell aging to various stress factors, as well as the application of accelerated sensitivity analysis in aging characterization.	Semi-empirical aging models, which are described by fit functions, are derived from empirical observations.	Need for a well-founded selection model input parameters in aging models for Li-ion cells. Also, the understanding of the impact of stress factors on aging effects.

Table 12. Data findings about results, tools, and results in battery degradation.

Author	Simulation or Experimentation	Object of Study	Measurement and Analysis Tools	Results
[63]	Experimental test	Understand the degradation mechanisms to improve battery performance and longevity.	Atomic Force Microscopy, X-ray diffraction, Photoelectron Spectroscopy, and Scanning Electron Microscopy.	Elevated temperatures improve the performance of Li-ion batteries, but also lead to irreversible capacity loss.
[64]	Simulation	Understanding the degradation of battery performance parameters under BEV operation.	Aging methods that are affected by different stress factors.	Need for practical guidance for prolonging battery life for users, battery designers, and vehicle manufacturers.
[62]	Simulation and Experimental Test	In-vehicle performance degradation of Li-ion batteries.	Battery aging models, GPS devices, IEC 62, TEMA platform, Matlab function, and Levenberg–Marquardt algorithm.	The combinations of Li-ion battery architectures and recharge strategies do not lead to battery capacity drop below 80% of its nominal value in less than five calendar years.
[65]	Experimental test	Compare capacity losses for different levels of regenerative braking.	BaSyTec CTS battery test system with 32 independent 5 A test channels and 3 thermal chambers.	Optimizing regenerative braking, managing temperature and SoC levels can help improve the longevity of Li-ion batteries in BEVs.
[67]	Simulation and experimental test	Evaluate the performance of different algorithms for SoC estimation	The battery test system Arbin BT2000 tester, host computer with Arbin MITS Pro Software, and Matlab R2012b Software.	The UK Filter was found to be more accurate than the EK Filter and the Particle Filter when SoC was correctly initialized.
[68]	Simulation tool	SoC of Li-ion batteries	Arbin BT2000, NEWARE BTS 4000, and a hardware-in-the-loop platform.	The limitations and future directions challenges of data-driven SoC estimation algorithms are explored rigorously.
[69]	Simulation	Performance of the algorithm to optimize the scheduling of charging requests for a fleet of BEVs	MATLAB R2020a	The algorithm is shown to be effective in identifying a suitable schedule for the charging requests of a large BEV fleet.
[66]	Simulation and experimental test.	The dependencies of aging in Li-ion cells under defined laboratory conditions for BEVs use.	BaSyTec XCTS25 battery test system and temperature chamber Memmert IPP110 plus.	Sensitivity analysis highlights the importance of understanding stress factors on aging effects.

In estimation and optimization algorithms, the literature highlights the crucial role of algorithms in managing battery health and extending life:

- **SoC and SoH Estimation:** The accuracy, stability, and computation time of battery algorithms for SoC estimation are rigorously evaluated under varying conditions, offering invaluable insights into the algorithmic foundation of battery management [67]. Data-driven methods for SoC estimation are comprehensively reviewed, dissecting their input features, configurations, execution processes, strengths, weaknesses, errors, limitations, and future directions, while probing critical implementation factors that shape their accuracy and robustness [68].
- **Fleet Charging Optimization:** Nature-inspired algorithms, such as the Hybridized Artificial Bee Colony (h-ABC) algorithm, are employed to optimize the scheduling of charging requests for BEV fleets, particularly those participating in Ancillary Service Markets. This aims to minimize power imbalances and forge a dynamic synergy between energy markets and BEV integration [69].

Also, the modeling approaches for lifetime prediction focus on the pursuit of robust battery lifetime models, which are as follows:

- **Empirical and Semi-empirical Models:** These models, often derived from empirical observations, are suitable for system design but are noted for their need for long-term validation, standardization, and reliance on expensive cell aging experiments [66].
- **Physics-based Lifetime Models:** These models aim to reduce testing time and guide future cell design by providing a deeper understanding of underlying electrochemical and mechanical degradation processes, pushing the boundaries of battery innovation [61].
- **Innovative Data-driven Models:** Building on empirical insights, innovative battery models are sculpted from degradation trajectories and real-world BEV operational data, offering a pathway to unravel the intricate dynamics of battery aging and performance enhancement.

