

Review

Empowering Electric Vehicles Batteries: A Comprehensive Look at the Application and Challenges of Second-Life Batteries

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Abstract: The surge in electric vehicle adoption has resulted in a significant rise in end-of-life batteries, which are unsuitable for demanding EV applications. Repurposing these batteries for secondary applications presents a promising avenue to tackle environmental and economic challenges associated with their disposal. The second-life battery (SLB) approach emerges as a mechanism to manage this massive amount of retired EV batteries. However, this approach poses significant challenges in determining and monitoring battery degradation and performance. After evaluating different scenarios for reusing or recycling retired EV batteries, this paper examines the main challenges associated with SLBs, including techno-economic aspects, uncertainty from first life, safety, characterization and screening, battery-management systems, and secondary applications. A comprehensive review of current state-of-the-art SLB research and implementations is provided, particularly emphasizing battery characterization and the requisite evaluation processes for SLB eligibility. This paper explores diverse measurement techniques for assessing SLB performance, evaluating them based on accuracy, complexity, and time consumption, which are essential for achieving cost-effective SLB applications. The overarching objective is to thoroughly understand the principal challenges associated with repurposing EV batteries and delineate the research imperatives necessary for their successful implementation and prolonged lifespan.

Keywords: battery characterization; electric vehicles (EVs); end of life (EOL); measurement technique; retired EV batteries; second-life batteries (SLBs); remaining useful life (RUL); state of health (SOH)



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1. Introduction

As society increasingly relies on devices powered by electrical energy, batteries have become ubiquitous [1]. Energy-storage systems (ESS) and batteries, in particular, play a vital role in mitigating the adverse effects of climate change resulting from the continued dependence on fossil fuels. Therefore, they constitute a critical component of the energy mix [2]. Li-ion batteries (LiBs) have become the primary choice for applications ranging from portable electronics to stationary storage and electric vehicles (EVs) [3]. As indicated in [4], the total capacity of LiBs introduced to the global market is projected to surge from 242 GWh to 2731 GWh between 2020 and 2030. This represents an extraordinary, more than 11-fold increase in LiB capacity within the global markets over a mere decade.

The automotive industry is a leading segment that relies on LiBs, as evidenced by the significant growth in global EV sales from just around half a million in 2016 to a whopping 14 million in 2023 [5]. This trend is expected to persist, with a projected surge to 66 million sales for passenger EVs by 2040, according to Bloomberg predictions [6].

An important facet of electric transportation involves battery capacity degradation, which diminishes battery performance and consequently reduces EV mileage. EV batteries are typically designed for an acceptable mileage range and longevity. Manufacturers employ extensive research and development to mitigate the battery performance decrement rate. Nevertheless, battery degradation remains an inherent aspect of EV batteries' durability and reliability, and consideration for eventual replacement as a part of sustainable EV ownership is unavoidable. EV batteries are typically replaced once they reach a certain threshold of an acceptable mileage range, corresponding to a specific battery State of Health (SOH) to circumvent conflicts with customers [7]. This threshold is typically defined by car manufacturers when the battery capacity has decreased by 20–30% relative to its initial capacity [8,9].

Multiple factors profoundly influence the sustainability of EVs concerning battery end-of-life (EOL). Firstly, there must be a clear delineation of responsibility, as appropriately addressing EOL demonstrates the genuine environmental commitment of EV manufacturers. Secondly, recycling involves various steps such as battery collection and transportation and additional strategies to recover primary materials like lithium, cobalt, nickel, etc. The eventual necessity to replace degraded batteries in EVs could pose a significant bottleneck and barrier to further growth in the EV market [10]. According to a forecasting model outlined in [11], there will be an estimated stockpile of approximately 16.8 million EV batteries available for repurposing between 2011 and 2040. Hence, effective battery EOL management becomes necessary, and utilizing the batteries in second-life applications should become a viable solution to extend the battery's useful life in a different application.

Etxandi-Santolaya, Maite et al. [12] underscore the imperative of aligning the surge in EV sales with sustainable practices, particularly concerning the EOL determination of LiBs in their initial life cycle. Their work raises concerns about the potential underutilization of batteries, especially as EVs evolve toward higher capacities, which could impede overall sustainability. Previous research studies have delved into various aspects of SLBs to provide a comprehensive understanding from diverse perspectives, elucidating their technical functionalities, economic viability, and real-world implementation [13]. Martinez-Laserna et al. [14] critically evaluate the concept of SLBs, transitioning from hope to reality and discussing their economic, technical, and environmental aspects. The paper poses essential questions from an economic viability standpoint, such as profitability, market potential, and the selling price of SLBs. In a perspective review conducted by Illa Font, Carlos Henrique et al. [15] on SLBs, critical questions regarding challenges are highlighted, including the disassembly process, SLB classification, determination of the EOL threshold, and trade-off considerations between extending the first life and maximizing the remaining useful life (RUL) for second-life applications. The paper underscores the importance of current business model maturity for SLBs without delving into the specific challenges hindering them.

Hossain, Eklas et al. [16] underscore the critical importance and opportunities associated with extending battery life through a second-use phase. Their study delineates the standard production procedure for SLBs, explores their diverse applications, and underscores the significant environmental and economic impacts of their utilization by addressing barriers such as technological challenges, safety concerns, cost competitiveness, and the necessity for robust business strategies and policies. Xu, Jianing et al. [17] proposed a fast identification approach for microhealth parameters characterizing negative electrode material and electrolyte performance in retired LiFePO₄ batteries. Microhealth parameters encompass the performance of both active materials and electrolytes within the battery, and changes in these parameters serve as indicators of the battery's internal health state. The study demonstrates improved efficiency in assessing battery health for second-use applications, enhancing the performance consistency of regrouped retired batteries. Hu, Xiaosong et al. [18] provide a review on repurposing retired LiBs specifically for stationary energy storage applications. The review elucidates the economic and operational aspects of SLBs, covering battery aging, repurposing processes, optimal sizing, and energy-

management strategies. It underscores the imperative for future advancements in sorting methodologies, accurate aging models, and the potential market for SLBs in renewable energy storage. The utilization of batteries in their initial application is subject to significant variability, influenced by factors such as user behavior, environmental conditions, driving modes, storage methods, and annual mileage. This variability results in a wide range of aging patterns and performance levels, often diverging significantly from the battery's initial performance characteristics. Matching batteries with compatible performance characteristics is a significant challenge that limits the SLB market.

Despite extensive investigations into the potential of retired EV batteries, encompassing economic viability, parameter inconsistencies, safety considerations, policy implications, and more, the field still requires further exploration and comprehensive study to mitigate uncertainties surrounding battery reusability. Our review paper endeavors to confront the challenges associated with battery reuse from both technical and socioeconomic perspectives. It is imperative to address these challenges to comprehend feasibility, identify potential barriers, and minimize uncertainties. Moreover, we advance beyond previous research by providing a thorough analysis of detailed measurement characterizations of SLBs, aiming to offer insights that transcend superficial overviews of research findings.

This paper's structure is as follows: Initially, it presents the primary motivation behind the study, along with a comprehensive overview of the key challenges associated with repurposing SLBs. Subsequently, it evaluates the two primary scenarios at the conclusion of the battery's initial life: recycling or reuse. The subsequent sections of this paper delve deeply into each of these main challenges, with each section emphasizing its significance, role, and current state-of-the-art techniques aimed at enhancing the suitability of retired EV batteries for stationary second-life applications. The focal point of this paper lies in addressing the challenges related to battery screening, wherein various measurement methods are scrutinized and compared based on their applicability, complexity, accuracy, and ease of implementation. Finally, this paper concludes by assessing the various assessment methods employed in the battery-screening process.

2. Motivation and Overview

The exponential proliferation of batteries in the market underscores the urgent need for implementing effective and sustainable strategies to manage their EOL phase. This is essential to mitigate potential environmental risks and optimize resource utilization. As batteries reach their EOL in primary applications, the imperative of managing and utilizing them efficiently becomes increasingly paramount. This could entail developing recycling technologies or exploring alternative uses for repurposed batteries [19,20]. Consequently, the realm of retired EV batteries has experienced a significant surge in scientific, business, and policy interest over the past decade. Figure 1 illustrates the notable uptick in the publication of papers during this period.

Considering the significance of this subject and its considerable potential in promoting circular economy principles, sustainable resource management, and economic opportunities, it is imperative to address the challenges and opportunities associated with SLBs. This paper delves into various scenarios concerning the management of EOL batteries and elucidates the potential obstacles hindering the implementation of effective SLB solutions. The overarching aim is to provide informed and actionable recommendations aimed at improving comprehension and clarity regarding the concept of SLBs, along with its associated challenges. These recommendations are intended to guide researchers, decision makers, industries, and policymakers toward fostering a sustainable and energy-efficient future.

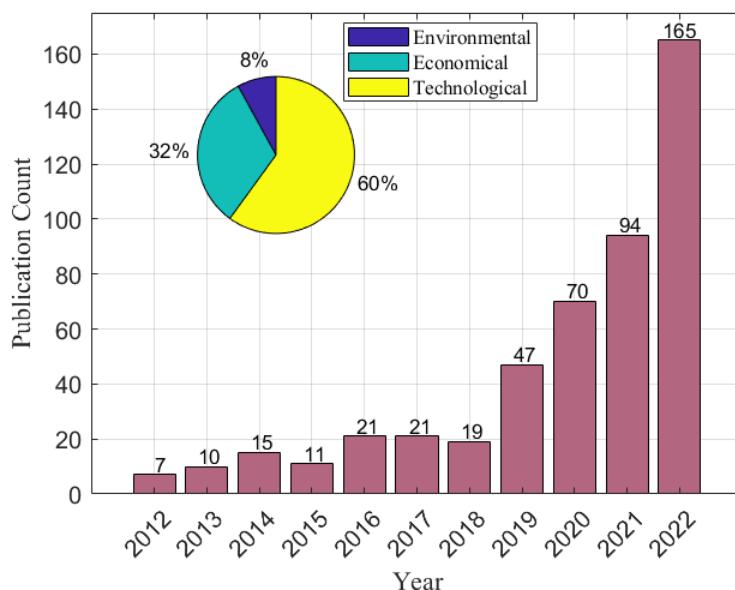


Figure 1. Research papers concerning retired batteries retrieved from Google Scholar using the search query intitle: “second-life batteries” OR intitle: “retired batteries” OR intitle: “echelon utilization” OR intitle: “battery reusing”. The figure clearly illustrates a rapid growth in publications in recent years. It has also been shown that around 60% of the research papers between 2010 and 2018 were related to the technical aspect of SLBs based on the data adapted from [21]. This percentage increased to more than 80% in 2022.

Figure 2 provides an overview of the main challenges related to battery repurposing, categorized into six groups:

- Screening challenges: Repurposing batteries for new applications demands meticulous attention to technical factors, notably performance degradation over time. This necessitates a rigorous screening process applied to cells and modules sourced from various packs.
- Safety challenges: The reuse of batteries may entail safety risks such as thermal runaway, fire, and explosion. It is imperative to prioritize safety throughout the reuse process, meticulously evaluating all potential safety hazards for the second application.
- Uncertainties from the first life: arises from the fact that batteries utilized in prior applications may have undergone varying usage patterns and environmental conditions, thus impacting their performance in a new application.
- Battery management challenges: Originate from the battery-management system (BMS), which needs to be customized for the battery pack in its second life. The primary challenges faced by the BMS include battery diagnostics and prognostics concerning the battery’s state of charge (SOC), SOH, and balancing of cells that may not be uniformly aged.
- Application challenges: the appropriateness of a previously used battery system for a specific application will be influenced by factors such as the compatibility of the battery with the new application and the anticipated cycle life of the battery.
- Techno-economic challenges: Incorporates challenges pertaining to the economic assessment and feasibility analysis of battery reuse. Understanding the primary costs associated with battery dismantling, collection, transportation, storage, and maintenance is crucial, as is analyzing the diminished performance of batteries in comparison to new ones.

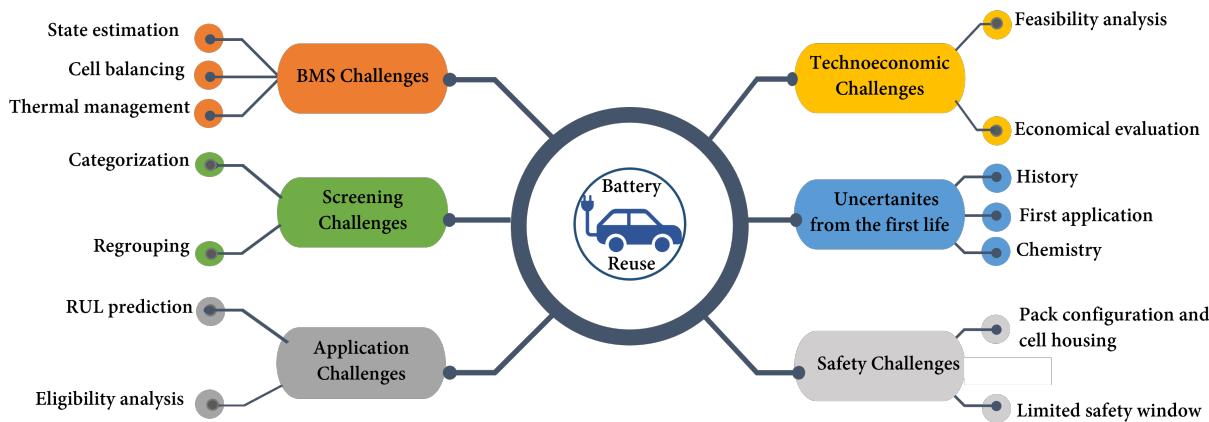


Figure 2. The challenges to SLBs are classified into six broad categories: management, screening, applications, techno-economic, uncertainties related to first life, and safety. Several secondary themes also emerge, including categorization, RUL prediction, BMS-related protection, etc.

3. A Comparative Analysis to Deal with EOL Batteries: Reusing and Recycling Approaches

3.1. Reusing Scenario

Battery reuse involves employing batteries that have fulfilled their original primary application, such as those in EVs. Although they are no longer viable for their initial purpose, these batteries still retain a considerable portion of their capacity and functionality [22]. Consequently, they can be repurposed for less-demanding secondary applications, prolonging their useful lifespan and mitigating the environmental consequences of battery disposal.

Before repackaging or repurposing a LiB into a second-life application, a comprehensive technical and economic evaluation must be performed to determine its eligibility and profitability for a possible second-life application. A battery performance assessment is the first technical step in the evaluation process, which helps to identify feasible strategies for repurposing, such as direct reuse or disassembling, by evaluating the SOH of the battery pack [23]. Following a positive performance assessment, the LiBs used in EVs can be repurposed for other applications following their first life use. The capacity remaining in SLBs varies depending on several factors, including the battery chemistry, usage conditions, and aging pattern in the first application [24].

SLBs have the potential to be employed in distributed energy-storage solutions for residential and commercial properties, allowing individuals, industries, and utilities to store solar- and wind-generated power [25–27]. However, practical implementation faces challenges beyond technical considerations. The transition from the first life of the battery to the second-life application requires qualification and regulatory approval, which is currently lacking. This absence of a regulatory framework hinders the adoption of SLBs in such applications. Furthermore, SLBs find utility in electric vehicle charging stations, which greatly helps to reduce grid peak loads and provide cost-effective charging solutions for EV owners [28–30]. However, it is important to note that the effectiveness of SLBs in maintaining high power densities over time may be affected by battery aging. Additionally, reusing batteries can create new revenue streams for businesses, as they can be sold or leased for various applications, such as stationary ESS [31–36], off-grid and remote applications [37,38], and uninterruptible power supply (UPS) as backup power [39], depending on their remaining capacity and performance characteristics. This can be particularly attractive for energy-storage providers and industries requiring large-scale battery systems. While several potential applications exist for SLBs, it is essential to consider their compatibility with grid-scale energy-storage systems. Although SLBs have been proposed as a solution for storing excess renewable energy and supporting fast frequency regulation [40–42], it is crucial to acknowledge the challenges they pose in meeting the particular requirements of the electrical grid. Balancing the electrical grid requires a high level of service guarantee and

a low failure rate, which require a high level of risk-management analysis for SLBs due to their less-controlled performance characteristics, including their lifespan, power, and capacity. In addition, using SLBs for large-scale ESS requires aggregating a large number of batteries to meet the grid's high energy and power requirements. However, the diverse characteristics of SLBs pose challenges in effectively balancing and managing such a diverse array of batteries.

Table 1 illustrates several large-scale ESS projects conducted in Europe utilizing SLBs, demonstrating the successful implementation of retired EV batteries. The concept of repurposing retired EV batteries for extended applications is a novel and innovative research area. As a result, the existing literature predominantly highlights successful implementations rather than unsuccessful trials. This scarcity is attributed to the nascent stage of SLB exploration, with many studies and projects still in the experimental or pilot phase. Researchers have primarily focused on showcasing the feasibility of reusing used batteries, pinpointing potential applications, and refining associated processes.

Table 1. List of some European projects utilizing second-life Li-ion batteries from EVs and repurposing them for large-scale ESS. These initiatives showcase the potential of SLBs to contribute to a cleaner and more sustainable energy future.

Location/Year/Company	Battery Source	Application	Capacity	Results/Achievements	Ref.
Herdecke, North Rhine-Westphalia, Germany, 2021, RWE, Audi	Li-ion batteries from Audi e-tron	Stationary ESS in pumped-storage power plant	4.5 MWh	<ul style="list-style-type: none"> - The energy-storage system is composed of 60 used battery systems from Audi e-tron. - The project demonstrates the possibilities and advantages of repurposing SLBs in stationary storage systems. - The SLBs can have an RUL of one to ten years. - Each unit battery of 90.7 kWh at the beginning of their life and over 75 kWh before implementation in the project. 	[31]
Nuremberg, Germany, 2021 Audi High-Power Charging Hub	Li-ion batteries from Audi Q4 e-tron	Audi's first charging hub located at the exhibition center in Nuremberg	2.45 MWh	<ul style="list-style-type: none"> - Testing of Audi's fast-charging concept in a real-world setting. - Use of battery buffers and second-life batteries from dismantled development vehicles for ultrarapid charging. - Reduction in costs, waste, and infrastructure complexity by using second-life batteries. - Energy on-site is substantial enough to charge up to 80 vehicles daily. 	[30]
ÜSTRA Hannoversche Verkehrsbetriebe AG, Hanover, Germany, 2021	NMC batteries from electric city buses	Stationary ESS	500 kWh	<ul style="list-style-type: none"> - The project aims to demonstrate the eco-balance improvement and extended use of the batteries in the eCitaro buses. - The SLBs reached the end of their service life in the eCitaro buses after 5–6 years, with a SOH of around 80%. - During stationary operation, the batteries retain their full functionality, which makes them suitable for energy storage applications. 	[32]

Table 1. Cont.

Location/Year/Company	Battery Source	Application	Capacity	Results/Achievements	Ref
Melilla, Spain, 2022 Enel, Nissan	Li-ion batteries from Nissan LEAF	Backup ESS in conventional power plant	1.7 MWh	- ESS serves as a backup to avoid situations of load shedding and improves the reliability and security of Melilla's grid, which is isolated from the mainland grid of Spain. The backup ESS comprises 48 repurposed Nissan LEAF batteries along with 30 new Nissan LEAF batteries. The EV battery packs were used directly in the storage system, eliminating the need for disassembly.	[43]
Gaydon, United Kingdom, 2022 Pramac, Jaguar Land Rover	NMC Li-ion batteries from Jaguar I-PACE	Portable zero-emission ESS	125 kWh	- The primary objective of this project is to create an off-grid ESS that operates without emissions. Solar panels will charge the system exclusively, ensuring a sustainable and eco-friendly energy source. Pramac is directly incorporating to reuse up to 85% of the Jaguar Land Rover battery into the storage unit, utilizing both the battery modules and wiring components. They believe that these batteries are appropriately designed to prioritize utmost safety and reliability during their second life, which occurs after the battery health no longer meets the demanding standards of an EV.	[44]
Umicore's industrial site in Belgium, 2020, Connected Energy, Groupe Renault	Li-ion batteries from Renault Kangoo Z.E.	Stationary ESS	720 kWh	- The battery system can deliver 1.2 MW of power. Second-life batteries were used to maintain grid stability and balance electricity supply and demand by providing a firm frequency response to the grid. The EOL of the battery was predicted for seven years.	[33]
Amsterdam's Johan Cruijff Arena, The Netherlands, 2018. Johan Cruijff Arena, Nissan, Eaton, BAM, and The Mobility House.	NMC batteries from Nissan LEAF	Stationary ESS for photovoltaic (PV) and peak shaving	3 MWh	- The second-life batteries store excess renewable energy generated by the stadium's solar panels and provide grid-stabilization services. The energy-storage system is also utilized for peak shaving, where the stored energy is discharged during periods of high electricity demand, reducing the need for drawing power from the grid. Johan Cruijff Arena's second-life batteries usage project showcases the potential of repurposing EV batteries for energy storage and grid stability, contributing to the arena's sustainability objectives and promoting the integration of renewable energy sources.	[34]

Table 1. Cont.

Location/Year/Company	Battery Source	Application	Capacity	Results/Achievements	Ref
Lünen, Germany, 2016 Daimler AG, Getec Energie and The Mobility House	Li-ion batteries from Smart Fortwo	Stationary power storage	13 MWh	<ul style="list-style-type: none"> - Largest 2nd-use battery storage in the world at the time of the project's completion. - The project demonstrates the efficient management of energy and material resources in electromobility. - The battery system is integrated into the German energy market, providing a primary controlling power range capacity. - The energy stored in the batteries can be automatically fed into the grid to stabilize power networks and improve power quality by peak shaving and frequency regulation. 	[35]
Hamburg, Germany, 2016 Vattenfall, BMW and Bosch	Li-ion batteries from BMW's ActivE and i3	Stationary ESS for peak shaving	2 MWh	<ul style="list-style-type: none"> - The exact number of BMW batteries used in the project is unspecified, but it is mentioned that "more than 100" batteries were used. - Utilize second-life EV batteries to create an energy-storage system that helps keep the electricity grid stable. - Demonstrate the adaptability and durability of EV batteries for stationary applications, extending their lifespan and repurposing them for grid stability and energy storage. 	[36]

3.2. Recycling Scenario

The recycling processes for EOL LiBs involve a series of complex processes to recover materials while minimizing environmental impacts [45]. These processes include collecting and sorting used batteries, discharge to ensure safety during handling, and subsequent dismantling to separate individual battery components [46]. The recovered components, such as cathodes, anodes, and electrolytes, are subjected to pyrometallurgical [47], hydrometallurgical [48], etc., processes to extract valuable metals [49]. Additionally, techniques to recover electrolytes and plastics contribute to a more comprehensive recycling approach [50].

A systematic review conducted by Lai, Xin et al. [51] comprehensively investigates strategies for the echelon utilization and material recycling of retired LiBs to turn waste into wealth. The paper provides a thorough analysis of the current status, recycling modes, industrial chains, policies, and technical challenges associated with echelon utilization and recycling. Resource recovery is a central aspect of battery recycling, offering significant benefits such as reduced reliance on primary raw material sources and conserving valuable metals like cobalt, nickel, and lithium. Moreover, effective recycling mitigates potential environmental hazards associated with improper battery disposal, thereby preventing soil and water contamination [52]. Life Cycle Assessment (LCA) methodologies are typically employed to quantify the environmental impact of recycling processes and compare them with primary production methods [53].

Various recycling technologies employ different approaches to recover materials, ranging from mechanical processes to high-temperature treatments and chemical extractions. Some techniques focus on specific components, like lithium recovery or Direct Cathode Recycling, while others aim for a more comprehensive recovery of multiple valuable metals. In the following, several commercially viable LiB recycling technologies are discussed.

These methods continuously evolve as researchers and industry experts seek more efficient, sustainable, and economically feasible ways to recycle LiBs.

- Mechanical Separation is the initial step in most recycling processes. It involves shredding the LiBs into smaller pieces to facilitate further processing. The shredded materials are then screened and sorted based on their physical properties. Different technologies, such as sieving, magnetic separation, and eddy current separation, are used to separate metals, plastics, etc. [54].
- Direct Cathode Recycling is a promising technology that seeks to recover cathode materials directly from retired LiBs. The process involves several methodologies, with the prevalent approach being cathode material leaching, wherein active materials like lithium cobalt oxide or lithium nickel cobalt manganese oxide are separated from conductive additives and binders [55]. Once the active materials are isolated, they are purified to ensure high quality and suitability for reintegration into battery manufacturing. This method has the potential to significantly reduce the environmental impact of battery production and decrease the reliance on mining for new cathode materials [56].
- Pyrometallurgical Recycling relies on high-temperature processes to break down the battery components [57]. The shredded materials are placed in a furnace and heated to high temperatures (typically above 1000 °C). During this process, the organic materials, such as plastics and electrolytes, burn off, leaving behind metal oxides and other compounds. The metal oxides are then further processed through techniques like smelting and refining to extract cobalt, nickel, and copper [58].
- Hydrometallurgical Recycling is an environmentally friendly alternative to pyrometallurgical methods [59]. It involves using chemical processes to extract metals from the battery components. The shredded materials are immersed in a suitable solvent or acid, allowing the metals to dissolve and form soluble compounds. Solvents commonly include sulfuric acid, hydrochloric acid, and citric acid [60]. Once the metals are in the solution, they can be separated and purified using various techniques such as precipitation, solvent extraction, and ion exchange [61].

Despite the promising potential of recycling EOL LiBs, several challenges and limitations exist. Ensuring safety during battery handling and recycling processes remains a critical concern due to the presence of hazardous materials. The establishment of an efficient and widespread battery collection infrastructure poses logistical challenges. Moreover, some recycling processes may still incur high costs and energy consumption, hindering widespread implementation. Establishing large-scale recycling facilities can significantly reduce processing costs, making recycling a financially attractive option. Government incentives and regulations play a crucial role in encouraging the adoption of recycling practices and fostering a sustainable market for recycled materials. Table 2 summarizes the advantages and disadvantages of each method.

Table 2. Advantages and disadvantages of different recycling methods for Li-ion batteries.

Method	Advantages	Disadvantages
Mechanical Separation	<ul style="list-style-type: none"> • Simple process and cost-effective. • Facilitates initial separation of materials. • Can recover valuable metals and plastics. 	<ul style="list-style-type: none"> • Limited recovery percentage. • Some valuable materials may be lost. • Might require additional processes to achieve high-quality materials.
Pyrometallurgical Recycling	<ul style="list-style-type: none"> • Efficient metal extraction at high temperatures. • Can recover a significant portion of valuable metals. • Can handle mixed battery chemistries and various battery sizes. • Proven technology with established infrastructure. 	<ul style="list-style-type: none"> • High energy consumption, leading to higher operating costs. • Potential emissions of pollutants and greenhouse gases during high-temperature processing. • Potential loss of certain metals through volatilization. • Generation of toxic emissions and residues. • Risk of metal composition changes due to high heat.

Table 2. *Cont.*

Method	Advantages	Disadvantages
Hydrometallurgical Recycling	<ul style="list-style-type: none"> Environmentally friendly with lower emissions. Selective extraction of metals. High metal recovery rates and purity. Ability to treat a wide range of battery chemistries. 	<ul style="list-style-type: none"> Requires careful handling of corrosive chemicals. Initial setup and operational costs may be higher. High chemical and processing costs due to the use of reagents and complex separation processes. Acidic wastewater treatment is necessary, leading to potential high disposal costs for chemical waste. Possibility of solvent loss during the recycling process.
Direct Cathode Recycling	<ul style="list-style-type: none"> Reduces the environmental impact of battery production. Supports a more sustainable battery supply chain. Decreases reliance on new cathode material mining. 	<ul style="list-style-type: none"> Requires efficient and selective cathode leaching. Complex purification processes may be needed. Limited applicability to certain cathode chemistries.

3.3. Reuse vs. Recycling

Recycling has become vital to a greener and more sustainable world, reducing the burden of electronic waste and bringing opportunities to enhance resource conservation and reduce the carbon footprint of battery production. Nevertheless, recycling is not the only solution to increase the sustainability of LiBs. Reusing the batteries, especially those with the potential of usability in less demanding applications, is beneficial by increasing the longevity of the batteries.