In essence, these multi-disciplinary endeavors involving advanced simulation tools, experimental validation, and sophisticated algorithms converge into a harmonious symphony of insights, poised to redefine the future of electric mobility. By bridging the gap between innovation and sustainability, these findings are critical for improving BEV performance, safety, and longevity.

3.2.6. Modeling Approaches for BEV Battery Characterization: Model-Driven, Data-Driven, and Hybrid Approaches

The diverse landscape of BEV battery characterization and degradation prediction employs various modeling paradigms, each with distinct advantages, limitations, and interpretability characteristics. Broadly, these approaches can be categorized into model-driven (also known as physics-based or white-box), data-driven (black-box), and hybrid (grey-box or physics-informed machine learning) methods. A critical comparison helps in selecting the most appropriate methodology for specific applications and understanding their deployment barriers.

- **Model-Driven Approaches:** These methods, rooted in electrochemical and thermodynamic principles, aim to simulate the internal states and degradation processes of batteries. Examples include equivalent circuit models (ECMs) for electrical behavior and electrochemical models (EMs) for detailed internal reactions. Their strength lies in providing mechanistic insights and their ability to extrapolate, but they often require extensive parameterization and can be computationally intensive for complex scenarios.

- **Data-Driven Approaches:** Leveraging the increasing availability of battery data from lab tests and real-world operation, these approaches use statistical analysis, machine learning (e.g., neural networks, support vector machines), and deep learning to identify patterns and predict degradation without explicit reliance on physics. They excel in accuracy when sufficient, high-quality data is available [44], but often lack interpretability and struggle with extrapolation beyond the training data range.
- **Hybrid Approaches (Physics-Informed Machine Learning—PIML):** Representing a growing trend, hybrid models combine the strengths of both paradigms. They embed physical constraints or known mechanisms into data-driven frameworks, or use data to refine parameters of physics-based models [70]. This synergistic approach offers improved accuracy, better interpretability than pure black-box models, and enhanced generalizability compared to purely data-driven methods [71].

Table 13 provides a detailed comparative analysis across key criteria, highlighting their respective merits and challenges. The choice of modeling approach often depends on the available data, computational resources, desired level of interpretability, and the specific application (e.g., real-time BMS vs. long-term design optimization).

Table 13. Comparative analysis of modeling approaches for BEV battery characterization.

Criterion	Model-Driven (Physics-Based)	Data-Driven (Black-Box)	Hybrid (Physics-Informed ML)
Description	Based on fundamental physical and electrochemical principles (e.g., ECMs, EMs).	Relies on empirical data and ML techniques (e.g., neural networks, SVMs).	Integrates physical modeling with data-driven learning using domain knowledge.
Advantages	High interpretability; generalizable with defined parameters; can predict beyond training data.	High accuracy with large datasets; handles non-linearities; adaptable to changing data.	Balances accuracy and interpretability; less data-dependent than pure ML; good generalization.
Limitations	High computational demand; complex parameter estimation; may miss real-world effects.	Requires vast, quality data; low interpretability; poor extrapolation; sensitive to noise/bias.	Complex to develop and validate; requires hybrid expertise; may inherit limitations of both.
Interpretability	High (mechanistic insight)	Low (correlational, not causal)	Moderate to High (enhanced with physical grounding)
Deployment Barriers	Needs detailed system knowledge and computational power; parameter uncertainty.	Demands infrastructure for data handling; privacy and trust issues; training costs.	Developmental complexity; need for interdisciplinary skills; delicate physics-ML balance.

3.2.7. New Battery-Pack Developments for BEV Applications

A growing number of automotive manufacturers have introduced proprietary battery pack designs that improve energy density, safety, and manufacturability. These innovations integrate chemistry improvements, thermal management, cell-to-pack (CTP) designs, and new form factors (e.g., tabless cylindrical cells). Table 14 provides a comparative summary of three leading commercial battery systems.

By analyzing these systems, it is evident that current state-of-the-art BEV battery technology is progressing toward platforms that optimize safety, manufacturability, and fast-charging capabilities alongside energy and cycle performance.

New battery-pack developments are central to advancing sustainable powertrain technologies, particularly for BEVs applications. The literature provides a comprehensive overview of evolving battery requirements for BEVs and Fuel Cell Electric Vehicles

(FCEVs) by 2030, alongside discussions of key technical challenges, innovative solutions, and future trends.