The concept of SLBs focuses on delaying the recycling process by repurposing used batteries in alternative applications. Extending the battery lifetime maximizes the energy-storage potential and minimizes the overall environmental impact associated with their production, disposal, and recycling. A comprehensive analysis is required to cover a wide range of assessments, from the energy efficiency and greenhouse gas emissions analysis, a systematic approach that evaluates the environmental impacts like the LCA, economic viability, and cost-effectiveness of each scenario, to the market potential for SLBs to compare different scenarios for EOL batteries. Moreover, in the context of large-scale energy storage applications, various factors such as cost-effectiveness, performance, environmental impact, scalability, reliability, and safety should be considered to have a comprehensive comparison between different types of ESSs. For instance, recent advancements have been made in cost-effective iron-based redox flow batteries (RFBs) [62]. Comparing SLBs with iron-based RFBs would provide valuable insights into their respective strengths and weaknesses, guiding decision-making processes in battery end-of-life management strategies. The choice between different technologies depends on specific project requirements, including cost constraints, performance criteria, and regulatory considerations.

Research in [63] investigated the life cycle processes of NiMH batteries, showing that reusing or recycling can reduce environmental burdens compared to non-recycling scenarios. The findings indicate that reusing or recycling a waste NiMH battery rather than sending it to a landfill can substantially reduce its overall environmental impact. Notably, in the reuse and recycle scenario, approximately 83 kg of CO₂ emissions, 1.37 kg of resource depletion, 0.044 m³ of landfill volume, and 1611 MJ of energy consumption can be conserved for each NiMH battery. Figure 3 shows various scenarios examined in this research and the corresponding outcomes regarding climate change impact, environmental burdens, and benefits.

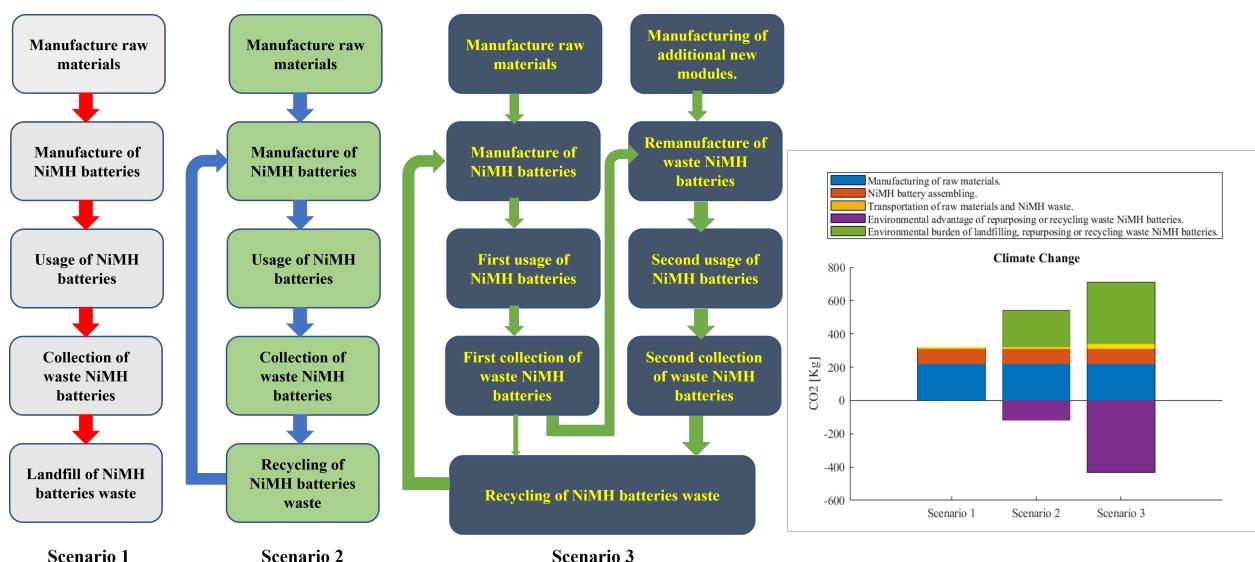


Figure 3. Different scenarios for NiMH batteries (adapted with permission from [63]). In scenario 1, the battery will experience the non-recycling process without reusing and recycling. Scenario 2 considers the end of the first use of the battery as EOL and then consigning batteries straight to the recycling plant. Finally, in scenario 3, after the first use of the battery, it will go through the reusing for its second usage. EOL is defined based on the end of the second battery usage and, finally, the recycling process. Results from the LCA analysis on the climate change impact of each scenario in terms of CO₂ emissions reveal that choosing to reuse or recycle waste NiMH batteries instead of directly disposing them in landfills significantly decreases the absolute environmental impact.

A comprehensive investigation was conducted to assess the environmental impact of NMC SLBs compared to other battery types in [64]. The study's primary objective was to determine whether delaying the recycling of NMC batteries by giving them a second life is beneficial while considering the associated drawbacks of postponing the recycling. Within the study's context, the NMC battery emerges as the more environmentally beneficial choice for most European regions than lithium iron phosphate (LFP) batteries. The study reveals that the choice of allocation and recycling input significantly affects the outcomes for NMC batteries. Under the assumption of 20% allocation to the second life and 10% recycling input, LFP batteries require less energy per equivalent full cycle (EFC) than second-life NMC batteries within a reasonable cycle life, suggesting that, based solely on energy demand, LFP outperforms second-life NMC batteries.

4. Screening Challenges

One of the main challenges in SLB implementation is ensuring battery cell consistency and stability in terms of capacity, voltage, and internal parameters [65]. Furthermore, the history of the battery's first life, including cyclic aging and the operating temperature, should ideally be considered to determine its suitability for SLB applications, but this information is usually unavailable, unfortunately. All these aspects make the screening process for second-life batteries complex and multi-disciplinary, requiring expertise in battery technology, electrical engineering, and data analysis.

There is variation in the internal parameters of cells in LiBs, even for fresh cells. Based on the outcome of the previous study and the measurements on 700 Li-Po cells [66], it was observed that cells belonging to the same manufacturer and batch are not identical in terms of internal parameters, as was illustrated in Figure 4. These inherent variations originate from the manufacturing process of the cells. Table 3 shows a list of studies that investigated fresh cell-to-cell variations. Different aspects, like variations in the thickness of the electrodes, condensation of active materials, and different formation processes, can all cause these cell-to-cell variations.

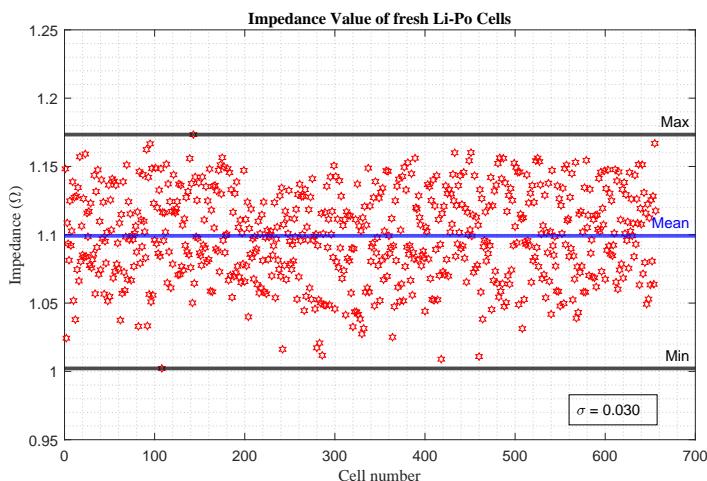


Figure 4. DC internal resistance measurement results for 700 fresh Li-Po Cells in the same SOC to show the variation after formation cycling with a variation coefficient (standard deviation/mean) of 0.030. The minimal and maximal resistances that define the window are 1 mΩ and 1.17 mΩ, respectively.

Table 3. List of some relevant literature and battery parameters on studying and investigating the cell-to-cell variation.

Ref	Number of Cells	Nominal Capacity	Positive Electrode	Negative Electrode
[67]	51	2800 mAh	LCO and NMC	GIC
[68]	48	2600 mAh	NMC	C
[69]	10	1900 mAh	LMO	C
[70]	100	300 mAh	LiCoO ₂	C
[66]	700	6300 mAh	Li-Po	Not disclosed
[71]	1100	3000 mAh	NMC	C

The variation in cell properties within a battery pack will increase during battery aging. Temperature, different charges/discharge rates, time, etc., are the primary external stress factors that cause increased variations in cell properties [72]. Since the temperature distribution is rarely uniform between the modules inside a battery pack and between the cells within a module, it can be considered the most influential factor in different battery aging, especially for their second life due to aging [73,74]. The battery degradation process is linked to irreversible chemical changes occurring within the battery over time. Each charge/discharge cycle of the battery changes a portion of the materials in different elements. The accumulation of this persistent degradation process constitutes the essence of the battery's aging [75]. Figure 5 outlines the primary aging mechanisms in the anode, cathode, and other inactive materials [76].

Due to the complexity of degradation mechanisms based on chemistry (internal) and the influences of driving patterns (external), determining the battery SOH is challenging, especially in SLBs. Generally, the SOH can be estimated during the battery operation (in situ) or measured or estimated while the battery is not operating. The battery categorization for SLB applications means evaluating the battery's performance in terms of its health condition. The battery's SOH is usually defined as its capability to store energy compared to that of a fresh battery. It describes the battery's current performance compared to its ideal situation as follows:

$$\text{SOH} = \frac{\text{Current Capacity}}{\text{Nominal Capacity}} \times 100\% \quad (1)$$

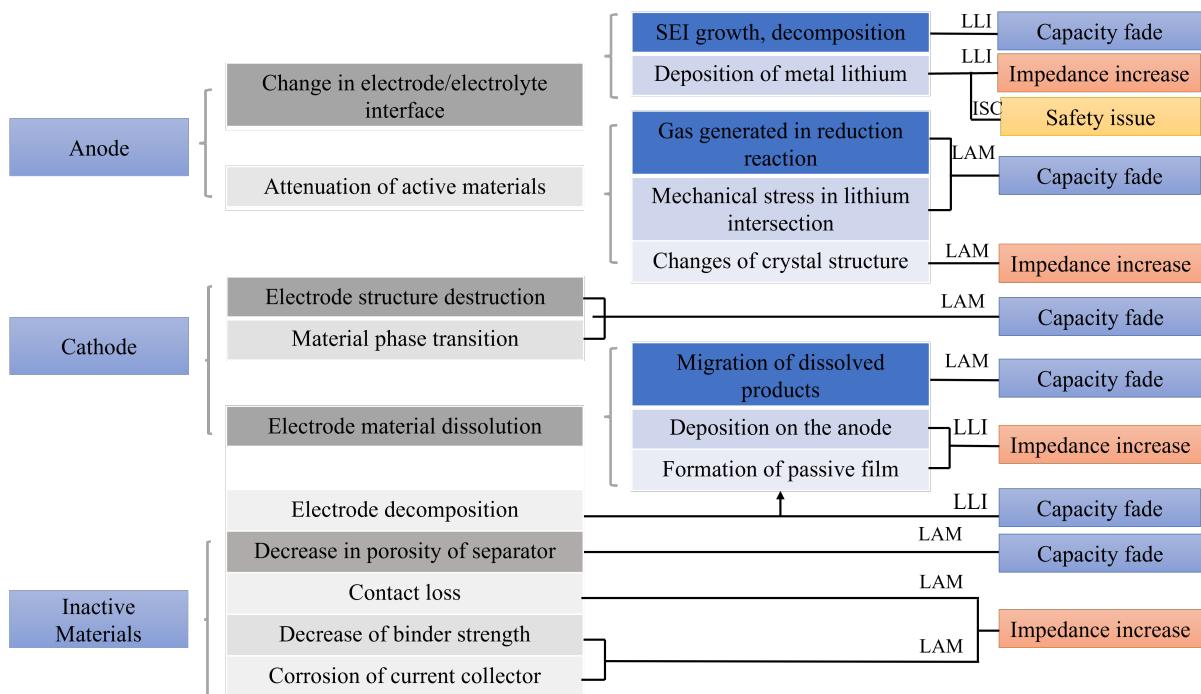


Figure 5. Main aging mechanism taking place in the battery's anode, cathode, and other inactive components with their main influences on either the reduction in capacity or the rise in impedance or, in the worst case scenario, leading to Internal Short Circuit (ISC) (adapted with permission from [76]). Loss of active material (LAM) and loss of lithium inventory (LLI) result in reduced capacity due to reduced electrode substance and lithium ions number. Growth in solid electrolyte interface (SEI) in anode materials also contributes to internal impedance increase.

The SOH is an essential indicator for decision making in finding the proper SLB application. It is necessary to categorize the batteries correctly, which usually happens by selecting the battery cells with a similar SOH to form a module and subsequently combining modules with a similar SOH. There are different approaches to measuring the battery SOH directly or estimating it based on battery indices related to degradation. Since the number of batteries at their EOL is increasing rapidly from the EVs or HEVs, it is rational to use methods that can estimate the SOH expeditiously. Rapid methods include the assessment of battery parameters that indicate the health condition of the battery. An incremental capacity analysis (ICA), differential voltage analysis (DVA), differential thermal voltammetry (DTV), electrochemical impedance spectroscopy (EIS), etc., are some examples of such methods that are investigated in the remainder of this chapter.

4.1. Incremental Capacity Analysis

An ICA is an indirect battery SOH estimation method based on the capacity variation corresponding to the voltage change in the battery. It can be formulated based on the derivative of capacity concerning voltage:

$$IC = \frac{\Delta Q}{\Delta V} = \frac{dQ}{dV} \quad (2)$$

The relation between the LiB's voltage with respect to the capacity is almost like a flat curve, so a small error in the battery voltage measurement leads to a large estimation inaccuracy. By taking the derivative of the curve, the ICA method converts this flat curve into a curve with distinguishable peaks. Information related to the battery electrochemical degradation mechanism can be found in the resulting IC derivative curves. This means that different indicators that come from the IC curve, e.g., the information related to the peaks, such as the peak amplitude, location, and area under the peak, can be used to estimate

the SOH of the battery. One of the major advantages of this technique is its capability to perform *in situ* measurements during the normal operation of the battery. The technique comes with considerable information about the internal phenomena of the battery. As an example, Figure 6 shows the IC curves of four modules from the same battery pack used for eight years in a hybrid electric vehicle (HEV). As expected from the capacity measurement of these four modules (module number 4 has the lowest capacity compared to other modules), module 4 has the lowest right-most peak. This means that this module experienced more loss of lithium inventory (LLI) than the other modules. The loss of active materials and the solid electrolyte interphase could be the potential causes of this peak. Ohmic resistance increases, usually happening when the battery ages and shifts the whole IC curve to the higher voltage [77], and can be seen for modules 2 and 3 in this experiment.

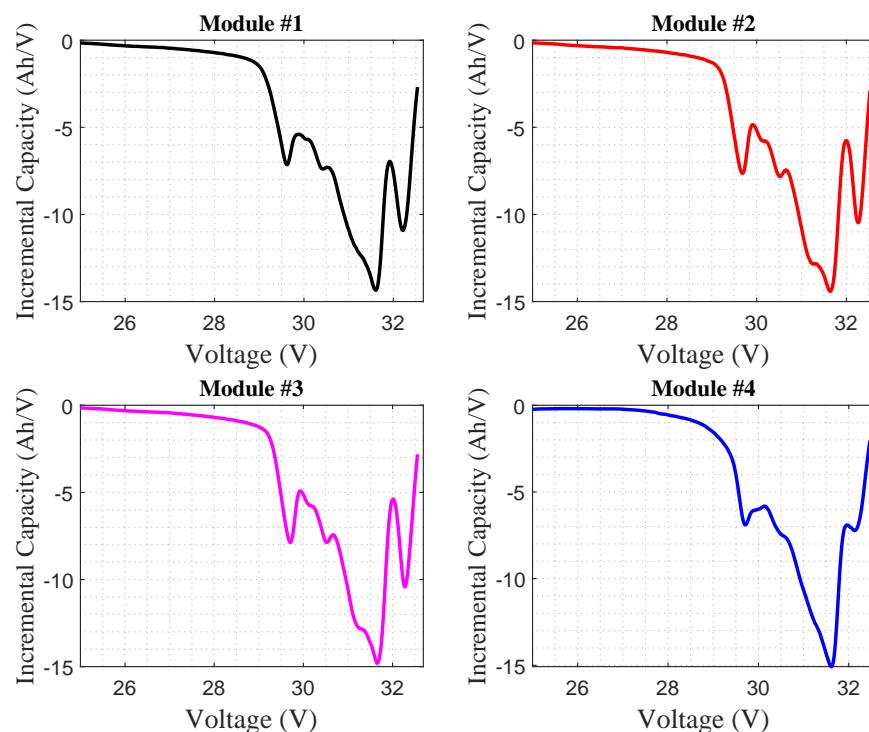


Figure 6. Measured ICA curve of four battery modules from an HEV during the discharge process. Module 4 shows a flattening of the right-most trough, indicating the discrepancy of its SOH relative to the other 3 modules.

Different chemistries of Li-ion batteries have different ICA characteristics, and changes in IC curves happen while the battery ages. Each peak corresponds to a different aging mechanism, e.g., loss of active material, loss of lithium inventory, and increase in battery impedance. Shifting the peak locations and changes in the magnitude of different peaks corresponding to the battery health condition makes the ICA method attractive in battery SOH measurement/estimation. The authors of [78] suggested this method for accurate battery diagnostics and prognostics and noticed a strong correlation between the battery SOH and the peak's shape, amplitude, and position. For example, a reduction in the amplitude of the first peak could indicate the loss of active material and increase the solid electrolyte interface, leading to the battery's higher internal resistance. More information related to the degradation of the battery and its relation to battery IC curves can be found in [79,80].

In conclusion, as a non-destructive method, the ICA method is rich in information about the degradation processes inside the battery. This method's main advantages are high accuracy, low computational burden, easiness of implementation, non-destructive nature, and applicability for different battery chemistries. On the other hand, this method is time-

consuming and improper for second-life battery screening. Furthermore, the method's applicability is mainly on the cell level, and there are still several uncertainties about pack-level SOH estimation. Finally, the accuracy of this method is very sensitive to the environmental operation of the battery.

4.2. Differential Voltage Analysis

The differential voltage analysis (DVA) methodology is similar to the ICA method. The unique aspect of this technique is that it assesses the battery features based on the voltage (V) response's deviation concerning capacity (Q) as follows:

$$DV = \frac{\Delta V}{\Delta Q} = \frac{dV}{dQ} \quad (3)$$

This method is usually used to analyze the battery degradation based on the main mechanisms, e.g., loss of active material, loss of lithium inventory, and loss of cathode materials. Figure 7 shows the DV curves of the same modules used in the ICA analysis of Figure 6. The curve reveals information related to battery aging and its SOH that can be interpreted from peak analyzing.

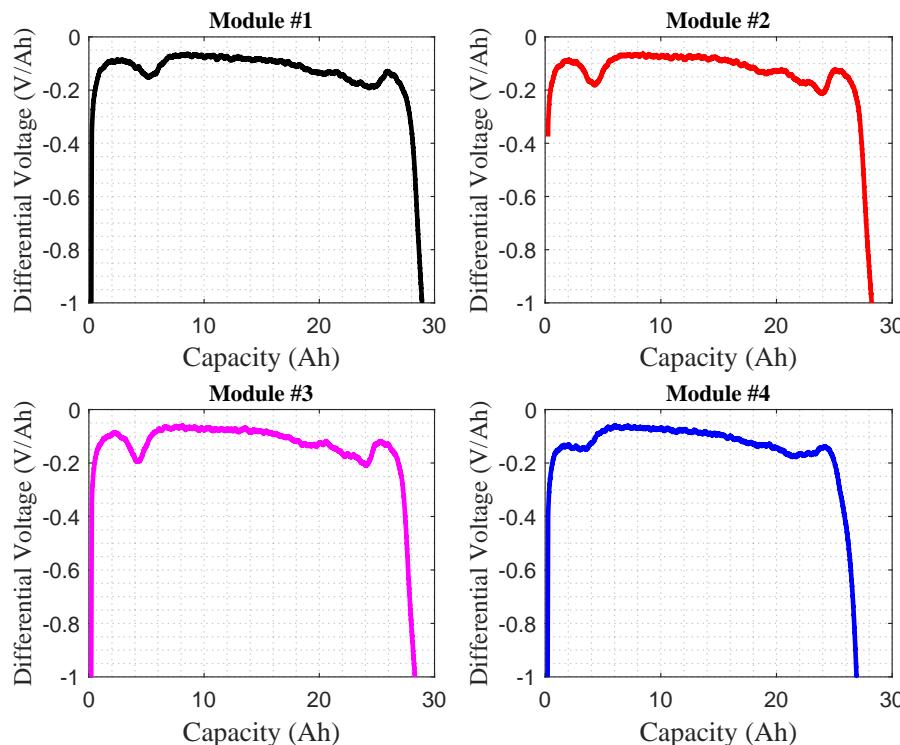


Figure 7. Measured DVA curve of four modules from the same HEV battery pack as in Figure 6 during the discharge process. The fading of the right-most peak in Module 4 and its impact on SOH is evident in the figure.

Like the IC curve, the location of the peak and magnitude can be used to indicate the health condition of the battery. ICA and DVA are both powerful tools for online battery SOH estimation. SOH estimations based on these methods are relatively simple since only voltage and capacity need to be measured and monitored. Even with its advantage of low complexity for SOH estimation, it is not considered for SLB screening due to the time-consuming nature of full charging and discharging.

4.3. Differential Thermal Voltammetry

Our experience based on laboratory measurements has shown that improving the method's accuracy and peak analysis in IC/DV curves requires measurements in low C_{rate} conditions, which takes several hours and is not feasible for battery repurposing. Figure 8 illustrates the result of the battery capacity measurement at three different discharge current rates on the same lithium-ion manganese oxide (LMO) battery module as Figures 6 and 7. Using a higher C_{rate} results in two significant changes in the IC curve. First, the increase in noise mandates the use of Gaussian filters, which leads to a loss of information, and more importantly, it becomes difficult to distinguish peaks. This was further observed in a subsequent measurement at high currents (voltages), where one peak became indistinguishable and therefore found missing.

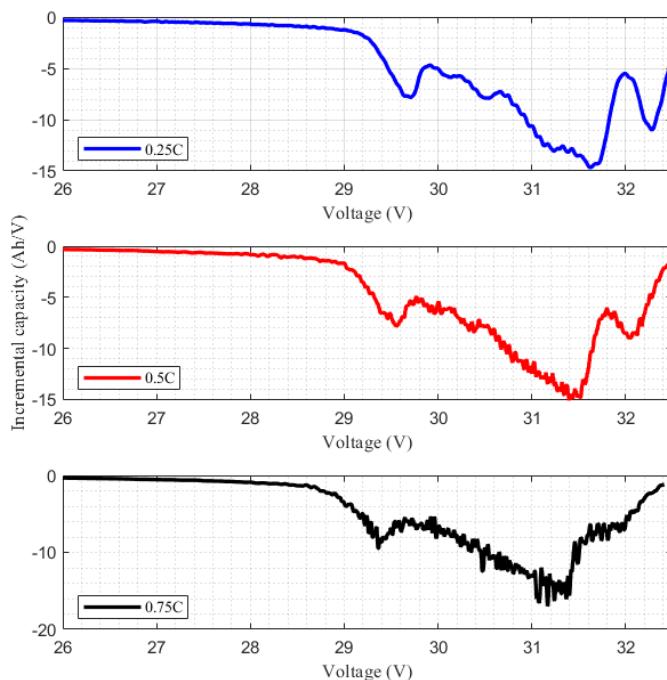


Figure 8. ICA curves at different C_{rate} for module 1 from the same HEV battery pack as Figures 6 and 7.

Generally, loss of lithium inventory, loss of active materials, and the formation of solid electrolyte interphases are the main contributors to changes in the first right-most peak; as the battery ages, this peak fades significantly. The fading of the right-most peak is a proper indicator that shows the battery SOH [81]. According to studies [82,83], each peak in the DVA curve can be linked to the electrochemistry inside the battery. The curve also shifts to a different voltage range during battery aging due to increases in the internal resistance.

Temperature is also an indicator that can be used to show the health condition of the battery. By increasing the C_{rate} during the battery charge/discharge, the temperature inside the battery and, consequently, on the surface, increases. The temperature profile is rich with information related to the battery's entropic behavior. Like ICA and DVA methods, it is a relatively easy method and only requires surface temperature measurement and voltage monitoring [84]. Differential thermal voltammetry can be formulated based on the temperature (T) derivative concerning voltage:

$$DT = \frac{\Delta T}{\Delta V} = \frac{dT}{dV} \quad (4)$$

Differential thermal voltammetry (DTV) is an in situ method for battery SOH measurements with low complexity. The analysis is based on the peak parameters in the DT curve to quantify the battery degradation and estimate the SOH [85]. DTV is a promising technique

due to its simplicity, which does not require additional hardware within the battery pack or BMS. However, like most battery diagnostics techniques, the operation conditions affect the accuracy of the measurement and, consequently, the SOH estimation [86].

To evaluate the applicability of this method, the authors monitored the temperature on four different modules from the same battery pack of an HEV. The experiment aimed to investigate the correlation and dependency of the DT curves on the module capacity. Each module contains eight cells, and a K-type thermocouple measured the surface temperature of each cell. During the temperature monitoring, it was noticed that the temperature of one cell inside a module is not only a function of the cell parameter itself but is also affected by the adjacent cells inside the module. The uncertainties related to the location of the cell within the module are always a big challenge for achieving good accuracy in the DTA method. It is also worth mentioning that the curves need data processing across all three differential methods to filter out high-frequency noise. During the filtering, some information will be lost, which again will affect the method's reliability and accuracy. Figure 9 shows the DT curves of eight cells inside a module concerning the voltage changes during the discharge at 1C.

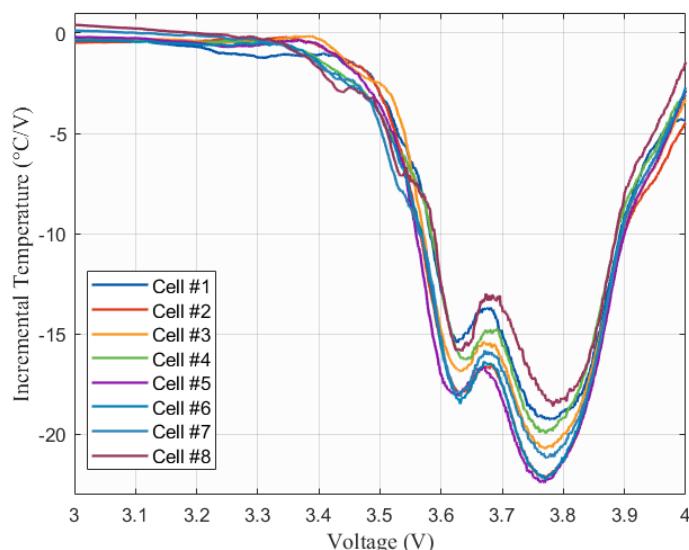


Figure 9. Differential thermal voltammetry analysis of a module with 8 LMO cells. Three features can be derived from the valley values, peaks, and the position of each peak, which can be analyzed separately to be linked to the degradation of the battery. It is evident that cells 5 and 6 in the pack show the lowest differential temperature while cells 7 and 8 have the highest.

In conclusion, DTV is a valuable tool for assessing the internal condition of the battery at the cell level with information for battery SOH monitoring. It is a minimally destructive method that only requires straightforward temperature and voltage measurement, which makes it suitable for *in situ* measurement. Since the temperature is highly correlated with the battery's internal resistance (figure of merit of this technique), it can be a very reliable technique for the battery SOH at the cell level in controlled operation conditions. On the other hand, this method strongly depends on accurate measurements, generally leading to limited accuracy. Also, the applicability of the method at the module and pack level is very dependent on the thermal management system (TMS) of the battery pack; as was mentioned above, the location of the cell inside the module and the location of the module inside the battery pack seriously affects the reliability of this method [87].