Table 14. Comparison of commercial BEV battery packs (2024).

Manufacturer/System	Cell Chemistry	Energy Density (Wh/kg)	Life Cycle (to 80%)	Fast Charge (10–80%)
Tesla 4680 (Model Y, Cybertruck)	NCA/NCM blend, tabless cylindrical	250–270	1000–1200 cycles	15–20 min (Supercharger V3)
BYD Blade Battery (Han, Seal)	LFP, prismatic, CTP design	160–180	3000+ cycles	30 min (DC fast, 100–150 kW)
GM Ultium Platform (Cadillac Lyriq, Hummer EV)	NMC (NCMA), pouch cells, wireless BMS	225–250	1000+ cycles	20–25 min (350 kW DCFC)

Where the batteries Requirements for 2030 [72] need to accomplish the next goal:

1. **Energy density:** 250 Wh/kg;
2. **Power density:** 2 kW/kg;
3. **Charging Time:** 80% SoC in 15 min;
4. **Battery Cycle life:** 1500 cycles;
5. **Battery Calendar life:** 10 years;
6. **Battery Self-discharge rate:** 1% per month at 100% SoC;
7. **Cost:** EUR 100/kWh.

Current research in new battery-pack developments primarily focuses on mitigating battery aging and enhancing performance through various strategies.

Advanced Battery Chemistries:

- **Hybrid Battery Systems (HBSs):** Investigations are exploring the potential of HBSs to extend battery life, enhance overall performance, and provide optimal operational recommendations [73]. These systems typically combine different battery chemistries (Li-ion with supercapacitors) or different types of Li-ion cells to leverage their complementary strengths.
- **Lithium-Sulfur (Li-S) Batteries:** While offering high theoretical energy densities and potentially lower costs due to abundant sulfur, the commercialization of Li-S batteries for mass production faces significant technical challenges, primarily related to their cycle life, material stability, and safety concerns [74]. Overcoming these hurdles is critical for widespread adoption.

Enhanced Battery Management and Diagnostics:

- **Data-Driven State of Health (SoH) Monitoring:** A prominent data-driven approach proposes using onboard vehicle data to develop accurate and robust algorithms for real-time battery health diagnosis, especially in dynamic electric vehicle environments [75].
- **SoH and Remaining Useful Life (RUL) Estimation:** Comprehensive reviews highlight various methods for assessing SoH and RUL estimation of Li-ion batteries. The goal is to formulate accurate and robust estimation methods, addressing previous challenges and offering recommendations for future research [76,77].
- **Parameter Identification for Degradation:** New methodologies are being suggested to precisely identify parameters affecting the degradation of Li-ion batteries. These methods aim to improve the accuracy of battery degradation diagnosis by more accurately modeling the electrochemical behavior of batteries [78]. Research also analyzes exist-

ing SoH estimation methods and their applications in BMS, discussing their benefits, limitations, and areas for further research in battery condition monitoring.

Accelerated Testing and Predictive Modeling:

- **Accelerated Aging Characterization:** Integrated advanced testing methodologies are proposed to simulate authentic automotive cell aging in a condensed timeframe while minimizing uncertainties [79]. This allows for more rapid assessment of new battery designs.
- **Data-Driven Diagnostics and Prognostics:** Research explores data-driven diagnostic and prognostic approaches for battery health and safety in electric vehicles. These methods have the potential to provide BEV owners with crucial information on SoH, State of Safety (SOS), and cycle life [80].
- **Predictive Models for Performance:** Accurately predicting battery performance under variable usage conditions is crucial. The literature discusses the development of predictive models that optimize charging protocols, estimate SoH, and predict degradation pathways [81].

Mitigation of environmental impacts like thermal management strategies are key factors affecting battery wear in BEVs, especially ambient conditions, are being thoroughly examined. Mitigation strategies, such as advanced thermal management systems, are proposed to improve battery longevity and performance, particularly under extreme temperatures [82].

These multi-disciplinary efforts in battery-pack development, spanning materials science, electrochemical modeling, and intelligent data processing, are collectively driving the automotive industry towards a more sustainable and efficient electric future.

3.2.8. Battery Lifecycle Management: Second-Life Applications and Recycling

While in-service battery degradation is a primary focus for BEV performance, a holistic understanding of battery behavior necessitates considering the entire lifecycle, extending beyond primary vehicle use to second-life applications and recycling. These downstream stages are not merely end-of-life considerations but crucial pillars of the BEV ecosystem's economic viability and environmental sustainability.