4.4. Electrochemical Impedance Spectroscopy

A powerful technique in battery diagnostics and prognostics is electrochemical impedance spectroscopy (EIS). This method has been getting more attention recently due to its non-destructive nature and the rich amount of information that can be derived from it on key

parameters that are linked to the battery's degradation and health condition [88]. There are several ways to make a graphical demonstration of the measured impedance over the frequency range used, but the most favorable way is the Nyquist plot. To interpret the EIS results from its Nyquist plot to meaningful information related to the battery degradation and also use it for battery SOC, SOH, and RUL estimation, it is essential to model the battery with parameters that can explain the electrochemical nature of the battery, as illustrated in Figure 10. This equivalent circuit model (ECM) is one of the most commonly used techniques for interpreting the EIS result. In this approach, the impedance from wide-range frequency spectra is represented by electrical elements that model the physics and chemistry of the battery. The circuit model will be obtained by finding a good circuit topology that can be an effective ECM with all important elements, e.g., series resistance in combination with RC networks.

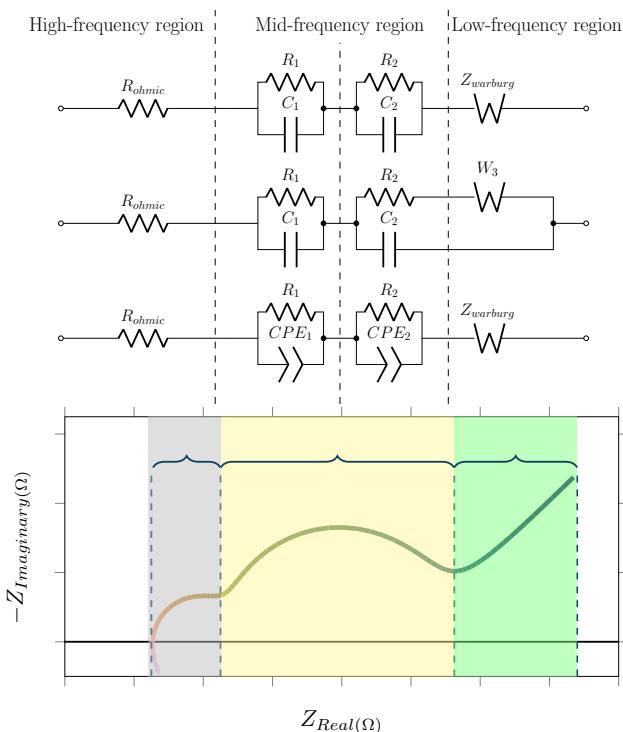


Figure 10. The diverse behavior of the battery impedance across distinct frequency ranges is effectively captured using suitable ECMS (top) adapted with permission from [89]. The figure showcases the interconnected parameters that correspond to various regions of the Nyquist plot of a randomly selected Li-ion cell (bottom). This depiction comprehensively illustrates impedance spectroscopy spanning a broad frequency spectrum from mHz to kHz. The semi-circle in the high-frequency range predominantly indicates the impact of the film's resistance and capacitance, while the arc in the medium-frequency range is caused by the charge-transfer resistance and the capacitance of the double layer. The linear slope at the low-frequency end is attributed to the diffusion impedance.

The ECM model can be used to link each electrical element with the three common degradation modes of the battery, each reflected in a response in a different frequency range [75,78]. The high-frequency region (kHz range) is usually modeled with series resistance and an inductor. The degradation mechanism affecting this region is the loss of lithium inventory, causing electrolyte decomposition. In the mid-frequency region, commonly modeled by RC networks, the degradation mechanisms that will lead to a change in the ECM are loss of active materials in the anode and cathode and the growth of a solid electrolyte interface (SEI). Finally, the low-frequency range shows the diffusion process, which is represented in the ECM model with a Warburg or a constant phase

element (CPE). The diffusion process is related to the battery degradation by loss of active material in the cathode that will lead to a change in the electrode's formation [89].

Degradation processes in LiBs have distinct effects on each of the three regions in the EIS spectrum, which thus can be used to understand the degradation mechanisms. The links between EIS spectra and degradation are well established, with certain degradation processes leading to specific changes in the EIS spectrum. There is a strong correlation between the ECM parameters obtained from EIS spectra with the battery SOH [90]. The authors of [89] conducted a comprehensive review on the link between the degradation process and ECM elements to analyze the strengths and limitations of EIS as a diagnostics tool for battery health monitoring. An acceptable correlation index between the battery ohmic and charge transfer resistance in the ECM with SOH was achieved in [88].

To illustrate the power of the EIS tool, we show the results of cycling aging for an NMC cell under a specific charge and discharge pattern. During the cycling, an EIS measurement is performed to analyze the degradation behavior regarding an increasing cycle index. The results given in Figure 11 show a clearly visible shift in the EIS spectra while the battery ages, with the mid-frequency region as the main link between the changing battery SOH and the changes in the EIS spectra.

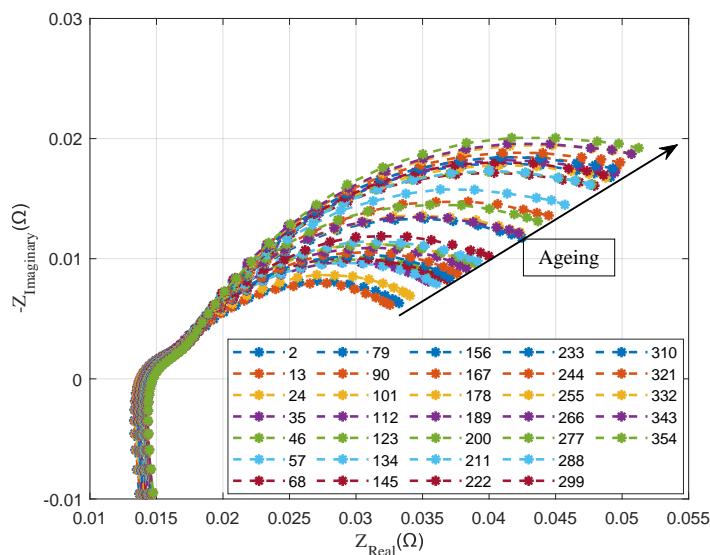


Figure 11. Nyquist plots for a single NMC cell under a specific cycling pattern of 4C discharge current rate and 80% DOD at room temperature for a measurement frequency between 20 Hz and 100 kHz. The results show a shift to the right and top of the mid-frequency spectrum caused by the degradation inside the battery with increasing cycle index, indicating this frequency range has a good correlation with the battery SOH.

Most of the research based on impedance-based models and EIS has been performed at cell level to find the effect of different aging patterns and temperatures on the battery model. EIS at cell level has been investigated in [91,92], and it shows a well-distinguishable SOH related to the second-life battery resistance parameters. This finding is crucial, especially for SLBs, due to their rapid growth and the fact that dismantling the battery to cell level is very time-consuming, so it is almost impossible to access each individual cell inside a battery pack. Furthermore, the fast measurement, which is one of the advantages of the EIS method, may be compromised if it is not applicable for module and pack levels on SLBs. The number of studies focusing on EIS measurements at the battery module level is very limited [93,94].

In general, the EIS method is getting increased attention as a non-destructive and fast method with high accuracy, especially for SLBs that do not require on-site measurement [91]. Still, time is an important factor in decreasing the labor cost of evaluating the battery for a possible new life in a second application. Accuracy, time efficiency, and the large amount

of information related to the battery's internal degradation are the main advantages of the EIS method. On the other hand, this method requires specialized equipment, making the measurement technique complex and expensive.

Table 4 presents an extensive comparison between the investigated methods in this study.

Table 4. Comparison of different indirect battery SOH assessment methods based on battery indices related to degradation investigated in this paper.

Method	Advantages	Disadvantages
Incremental capacity analysis (ICA)	<ul style="list-style-type: none"> Peak's shape, amplitude, and position identify different aging mechanisms inside the battery. Minimally destructive method (still requires full charge/discharge for each measurement). 	<ul style="list-style-type: none"> Limited to specific battery types and chemistries. The accuracy of the method depends on the quality of the voltage measurement and requires precise capacity measurement. Time-consuming method since the method requires full cycle with a low C_{rate}.
Differential voltage analysis (DVA)	<ul style="list-style-type: none"> Like the ICA method, the location of the peak and magnitude can be used to indicate the health condition of the battery and quantify different aging mechanisms. Minimally destructive since it requires a full charge/discharge cycle. 	<ul style="list-style-type: none"> Not suitable for all battery chemistries, especially the batteries with a flat voltage curve. Time-consuming nature because of full charging and discharging. Using Gaussian filters to smooth the data and filter the noise might lead to loss of information related to the degradation.
Differential thermal voltammetry (DTV)	<ul style="list-style-type: none"> Relatively easy method, only requires straightforward temperature and voltage measurement, which makes it suitable for in situ measurement. Non-destructive method. Reliable method on cell level due to the high correlation between the battery internal resistance and the surface temperature. 	<ul style="list-style-type: none"> Environmental and operation conditions affect the accuracy of the measurement and, consequently, the SOH estimation. Suffer from the uncertainties related to the location of the cell within the module and the pack to achieve good accuracy. Possibility of losing information during the data processing to filter out the high-frequency noise.
Electrochemical impedance spectroscopy (EIS)	<ul style="list-style-type: none"> Non-destructive method. Fast method in specific frequency ranges. High accuracy. Rich with information about the battery's complicated internal electrochemical reactions and aging patterns. 	<ul style="list-style-type: none"> Requires special and complex measurement in the frequency domain with specialized equipment. Challenging at module and pack level. Relatively expensive and complex method.

5. Safety Challenges

Safety remains a paramount concern in the realm of LiBs, given their status as a relatively young technology. Due to their high energy density, LiBs have the potential to release a significant amount of energy in a short span, posing substantial safety risks. Despite notable advancements in safety-oriented battery design in recent years, incidents related to battery hazards continue to occur with some frequency.

Based on data from the National Fire Protection Association (NFPA) and the U.S. Department of Transportation, "there is approximately one vehicle fire per 30 million kilometers for petrol cars". In comparison with Tesla, this number is one Tesla fire per 330 million kilometers, based on data from 2012 until 2020 [95]. These data show that EVs are significantly safer than other types of vehicles. However, there is always a potential fire risk with LiBs due to their high energy density. Based on reports from the NFPA journal, the failure rate of Li-ion batteries is between 1 in 10 million and 40 million, considering both the higher and lower end of the spectrum, respectively [96]. Recent battery fire incidents in EVs have been reviewed in [97] to investigate varied and robust designs considering system safety features and architectures.

Safety is one of the main reasons that EV car manufacturers define an SOH close to 80% as the threshold for battery replacement. A safe charge/discharge operation window

exists for Li-ion batteries to achieve optimal performance and life from the battery. This window must be stricter for the battery's second life as the battery-safe operation window depends on non-linear battery aging and related detrimental effects [98].

The operation window of the battery is usually defined by factors such as temperature, current, and voltage/SOC. These parameters have a recommended range for most batteries that can vary depending on the battery's chemistry and intended application. Operating the battery outside its recommended range can reduce performance, lead to a short lifespan, or pose a safety risk. It is important to note that the safe operation window for batteries can be affected by other factors as well, such as the operating environment, the battery's design, its age, and its usage history. It is always best to consult the manufacturer's specifications for the specific battery to determine its safe operating conditions [99].

Identifying the degradation mechanism in Li-ion batteries is complicated as the electrochemical phenomenon in action depends on several parameters. This field is still nascent and requires further experimental and simulation studies [100]. The main improvements are expected to occur at the cell or BMS level. Furthermore, the battery aging mechanism is not linear, and this non-linearity is more critical in the battery's second life [101,102]. Further, in [103], the influence of battery cyclic aging on thermal runaways has been investigated at low-pressure conditions. The results showed that with increasing cycling, the thermal runaway surface decreases, leading to conditions that accelerate thermal runaway. Table 5 presents some relatively recent incidents involving Li-ion batteries.

Generally, the BMS within the battery pack has the prominent role of guaranteeing the optimal and safe operation of the pack [104]. The role of the BMS in SLBs is more critical due to increased uncertainty and reduced reliability in these batteries. The BMS represents the intelligence of a battery pack, and it is involved in all battery safety control systems, charge and discharge, thermal management, cell balancing, and battery state estimation [105]. In SLBs, accurate SOH estimation and RUL prediction are more difficult due to the lack of information about aging in their first use. Furthermore, SOH estimations are typically defined for fresh batteries based on their first-life data. Any optimistic or pessimistic estimate in battery states by the BMS in a second-life application can strongly decrease the battery lifetime, or even, in the worst case, can cause a fire/explosion. Table 6 shows the reusing challenges of Li-ion batteries with respect to potential hazards. Implementing appropriate safety measures to mitigate potential risks is crucial in avoiding these hazards. Robust standards, as discussed in the techno-economic section, beyond their significant impact on market growth, can play a crucial role in the safe operation condition of SLBs. It is also worth mentioning that investing in user education and training is equally important beyond all technical aspects of the safe usage of SLBs due to all the above-mentioned risks and hazards.

Table 5. Some of the most well-known fire incidents involving Li-ion batteries illustrate the potential hazards associated with Li-ion batteries and the importance of proper safety system design.

Country	Description	Year	Ref.
United States	<ul style="list-style-type: none"> • Boeing 787 Dreamliner was grounded due to issues with the lithium-ion batteries in the auxiliary power unit. • Smoke and flames originated from the batteries, causing safety concerns. • The grounding lasted for several months as the batteries were prone to overheating. 	2013	[106]
Global Recall	<ul style="list-style-type: none"> • Samsung recalled millions of Galaxy Note 7 smartphones to prevent further safety hazards. • The problem related to the battery, specifically the insulation material inside, and a design flaw. • These issues caused the phone to overheat and, in some cases, catch fire. 	2016	[107]

Table 5. Cont.

Country	Description	Year	Ref.
Belgium	<ul style="list-style-type: none"> Fire in a 1 MWh Engie Ineo Li-ion battery container in the first grid-connected utility plant. The cause of the fire is still not known. 	2017	[108]
South Korea	<ul style="list-style-type: none"> Fire at a cement plant in Jecheon, North Chungcheong Province (South Korea). USD 3.63 million in damage. LG Chem and LG CNS structure the ESS. 	2018	[109]
United States	<ul style="list-style-type: none"> Explosion in a 2.16 MWh Li-ion ESS in Surprise, Arizona, USA. The predominant factor was the malfunction of a single cell within the battery. Caused a series of thermal runaways that affected the whole system. 	2019	[110]
China	<ul style="list-style-type: none"> Incident for a Tesla Model S in a parking garage. Based on the results of a subsequent investigation, failure in a module positioned at the front of the car caused a severe fire. 	2019	[111]
Netherlands	<ul style="list-style-type: none"> Fire in a dealership showroom in Tilburg, North Brabant province. The cause of the fire for the BMW i8 has not been identified thus far. The firefighters dropped the car in a massive water container to extinguish the fire. 	2019	[112]

Table 6. Safety challenges regarding reuse of Li-ion batteries, illustrating the potential extra safety risks for second-life batteries and the possible hazards.

Reusing Challenges	Description
Aging	<ul style="list-style-type: none"> Battery aging can lead to capacity degradation. Capacity degradation can increase the risk of failure, thermal runaway, and overcharging. These risks can potentially cause safety hazards and reduce the battery's lifespan.
Inhomogeneity	<ul style="list-style-type: none"> The aging pattern of the cells and modules within the pack is not uniform. This inhomogeneity can lead to thermal runaway and be a potential safety hazard depending on the intended second application.
Unbalanced charge/discharge	<ul style="list-style-type: none"> Mismatching between cells and modules occurring in a battery pack. An unbalanced charge/discharge pack can result from this mismatching. An unbalanced pack can increase the risk of thermal runaway and overcharging. These risks can potentially cause safety hazards and reduce the lifespan of the battery pack.
Diagnostics and prognostics	<ul style="list-style-type: none"> Battery SOC, SOH, and RUL estimation and prediction are much more difficult for second-life batteries due to the uncertainties mentioned in the paper. Inaccurate estimation can lead to the risk of overcharging, underdischarging, and in the worst case, thermal runaway and fire/explosion.
Mechanical damage	<ul style="list-style-type: none"> These batteries might have mechanical damage from the first use, which can compromise their safety and lead to thermal runaway.

Degradation processes within the LiBs are characterized by various chemical, electrochemical, and physical phenomena throughout the battery's lifespan [113]. As LiBs experience cycling and aging, various degradation mechanisms gradually compromise their performance and reliability. During the early stages of battery life, degradation progresses relatively slowly and predictably. Electrode material degradation, electrolyte decomposition, and the formation of the solid–electrolyte interphase layer lead to capacity loss and internal resistance increase during this stage [114]. These mechanisms operate relatively linearly during this period of battery operation [115]. However, as the battery cycles and ages, secondary degradation mechanisms become more prominent, especially phenomena such as lithium plating as an unwanted side reaction [116]. In this stage, which is called the aging knee, there is a notable acceleration in degradation rates, leading to accelerated capacity fade and internal resistance rise [115,117]. Operating conditions such as high/low temperatures, overvoltage/charge, deep discharge/undervoltage, and a high C_{rate} play a significant role in influencing the aging knee [117].

Operating batteries beyond the aging knee poses increased safety risks, and identifying the aging knee is crucial to determining the EOL of LiBs, particularly in second-life applications repurposed from their first EV cycling/calendar aging. Understanding the factors influencing the aging knee and its implications is essential to mitigate the risk of SLB implementation and safe operation in various applications. Fan, Wenjun et al. [118] present a novel knee-point prediction method for predicting non-linear degradation in LiBs during long-term usage. Martinez-Laserna, Egoitz et al. [119] conducted a comprehensive investigation into the non-linear performance and degradation behavior of SLBs. The study emphasized the necessity of considering the first-life aging performance of batteries when evaluating their suitability for second-life applications. The authors noted that upon reaching the knee point in the first life, there was no deceleration in the aging trend of the retired batteries when used in second-life applications. An interesting finding of the study was related to the conventional criterion of 70%-80% remaining capacity as a standard automotive battery retirement threshold. It was demonstrated that relying solely on the remaining capacity as a benchmark for EOL might not effectively evaluate the applicability of the battery for its second life.

Identifying the retirement point for SLBs is crucial for the effective use of these batteries while ensuring safety and sustainability [120]. Capacity degradation is always an important endpoint criterion [121]. Unlike first-life batteries, which often come with manufacturer-specified guidelines, SLBs undergo diverse usage histories with different degrees of degradation before entering their second life, which makes it difficult to define a common SOH as an EOL threshold. Defining specific safe endpoints can be complex and highly dependent on various factors, including battery chemistry, usage conditions, and intended second-life application.

6. Uncertainties from the First Life

Battery degradation occurs in different proportions, subject to every operating condition to which the cells within modules/packs are exposed. Operating temperatures (high/low), overvoltage/charge, deep discharge/undervoltage, and a high C-rate are the main factors that accelerate the aging of batteries. Battery degradation is a complicated subject due to the electrochemical reactions occurring within the anode, cathode, and electrolyte, each impacting the performance and longevity of the battery [122,123]. Even a simple battery operation (charge/discharge) impacts the battery's lifetime and the internal degradation processes [124]. The cycle life is a vital durability indicator, representing the battery's number of full charges and discharges under a specific operating condition. This number corresponds to the battery performance while still in its acceptable range of capacity fade [125,126]. Since battery health, lifetime, and efficiency are decremental over the lifetime, a deep knowledge of the aging process of different battery chemistries paves the way for more extended longevity and safer batteries.

Batteries in EVs face a wide range of operating conditions; generally, batteries in EVs experience harsh operation conditions. Different battery utilization patterns in different EVs mean each battery has its unique degradation mechanism. With many batteries reaching their EOL in EVs, thousands of spent packs and modules become available that have experienced different aging processes. This makes it exceedingly difficult to perform reliable SLB diagnostics and prognostics.

The lack of data from a battery's first life or the unavailability of accurate information about its history poses significant challenges to its utilization for second-life applications. The diverse driving habits, charge and discharge patterns, ambient temperature, and cell chemistry uncertainties all contribute to battery degradation and alter its internal parameters. These variations in degradation patterns result in different lifetimes for batteries, and the absence of historical data makes it arduous to predict the battery pack's lifetime. Moreover, measuring the battery's SOH is a challenge, as even cells with the same capacity can have different internal parameters. These complexities underscore the difficulty in repurposing batteries for second-life applications.

The unavailability of data from the first application will bring uncertainties in battery model parameters and measurements from the battery offline health estimation. Consequently, this will also impact the real-time battery state estimation. These uncertainties also make it difficult to predict the rate of aging and degradation, leading to unreliable performance for second-life applications.

Without proper information, it is also challenging to determine the compatibility of the SLBs with the new applications and systems, leading to potential performance issues. These uncertainties surrounding the battery's first life can lead to a trade-off between the price and reliable performance, which is also a techno-economic barrier to SLB utilization.

In recent years, there have been some reports of the use of intelligent battery systems to continuously measure the critical parameters of the battery and process these over the cloud [127,128]. This intelligent battery passport program allows EV manufacturers to continuously monitor battery aging patterns for improved battery reliability. Having access to such data is crucial for performing both diagnostics and prognostics of EV batteries, and at the same time, accessing BMS data poses significant challenges. Manufacturers often secure and encrypt BMS data, making it difficult to obtain without agreements with battery or car manufacturers. It is still unclear when and whether these data will be available for the companies working on SLBs. Data from the first life of the battery that provides the battery SOH without further measurements will decrease the prospective measurement uncertainties and make the utilization of the SLBs more affordable. Table 7 provides a concise overview of the main challenges regarding the uncertainties from the lack of information from the first life.

Table 7. Overview of the main challenges regarding the uncertainties originating from the lack of data and information from the battery's first life.

Reusing Challenges	Description
Unpredictable Aging	<ul style="list-style-type: none"> • Unavailability of data is more problematic in predicting the second-life battery behavior than its first life. • This unavailability of data will lead to difficulty in predicting the battery's lifespan in the second-life application.
Compatibility issue	<ul style="list-style-type: none"> • It is difficult to determine the compatibility of the batteries with new systems and applications without accurate information about the first-life use of the batteries.
Techno-economics trade-off	<ul style="list-style-type: none"> • Limited information will lead to uncertainty about the battery's performance. • This uncertainty can result in trade-offs between performance and cost of the battery. • Optimizing the performance by keeping the cost at an acceptable level is challenging.
Diagnostics and prognostics	<ul style="list-style-type: none"> • Battery SOC and SOH are two of the most crucial battery parameters. • Accurate estimation of the battery states is a function of the model prediction of the battery and the available data from the history of the battery. • Limited data will lead to inaccurate estimation, which will cause safety issues.

7. Battery-Management System Challenges

The battery-management system (BMS), often likened to the brain within the battery pack, is a sophisticated electronic component with pivotal responsibilities for the monitoring and management of the cells and modules that comprise the battery pack. It plays a prominent role in optimizing battery performance, regulating charge/discharge processes, ensuring safety, and extending battery longevity. Given the high energy density of LiBs,

customizing a BMS for different applications is imperative to ensure safety, protect the battery against abnormal situations, and minimize the likelihood of potential hazards [129].

There is an evident necessity for enhancement across all aforementioned functions of BMS, particularly in light of the increasing utilization of new battery types boasting higher energy densities, necessitating elevated safety measures [130]. During the battery's initial life cycle, several challenges remain unconsidered. These encompass issues in battery diagnostics and prognostics pertaining to SOC, SOH, and RUL prediction, as well as challenges associated with balancing the battery during the charge and discharge processes. Furthermore, challenges persist in safeguarding the battery during rapid charge/discharge conditions, managing thermal dynamics, and mitigating issues arising from non-uniform temperature distributions within battery modules/packs.

Azizighalehsari et al. [124] present a state-of-the-art review focusing on the primary challenges encountered in battery diagnostics and prognostics concerning battery state estimation. Numerous unresolved issues persist in battery state estimation due to the intricate electrochemical behavior of batteries. Various techniques for battery state estimation have been explored, and a comparative analysis of these methods has been conducted based on their individual strengths and weaknesses. The comparison encompasses considerations such as computational burden, implementation complexity, accuracy, and suitability for onboard applications.

At the BMS level, the precision of the battery state estimation method, such as the SOC and SOH, inherently depends on the application's sensitivity [131]. An accurate SOC estimation is crucial for effectively utilizing SLBs in various applications. Traditional SOC estimation methods, such as voltage-based methods [132], suffer from inaccuracies caused by non-linear voltage responses and capacity degradation over time. Similarly, coulomb counting methods [133] rely on integrating charge and discharge currents, but they may encounter challenges in accurately tracking capacity changes and accounting for aging effects. Model-based approaches [134], including equivalent circuit models and electrochemical models, offer higher accuracy but require detailed knowledge of battery characteristics and may be computationally intensive. Additionally, data-driven methods [135], such as machine learning algorithms, have gained attention for their ability to learn complex battery behaviors from data, but they may require extensive training datasets and computation burden [134]. Hybrid approaches [136,137], combining multiple methods, aim to leverage the strengths of different approaches while mitigating their limitations. However, integrating these methods for SOC estimation in SLBs remains a significant challenge, requiring careful consideration of battery aging effects, heterogeneity, and environmental conditions. Recently, there has been interest in employing approaches involving non-destructive methods, such as ultrasonic wave-based techniques [138], which have shown potential for detecting SOC and temperature simultaneously, providing valuable insights into the internal dynamics of batteries without causing damage. Ultrasonic wave-based methods, as demonstrated by Zhang et al. [138], utilize piezoelectric transducers to emit and receive ultrasonic signals, which propagate through the battery and reflect back to the transducer. Analyzing the characteristics of these reflected waves, including their amplitude, frequency, and phase, makes it possible to infer both the SOC and temperature levels within the battery. In general, there is a perpetual trade-off between the complexity of the method and its accuracy [139]. Still, there is a tendency for more precise battery state estimation as this helps prolong the battery lifespan by maintaining it within its optimal operating range.

In Section 4, we extensively explored various measurement techniques and indirect methods for assessing battery SOH based on battery indices associated with degradation. These methods offer insights into the health condition of batteries by analyzing key parameters or indicators that are indicative of degradation processes occurring within the battery [140]. Similar to SOC estimation, numerous methods have been proposed for estimating the SOH of batteries. Model-based methods [141] and data-driven methods [142–144] have gained attention for SLBs as a promising approach compared to traditional capacity-based SOH estimation methods, which often require extensive test-

ing times [145]. Model-based methods (physics-based models/empirical models) utilize mathematical models that describe the physical and chemical processes occurring inside the battery, providing insights into the underlying mechanisms of degradation. These methods often require an understanding of battery physics and chemistry, and with that understanding, they are capable of achieving high accuracy in SOH estimation. In contrast, data-driven methods do not rely on detailed knowledge of battery physics but instead utilize large datasets of aging data. The effectiveness of data-driven methods heavily relies on the quantity and quality of the available data and the extent to which they cover all relevant operating conditions.

Transitioning batteries into a second life poses unique challenges in battery management, requiring sophisticated strategies to address the complex interplay between the battery's past usage, current condition, and intended application. One key challenge involves developing effective techniques to accurately assess retired batteries' health and remaining capacity. End-of-first-life battery performance can vary significantly based on usage patterns, operating conditions, and degradation profiles from their primary application. As a result, BMSs designed for first-life applications may lack the precision needed to optimize performance in a second-life scenario.

In SLBs, BMS designs must prioritize reduced complexity to meet application requirements and lower pack costs. However, achieving an acceptable accuracy range for battery state estimation poses challenges due to accelerated aging or degradation compared to the first life. Increased aging also raises the risk of battery failure, and overly optimistic or pessimistic estimations may lead to complete battery failure, exacerbating safety concerns, or unnecessarily reducing the remaining useful second life. Unfortunately, the majority of battery state estimation research focuses on batteries in their first life, with models typically based on cycling data until 70–80% SOH. Limited historical battery information and limited insight into the impact of aging conditions further complicate RUL prediction for SLBs. Consequently, diagnosing and prognosticating battery health in their second life proves more challenging than for fresh batteries.