With the increasing deployment of BEVs, battery packs nearing end-of-life present an opportunity for reuse. These include grid energy storage, backup power, and renewable integration systems, which operate under less demanding cycles compared to automotive use [83].

As BEV batteries reach the end of their primary life (typically when their capacity degrades to 70–80% of initial capacity, rendering them unsuitable for demanding automotive applications), they often retain significant energy storage capabilities suitable for less stringent uses. This concept of “second-life batteries” (2ndLBs) offers substantial benefits:

- **Economic Value Retention:** Repurposing batteries extends their useful life, recouping more value from the initial manufacturing investment and delaying the need for costly new battery production.
- **Resource Conservation:** By utilizing existing battery assets, the demand for virgin raw materials (lithium, cobalt, nickel) and the energy-intensive manufacturing processes for new batteries are reduced.
- **Environmental Impact Reduction:** Extending battery life reduces the overall carbon footprint per unit of energy stored/delivered over the battery's total lifespan, contributing to a more circular economy [17].
- **Grid Stability and Renewable Integration:** A major application for 2ndLBs is stationary energy storage, where they can support renewable energy integration (e.g.,

storing solar or wind power), provide grid balancing services, and offer backup power solutions [18]. They are also being explored for less demanding mobile applications like low-speed electric vehicles or forklifts.

However, challenges persist in the widespread adoption of 2ndLBs:

- **Accurate Characterization and Grading:** Precisely assessing the SoH, Remaining Useful Life (RUL), and individual cell variability of aged EV battery packs is complex but critical for safe and effective repurposing. Degradation models and simulation tools play a vital role here, predicting residual capacity and potential performance.
- **Safety and Reliability:** Ensuring the continued safety and reliable operation of batteries that have undergone years of automotive use requires rigorous testing, robust BMS adaptations for second-life scenarios, and appropriate thermal management.
- **Standardization and Cost:** Lack of standardization in battery pack designs and the costs associated with disassembly, testing, sorting, re-assembly, and integration can hinder economic viability.

Ultimately, when batteries are no longer suitable for any useful application, efficient and sustainable recycling becomes paramount. This closes the loop in the circular economy for BEVs, addressing critical environmental and resource concerns:

- **Critical Material Recovery:** Recycling allows for the recovery of valuable and often critical raw materials (e.g., lithium, cobalt, nickel, manganese) that are essential for new battery production, reducing reliance on virgin mining and mitigating geopolitical supply chain risks.
- **Waste Reduction and Pollution Prevention:** Proper recycling prevents hazardous battery waste from accumulating in landfills, where it could leach toxic chemicals into the environment.
- **Recycling Technologies:** Current methods include:
 - **Pyrometallurgy:** High-temperature smelting to recover metals, which is often energy-intensive and may not recover lithium efficiently.
 - **Hydrometallurgy:** Leaching metals using chemical solutions, offering higher recovery rates for a wider range of materials and generally more energy-efficient.
 - **Direct Recycling:** The most promising approach, aiming to regenerate cathode and anode materials directly without destroying their crystal structure, significantly reducing energy and cost, but highly challenging for mixed chemistries [84].
- **Policy and Regulations:** Evolving regulations (e.g., in the EU and China) are increasingly mandating higher recycling efficiencies and recycled content targets, driving innovation and investment in the sector.

Adaptive BMS technologies play a key role in second-life applications by accurately estimating SOH and enabling safe discharge/charge control under new duty cycles. Integrating aging-aware algorithms ensures that repurposed cells are matched and balanced correctly. Also, simulation tools can contribute to recycling by optimizing processes (energy consumption, material flow), designing for recyclability, and assessing the overall environmental impact through life cycle assessment (LCA) models.

The pursuit of extended battery life through advanced algorithms (e.g., predictive maintenance, physics-informed ML, edge-based BMS strategies) directly contributes to the broader sustainability goals of the BEV industry. Some of these goals can be measured for the next indexes:

- **Reduced Material Usage and Carbon Footprint:** By prolonging the operational lifespan of BEV batteries, these strategies inherently reduce the frequency of battery replacements. This translates directly to a lower demand for new battery manufacturing, thereby decreasing the consumption of virgin raw materials and mitigating the

substantial energy and associated carbon footprint embedded in the production process of new battery cells and packs [19]. Effectively, a longer-lasting battery amortizes its manufacturing impact over a greater operational period.