SLBs, after reaching the EOL in the first application, always suffer from imbalanced impedance values between the cells and between modules due to different aging patterns that originate from non-uniform temperature distribution [68,146]. The impedance mismatch in turn causes heterogeneous temperature distributions that will lead to different aging patterns (also depending on the cell's position inside the pack), making it more difficult for the thermal management system (TMS) functionality of the BMS in the second application to assure the reliable operation of the SLB [147]. As an example, Figure 12 shows the temperature discrepancy on the surface of the cells inside an aged module from an HEV during a discharge process.

The work in [148] comprehensively reviewed challenges in LiB thermal management systems. The review analyzed thermal management technologies separately and described the advantages and disadvantages of each method and the need for more investigation and improvement in the efficiency of the systems for both cooling and heating of the battery. Table 8 shows the analyzed methods and their pros and cons. Battery performance in terms of energy efficiency, lifetime, and safety is a function of the operating temperature. The temperature significantly affects battery degradation, leading to capacity fading of the battery. Any non-uniform temperature distribution between the cells within a module will increase the failure probability of the battery pack [149]. A proper TMS is needed to guarantee an acceptable safety level for LiB operation. With an increasing battery charge/discharge rate, the battery's temperature increases as well, and the failure risk will be higher. It is also essential for the battery's second life to have the battery pack temperature as uniform as possible. If the pack is not tailored with an efficient TMS, the aging pattern of the cells and modules within the pack will be different, creating many challenges for the BMS in the second application.

Table 8. Comparison of the advantages and disadvantages of different thermal management systems (TMSs) [148].

Method	Advantages	Disadvantages
Air cooling system	<ul style="list-style-type: none"> – Low complexity. – High reliability. – Cheap technology. 	<ul style="list-style-type: none"> – Low efficiency. – Non-uniformity.
Liquid Cooling System	<ul style="list-style-type: none"> – High Thermal Performance. – More efficient than air cooling systems in hot and humid environments. 	<ul style="list-style-type: none"> – Leakage probability. – Complex layout. – Higher installation cost than air cooling system.
Phase Change Material Cooling System	<ul style="list-style-type: none"> – No power consumption. – High Heat Capacity. 	<ul style="list-style-type: none"> – Low Conductivity. – Variable volume.
Heat Pipe Cooling System	<ul style="list-style-type: none"> – High Thermal Conductivity. – Low maintenance cost. 	<ul style="list-style-type: none"> – Low efficiency.
Thermoelectric Cooling System	<ul style="list-style-type: none"> – Low power consumption. – Green technology. 	<ul style="list-style-type: none"> – Low efficiency.

The temperature changes in the cells during the discharge process at the same C_{rate} are more significant than those during the charging process. Charging happens for LiBs in constant current-constant voltage mode (CC-CV), which means that when the voltage reaches the cut-off limit, the constant current in the first charging part is decreased and charging is continued in a CV mode. Based on our initial work [87] and the infrared image of Figure 12, the location to monitor the surface temperature was chosen in the middle of the cell. There is an almost 2 °C temperature discrepancy between cell number 2 and cell number 6 in this aged module that underlines the necessity for a proper TMS in an SLB. It is noted that degraded cells can affect their adjacent cells and increase the working temperature (and thus aging) of these neighboring cells.

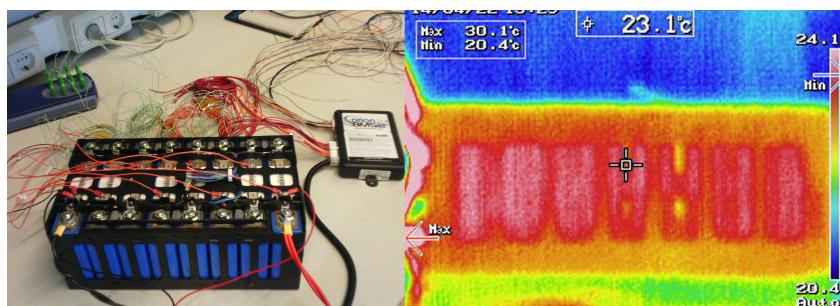


Figure 12. Infrared image (right) of an HEV module (pictured left) showing the temperature distribution on the cells' surface within the module during 1C discharging. The HEV module has been used regularly for eight years and has undergone significant charge/discharge cycles, finally reaching 70% of its initial capacity. More detailed temperature measurements are conducted with an 8-channel K-type thermocouple system for surface temperature monitoring (pictured left). The infrared camera was used to track temperature distribution across the surface of the cells within the module.

8. Application Challenges

SLBs, with their potential to delay the recycling process and reduce the need for manufacturing new batteries, play a significant role in mitigating climate change and are thus an intriguing component of the energy transition. In addition to considering the advantages and challenges presented at various levels of the battery structure, from cell to module and pack, it is crucial to carefully assess the applications for which these batteries will be utilized.

The eligibility of the retired battery for a particular second-life application and the longevity of the battery for a new application are two important characteristics that need special attention in SLB analysis. In [14], a technical assessment of the performance of an SLB was performed based on the aging history of the battery in its first life. The two applications considered in this study are the residential demand response and power smoothing integration. The result indicates that the aging pattern of the battery in the first life is a missing link between the first and second life and significantly affects its performance and technical viability.

Cycle life is a notable indicator to assess the durability of the SLB; it means it is necessary to know how many full cycles the battery can be used or deliver power and energy before reaching its failure threshold. It is always crucial for the customer of the SLB to know the remaining useful life and health condition of the battery.

RUL methods aim to predict the future state of the battery to prevent any failure within the battery that comes from battery degradation [150]. An accurate estimation of the replacement time of the battery for the safe operation of the battery will decrease the failure risk. Naturally, accurate battery aging data are key to the RUL prediction. These data can be gathered from the current operation of the battery, which is compared with historical data gathered on the same battery, or it can be performed based on the data that have been collected from the different aging patterns and operational conditions in the laboratory.

Based on the type of data and the comparison methodology, the RUL prediction approaches can be categorized into four groups, i.e., physics model-based, statistical model-based, artificial intelligence, and hybrid approaches [151]. The work in [152] comprehensively compared these methods for RUL predictions in first-life battery applications. The accuracy of different approaches is related to the method's complexity. Finding a trade-off between the accuracy and complexity of the method is always challenging. To achieve maximum accuracy, hybrid approaches with accurate models and high-quality data are to be used [87].

The impact of the application in RUL prediction of the battery comes from the operating condition of the SLB, depth of discharge (DOD), temperature, C_{rate} rate, and calendar aging. Less DOD will lead to a higher lifetime: the study of [153] showed a strong potential to increase the battery lifetime just by avoiding a high SOC and not keeping the battery charged while storing it to prevent short calendar aging periods. The impact of different stress factors on the battery lifetime was investigated in [154]. The results show that temperature has the highest effect on the battery lifetime and then C_{rate} and DOD, consequently, on prismatic Li-ion cells.

The capacity data for a lithium manganese oxide/graphite battery, obtained from thirty-two used modules and ten new modules from [19], is illustrated in Figure 13. In this study, the total difference between the modules from the average capacity for second-life modules is 11.3%, whereas this parameter for fresh modules is 3%. This figure calculates the coefficient variation by dividing the standard deviation by the average capacity. According to their capacity measurement, the range is the capacity difference between the best and worst modules. The result shows the importance of the first-life history for the modules and proper characterization at the beginning of their second life.

The cycling aging of six second-life cells from a Nissan LEAF was performed in [115]. The results show that these cells can be used at least for 2033 equivalent complete cycles before their EOL, which is equal to at least five years of usage in a normal photovoltaic system with daily charge and discharge usage. In this study, EOL was defined as the time that the cells reach their aging knee. This study's experimental results show that the cells' aging is not linear in their second life. The DC internal resistance (DCIR) and capacity fading of the cells as degradation indicators demonstrate a linear behavior in the first life. Then, the DCIR will go to the non-linear stage; consequently, the capacity fading will increase and go to the non-linear stage.

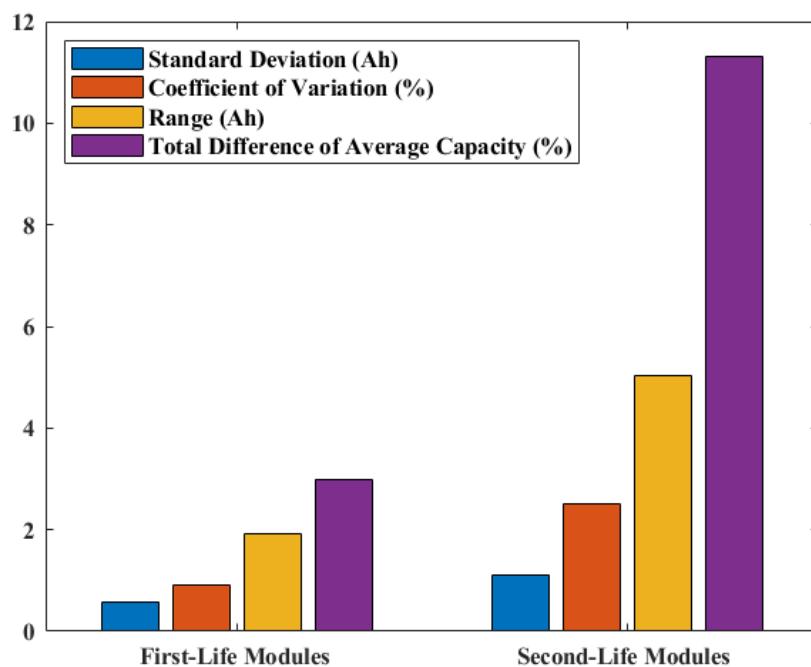


Figure 13. Comparison of capacity data between first- (left) and second-life (right) modules based on capacity measurement data of 32 second-life modules and ten new modules (data adapted from [19]).

9. Techno-Economic Challenges

The techno-economic analysis holds significant importance for several reasons, primarily to assess the feasibility of commercially exploiting SLBs. Understanding the technical and financial benefits of battery repurposing is crucial to determine its viability on an industrial scale and ensure widespread acceptance.

Analyzing the market potential, price, and environmental benefits gives insight into the techno-economics of SLBs. SLBs offer a cost advantage compared to new batteries since they are supposed to be significantly cheaper, as recycling and repurposing costs are expected to be lower than producing new batteries from raw materials [155]. From the ecological perspective, SLBs, by decreasing the demand to mine raw materials and supporting renewable energy resources, can help reduce the environmental impact, including greenhouse gas emissions. There is a vast market potential for SLBs, which can significantly promote sustainability and reduce the energy sector's environmental impact.

A study released by the Sandia National Laboratory highlights the analysis of SLBs and their associated costs [156]. This study identifies critical contributors to SLB expenses, including funds for production, labor costs, administrative overhead, and packaging materials. As illustrated in Figure 14, the retired battery procurement is the most significant cost, encompassing a substantial 56% of the total SLB expenses. Labor cost also has a big share in this cost breakdown, which mainly comes from the technical assessment of the batteries at their EOL. The modular design of the battery within its first life can extend the economic viability of the batteries by facilitating the complex technical process from the repackaging, screening, and cell/module replacement, which can significantly reduce the labor cost.

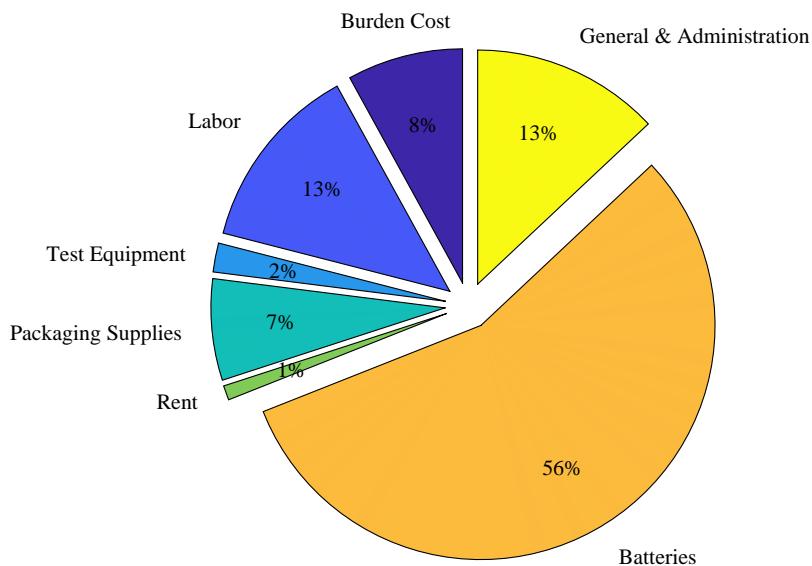


Figure 14. Cost breakdown of second-life stationary battery packs, highlighting the significant impact of various factors on total battery pack costs, with battery procurement representing the largest portion. Labor costs, including employment and overhead, also contribute significantly, as do materials required for repackaging used EV modules into battery packs (adapted with permission from [156,157]).

A comprehensive feasibility analysis on SLBs regarding their lifetime, economic impact, and environmental effect was performed in [158] and proved that SLBs would provide a considerable profit besides their significant influence on mitigating environmental issues. A performance evaluation and economic assessment on SLBs for peak shaving as an ESS were executed in [159] to make the impact of reusing batteries on global warming more visible. The work concludes that using SLBs for power peak shaving is technically and economically feasible, and the batteries have enough capacity and lifetime for the application.

A performance evaluation on six different batteries from different EVs to be used for frequency regulation purposes was conducted in [40] to weigh different SLBs based on their performance metrics for different specific frequency regulation cases. The results show that repurposed batteries have a sufficient capacity and reliability for grid frequency regulation and can provide this service for several years. Therefore, this application shows that using SLBs is a promising solution to reduce costs and support a more sustainable energy system.

The finding of the research on reusing batteries and its impact on the circular economy shows that it can lead to significant environmental benefits, including reducing CO₂ emissions and decreasing the demand for raw materials [160]. The result of evaluating the environmental impact of reusing LFP batteries in different scenarios, including frequency regulation, energy storage, and power peak shaving, shows the positive impact of reusing LFP batteries in different scenarios in SLB applications [161]. Additionally, the study finds that various SLB applications have varying levels of environmental impact, with frequency regulation having the lowest and energy storage having the highest environmental impact.