- **Enhanced Resource Efficiency:** Algorithms that optimize charging, discharging, and thermal management, informed by precise degradation models, ensure that the battery operates within its healthiest parameters. This not only extends life but also maximizes the energy yield and useful work extracted from the existing materials. Predictive maintenance, for instance, allows for proactive interventions to prevent catastrophic failures, thereby preventing premature battery disposal.
- **Total Cost of Ownership (TCO):** While primarily an economic metric, a reduced TCO for BEVs (partially due to longer battery life and reduced replacement costs) enhances their market appeal, accelerating the transition away from fossil-fuel vehicles, which has significant environmental benefits.
- **Circular Economy Integration:** Lifecycle sustainability metrics, such as material circularity index, embodied energy per kilometer driven, and carbon footprint per unit of energy delivered, are directly improved by strategies that extend first life, enable robust second-life applications, and facilitate efficient recycling. The algorithms and models discussed in this review provide the foundational intelligence to achieve these improvements, enabling more intelligent designs and operational choices that prioritize resource efficiency and environmental stewardship across the entire BEV value chain.

Furthermore, recycling is becoming essential to reclaim critical materials like lithium, cobalt, and nickel. Closed-loop recycling processes—such as hydrometallurgical, pyrometallurgical, and direct recycling—have been explored in [85], aiming to reduce both economic and environmental costs associated with virgin material extraction.

Policy and standardization efforts are needed to facilitate battery collection, grading, and traceability—especially to differentiate between cells suited for second life versus direct recycling. These efforts will ultimately support a sustainable battery life cycle aligned with circular economy models.

4. Conclusions and Future Directions

The rise of electromobility has captured significant research attention, driven by the imperative to accelerate the adoption of BEVs and phase out ICEVs. This focus encompasses improving BEV efficiency, reducing costs, and extending range, alongside adapting to the expanding commercial BEV market, which now features a broader array of competitors beyond initial pioneers.

Based on the review of current literature and the categorization of contributions related to battery pack operation, management, and optimization, it is evident that electromobility faces significant challenges. Addressing these necessitates a deeper understanding of battery behavior, which can be achieved through the development of more precise simulation tools that accurately account for factors influencing battery degradation and aging. Implementing appropriate tools will require integrating novel hardware and software components to enhance battery optimization specifically for BEV applications.

This review identified numerous critical areas for future research and development, directly addressing the third research query. These areas represent key instruments for advancing BEV technology and consolidating information, thereby focusing efforts on new BEV research priorities. The following points detail these promising avenues:

- **External Conditions for Vehicle Design:** Future efforts should focus on developing advanced tools for the design and synthesis of realistic driving cycles. This includes incorporating user driving styles and detailed characterizations of diverse terrains

(track types, road conditions, slopes, traffic density). More accurate characterization and synthesis will lead to improved energy consumption models and the development of optimized BEV driving strategies. These analyses will be particularly valuable for heavy-duty vehicles, given their substantial power requirements.

- **Electronics Components in BEVs:** There is a need for design tools that simulate the energy consumption map of individual electronic components within BEVs. Such maps would enhance understanding of the performance of key electronic elements during driving and facilitate the development of models, methodologies, or algorithms for optimal charging times that consider vehicle type and electronic load, preventing excessive strain on the battery pack. Furthermore, research should aim to establish clear relationships between temperature and the charging capacity of various electrochemical Li-ion batteries, potentially yielding valuable datasets. Ultimately, a significant area of opportunity lies in developing analytical models for the life cycle cost analysis of different electrical components in BEVs.
- **Adaptive Battery Management System (ABMS) Innovations:** New generations of ABMSs should integrate advanced automatic driving control strategies, such as adaptive speed adjustments in urban environments, to minimize energy consumption. This includes the implementation of robust SoH estimation models capable of evaluating diverse operating conditions and performing accurately in real-world scenarios. Another crucial direction involves validating battery thermal management system (BTMS) models through rigorous laboratory tests, incorporating new factors affecting external and internal battery temperatures. Additionally, developing novel sensing techniques for measuring internal battery states and parameters within a BMS, or advancing fault diagnosis and health management systems, will be key to optimizing battery health and improving power conversion efficiency.
- **External Simulations for Battery Pack Degradation:** Future work should focus on developing comprehensive battery aging and degradation models that closely replicate real-world BEV behavior, validated through extensive testing on actual vehicles. Standardization of experiment design is essential to verify and improve existing aging models. Research should also prioritize “charge-while-driving” concepts and comprehensively characterize all operating parameters influencing battery degradation, encompassing both electrical and thermal factors.
- **Batteries Technology:** In the realm of battery behavior, developing robust relationships and models for all factors and parameters affecting the battery is critical. This includes enhancing the effectiveness of battery models (State of Charge, State of Discharge, State of Health, Depth of Discharge) across a range of real-world conditions (stress factors, thermal effects, varying currents, internal resistance). To further increase effectiveness, researchers need to thoroughly characterize charging strategies under all operational conditions, leading to standardized techniques for battery characterization, aging, and testing. Finally, a deep focus on understanding and promoting capacity recovery in Li-ion batteries holds significant potential for extending battery life.

The widespread development of BEVs necessitates extensive research in optimizing their design, integration, and performance, particularly in urban areas globally. While current BEV markets in regions like Latin America remain relatively concentrated in freight centers of developed cities, with limited BEV offerings from many automakers, the landscape is rapidly evolving.

The construction of smart cities is also a crucial intermediary step toward broader BEV deployment and the ultimate objective of autonomous vehicle mobility. Autonomous vehicles, relying on BEV powertrains, require substantial electronic systems that extend far

beyond basic driving functionalities. As the automotive industry transitions from ICEVs to BEVs, the rising demand for electronic components and their associated environmental impact underscore the critical need for advanced recycling strategies. These strategies must encompass both electronic waste and comprehensive end-of-life battery pack management to ensure sustainable resource use.

Current life cycle assessment (LCA) studies are also exploring the transformation of ICEVs to autonomous vehicles without necessarily converting them to BEVs. However, it is recognized that the production and end-of-life handling of BEVs can generate a higher initial environmental impact compared to ICE vehicles. This is primarily due to the increased use of advanced materials, complex electronics, and, in some regions, limited recycling infrastructure. Therefore, it is essential to establish a comprehensive framework for BEVs that considers their entire life cycle—from design and material selection to manufacturing, usage, and end-of-life management—to truly assess and minimize their environmental footprint.

Future research should also focus on optimizing second-life battery integration, adaptive BMS for reuse, and scalable recycling systems. These developments are critical for minimizing waste and reducing the total life-cycle impact of BEVs. Cross-sector collaborations between OEMs, recyclers, and grid operators are necessary to unlock the full potential of circular battery economies.

Finally, while electric vehicle technology is progressing, its acceleration is vital to match and eventually surpass the capabilities of current internal combustion engines. The year 2030 is in fact poised to be a critical turning point in the automotive industry, necessitating significant changes to reduce pollution and improve sustainability. Historically, Tesla has pioneered the development and penetration of the BEV market, but recent years have witnessed the emergence of Chinese manufacturers as dominant global players.

Companies such as BYD, NIO, and XPeng have rapidly expanded their production capacity, technological innovation, and market share, particularly in Asia and Europe. In 2023, Chinese BEVs accounted for more 50% of global sales of electric vehicles, driven by strong government support, competitive pricing, and significant advances in battery technology [7,86]. This shift underscores a new phase in the electrification of transportation, highlighting the critical importance of studying and incorporating Chinese technological trends and strategies into future global BEV research and development.

Author Contributions: Conceptualization, P.S.G.-R., J.d.J.L.-S., J.C.T.-M., L.C.F.-H. and H.G.G.-H.; methodology, P.S.G.-R. and J.d.J.L.-S.; software, P.S.G.-R.; validation, P.S.G.-R. and J.d.J.L.-S.; formal analysis, P.S.G.-R., J.d.J.L.-S., H.G.G.-H., J.C.T.-M. and L.C.F.-H.; investigation, P.S.G.-R.; resources, J.d.J.L.-S. and H.G.G.-H.; data curation, P.S.G.-R., J.d.J.L.-S., J.C.T.-M., L.C.F.-H., and H.G.G.-H.; writing—original draft preparation, P.S.G.-R.; writing—review and editing, H.G.G.-H., J.C.T.-M. and L.C.F.-H.; visualization, P.S.G.-R.; supervision, H.G.G.-H.; project administration, J.d.J.L.-S. and H.G.G.-H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

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