A recent experimental cycle aging appraisal on six Li-ion modules from different Nissan LEAF cars was performed in [19]. The results show that they can be used for at least five years on a PV-based storage application with daily cycling, and in some cases, the SLBs can even be employed for up to 11 years. The implementation of second-life batteries in microgrids by proposing four configurations was investigated in [162]. This work proves the cost-effectiveness and feasibility of SLBs compared to the use of new Li-ion batteries. The results show that a grid-connected system could reduce energy consumption by more

than 70% compared to the off-grid models. The most economically viable model consisted of PV modules, floating photovoltaic modules, wind turbines, and a biogas generator connected to the grid using fresh Li-ion batteries. Further analysis of the same model with second-life Li-ion batteries showed that using 0.8 kWh SLBs was their study's most economically viable solution. The McKinsey Center for Future Mobility predicts that the extent of SLBs in use in stationary applications could go beyond 200 GWh/year by 2030 and believes that SLBs have the potential to be considered the latest value pool in energy storage [163]. The results of the EU Joint Research Center technical report on the sustainability assessment of SLBs [164] also shows that it is technically viable and environmentally beneficial to use EV batteries in second applications. In addition, the battery lifespan would increase by 35% by repackaging batteries in residential buildings [165]. A further study proves that the battery's second life can accelerate the electrification process by reducing the costs of EVs upfront [166]. A recent paper published by Nature [167] revealed that integrating SLBs significantly reduced the cost of electricity by 5.6 % to 35.3% in most cases compared to using new batteries. Using SLBs also speeds up the time it takes for the system to pay for itself, making it financially beneficial. The quickest payback period was about 2.9 years for a setup with 5 kW solar panels and 5 kWh storage. The study demonstrates that SLBs can be an economical and effective option, providing a similar service to new batteries mainly in regions with limited access to energy while also helping to reduce waste.

Different studies demonstrate a significant pricing range for SLBs depending on factors such as the particular market conditions and application [168,169]. According to a study conducted for Global Battery Alliance, used batteries are traded at varying prices, typically between USD 60 and USD 300 per kWh, depending on the market and how they have been used. This study predicts that by 2030, these prices could drop to around 43 USD/kWh. This drop aligns with the overall trend of lowering battery costs, like the prices of new batteries [170]. Technological advancements have led to a considerable reduction in battery costs, making new, latest-generation batteries more cost-effective than ever before. Pricing remains a critical concern within the SLBs market, particularly given the notable decrease in cost per kilowatt-hour observed over the past decade for latest-generation batteries.

To highlight specific industrial implementations, RWE, a German energy company, is working on a project that uses EOL batteries from Audi e-Tron cars for energy storage applications since they believe that next to its ecological advantages, it is cheaper than new batteries [171]. In addition, Audi also employs SLBs in its high-power charging hub in Nuremberg [30]. The number of projects using EV batteries for stationary applications is rapidly growing, as was discussed in Table 1 in Section 3. However, this market has uncertainties that necessitate techno-economical investigations to find a strong case for the specific development in question.

Figure 15 shows the potential impact of a lack of standardization and certification as an important techno-economic challenge for the market growth of SLBs. As illustrated, a lack of standardization and accreditation can create various challenges and risks (safety concerns, compatibility issues, regularity, legal challenges, etc.), leading to limited market growth. Global standardization can increase the compatibility between different manufacturers' SLBs with an acceptable range of safety and reliability, leading to increased market trust.

In conclusion, while second-life batteries can offer cost and environmental benefits, there are several technical, economic, market, and regulatory challenges and uncertainties to reusing batteries for a second application that need to be overcome for the technology to reach its full potential [14].



Figure 15. Impacts of lack of standardization and certification on SLBs market.

10. Conclusions

Addressing the urgent need for sustainable solutions to mitigate the environmental consequences of batteries highlights the critical importance of developing a mechanism to manage the vast quantity of batteries reaching the end of their first application-related lifespan. While SLBs present clear advantages, reusing EV batteries for second-life applications poses inherent complexities. Various challenges demand our focus and creative thinking, yet overcoming these hurdles often paves the way for innovation and progress within the field. This study extensively explores the complexities associated with these challenges to grasp feasibility and potential barriers. It aims to enhance the utilization of these batteries in SLB applications, offering a cutting-edge perspective on the significance of diverse techniques to enhance SLB viability and overcome bottlenecks.

A significant portion of this review is dedicated to the challenges associated with screening SLBs. Various measurements and analysis techniques can be applied to a single battery module, each differing in applicability, complexity, time consumption, and accuracy. The methods under scrutiny include battery capacity measurement, incremental capacity analysis, differential voltage analysis, differential thermal voltammetry, and electrochemical impedance spectroscopy. The accuracy of different techniques for estimating SOH and their complexity varies depending on the second-life application and its sensitivity to precise measurement. Often, a trade-off between different performance indicators is crucial to ensure sufficient applicability. Individual methods or hybrid approaches combining multiple techniques can be employed to optimize the efficiency of the evaluation process.

Research on SLBs is still in its infancy, with anticipation for further exploration in the years ahead to address existing gaps. A key aspect in bridging these gaps lies in gaining a deeper understanding of battery degradation characterization across different chemistries, which is crucial for mitigating challenges impacting the long-term performance, reliability, and stability of SLBs. Since battery degradation is significantly influenced by its prior usage history, accessing data from its initial life cycle is pivotal, acting as a catalyst for the growth of the SLB market. The future of SLBs undeniably hinges on technological advancements and collaborative efforts among stakeholders to establish transparent protocols for collecting, analyzing, and sharing data among researchers, industry players, and policymakers.

In essence, reusing EV batteries has become a pressing concern, elevating the importance of addressing associated challenges within the EV industry. Additionally, upcoming trends such as solid-state batteries (SSBs), silicon-based anodes, and Co-free/low-Co cath-

odes paired with Li-metal anodes, extending beyond conventional Li-ion chemistry (Na-ion, etc.) hold promise for cost reduction, enhanced safety, performance, and increased energy density. These advancements will undoubtedly impact performance, environmental aspects, and the potential gains in second-life applications, which need further studies, including impact assessments and life-cycle evaluations.

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References

1. Ferreira, B. Batteries, the New Kids on the Block. *IEEE Power Electron. Mag.* **2019**, *6*, 32–34. [CrossRef]
2. Vermeer, W.; Chandra Mouli, G.R.; Bauer, P. A Comprehensive Review on the Characteristics and Modeling of Lithium-Ion Battery Aging. *IEEE Trans. Transp. Electrif.* **2022**, *8*, 2205–2232. [CrossRef]
3. Krishan, O.; Suhag, S. An updated review of energy storage systems: Classification and applications in distributed generation power systems incorporating renewable energy resources. *Int. J. Energy Res.* **2019**, *43*, 6171–6210. [CrossRef]
4. Estimated Capacity of Lithium-Ion Batteries Placed on the Global Market in 2020 with Forecast for 2021 through 2030 (in Gigawatt Hours). Available online: <https://www.statista.com/statistics/1246914/capacity-of-lithium-ion-batteries-placed-on-the-global-market/> (accessed on 9 May 2024).
5. IEA. Electric Car Sales, 2016–2023. 2023. Available online: <https://www.iea.org/data-and-statistics/charts/electric-car-sales-2016-2023> (accessed on 9 May 2024).
6. At Least Two Thirds of Global Car Sales Will Be Electric by 2040-Bloomberg. Available online: <https://www.bloomberg.com/news/articles/2021-08-09/at-least-two-thirds-of-global-car-sales-will-be-electric-by-2040> (accessed on 9 May 2024).
7. Jinlei, S.; Lei, P.; Ruihang, L.; Qian, M.; Chuanyu, T.; Tianru, W. Economic operation optimization for 2nd use batteries in battery energy storage systems. *IEEE Access* **2019**, *7*, 41852–41859. [CrossRef]
8. Nováková, K.; Pražanová, A.; Stroe, D.I.; Knap, V. Second-Life of Lithium-Ion Batteries from Electric Vehicles: Concept, Aging, Testing, and Applications. *Energies* **2023**, *16*, 2345. [CrossRef]
9. Yang, Y.; Qiu, J.; Zhang, C.; Zhao, J.; Wang, G. Flexible Integrated Network Planning Considering Echelon Utilization of Second-Life of Used Electric Vehicle Batteries. *IEEE Trans. Transp. Electrif.* **2021**, *8*, 263–276. [CrossRef]
10. Millions of Electric Car Batteries Will Retire in the Next Decade. What Happens to Them? | Environment | The Guardian. Available online: <https://www.theguardian.com/environment/2021/aug/20/electric-car-batteries-what-happens-to-them> (accessed on 9 May 2024).
11. Abdelbaky, M.; Peeters, J.R.; Dewulf, W. On the influence of second use, future battery technologies, and battery lifetime on the maximum recycled content of future electric vehicle batteries in Europe. *Waste Manag.* **2021**, *125*, 1–9. [CrossRef]
12. Etxandi-Santolaya, M.; Casals, L.C.; Montes, T.; Corchero, C. Are electric vehicle batteries being underused? A review of current practices and sources of circularity. *J. Environ. Manag.* **2023**, *338*, 117814. [CrossRef]
13. Li, J.; He, S.; Yang, Q.; Wei, Z.; Li, Y.; He, H. A Comprehensive Review of Second Life Batteries Towards Sustainable Mechanisms: Potential, Challenges, and Future Prospects. *IEEE Trans. Transp. Electrif.* **2022**, *9*, 4824–4845. [CrossRef]
14. Martinez-Laserna, E.; Gandiaga, I.; Sarasketa-Zabala, E.; Badeda, J.; Stroe, D.I.; Swierczynski, M.; Goikoetxea, A. Battery second life: Hype, hope or reality? A critical review of the state of the art. *Renew. Sustain. Energy Rev.* **2018**, *93*, 701–718. [CrossRef]
15. Illa Font, C.H.; Siqueira, H.V.; Machado Neto, J.E.; Santos, J.L.F.d.; Stevan Jr, S.L.; Converti, A.; Corrêa, F.C. Second Life of Lithium-Ion Batteries of Electric Vehicles: A Short Review and Perspectives. *Energies* **2023**, *16*, 953. [CrossRef]
16. Hossain, E.; Murtaugh, D.; Mody, J.; Faruque, H.M.R.; Sunny, M.S.H.; Mohammad, N. A Comprehensive Review on Second-Life Batteries: Current State, Manufacturing Considerations, Applications, Impacts, Barriers Potential Solutions, Business Strategies, and Policies. *IEEE Access* **2019**, *7*, 73215–73252. [CrossRef]

17. Xu, J.; Sun, C.; Ni, Y.; Lyu, C.; Wu, C.; Zhang, H.; Yang, Q.; Feng, F. Fast identification of micro-health parameters for retired batteries based on a simplified P2D model by using padé approximation. *Batteries* **2023**, *9*, 64. [CrossRef]
18. Hu, X.; Deng, X.; Wang, F.; Deng, Z.; Lin, X.; Teodorescu, R.; Pecht, M.G. A review of second-life lithium-ion batteries for stationary energy storage applications. *Proc. IEEE* **2022**, *110*, 735–753. [CrossRef]
19. Braco, E.; San Martín, I.; Berrueta, A.; Sanchis, P.; Ursúa, A. Experimental assessment of first-and second-life electric vehicle batteries: Performance, capacity dispersion, and aging. *IEEE Trans. Ind. Appl.* **2021**, *57*, 4107–4117. [CrossRef]
20. Zhu, J.; Mathews, I.; Ren, D.; Li, W.; Cogswell, D.; Xing, B.; Sedlatschek, T.; Kantareddy, S.N.R.; Yi, M.; Gao, T.; et al. End-of-life or second-life options for retired electric vehicle batteries. *Cell Rep. Phys. Sci.* **2021**, *2*, 100537. [CrossRef]
21. Melin, H.E. State-of-the-art in reuse and recycling of lithium-ion batteries—A research review. *Circ. Energy Storage* **2019**, *1*, 1–57.
22. Ahmadi, L.; Young, S.B.; Fowler, M.; Fraser, R.A.; Achachlouei, M.A. A cascaded life cycle: Reuse of electric vehicle lithium-ion battery packs in energy storage systems. *Int. J. Life Cycle Assess.* **2017**, *22*, 111–124. [CrossRef]
23. Lee, K.; Kum, D. Development of cell selection framework for second-life cells with homogeneous properties. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 429–439. [CrossRef]
24. Chai, S.; Xu, N.Z.; Niu, M.; Chan, K.W.; Chung, C.Y.; Jiang, H.; Sun, Y. An evaluation framework for second-life ev/phev battery application in power systems. *IEEE Access* **2021**, *9*, 152430–152441. [CrossRef]
25. Assunção, A.; Moura, P.S.; de Almeida, A.T. Technical and economic assessment of the secondary use of repurposed electric vehicle batteries in the residential sector to support solar energy. *Appl. Energy* **2016**, *181*, 120–131. [CrossRef]
26. Kootstra, M.A.; Tong, S.; Park, J.W. Photovoltaic grid stabilization system using second life lithium battery. *Int. J. Energy Res.* **2015**, *39*, 825–841. [CrossRef]
27. Stecca, M.; Soeiro, T.B.; Elizondo, L.R.; Bauer, P.; Palensky, P. Lifetime Estimation of Grid-Connected Battery Storage and Power Electronics Inverter Providing Primary Frequency Regulation. *IEEE Open J. Ind. Electron. Soc.* **2021**, *2*, 240–251. [CrossRef]
28. Kamath, D.; Arsenault, R.; Kim, H.C.; Anctil, A. Economic and environmental feasibility of second-life lithium-ion batteries as fast-charging energy storage. *Environ. Sci. Technol.* **2020**, *54*, 6878–6887. [CrossRef] [PubMed]
29. Deng, Y.; Zhang, Y.; Luo, F.; Mu, Y. Operational planning of centralized charging stations utilizing second-life battery energy storage systems. *IEEE Trans. Sustain. Energy* **2020**, *12*, 387–399. [CrossRef]
30. Electrive. Audi High-Power Charging Hub Now Live in NUREMBERG. 2021. Available online: <https://www.electrive.com/2021/12/20/audi-high-power-charging-hub-now-live-in-nuremberg/> (accessed on 9 May 2024).
31. RWE Generation. Second Life for EV Batteries. 2021. Available online: <https://www.rwe.com/en/press/rwe-generation/2021-1-2-28-second-life-for-ev-batteries/> (accessed on 9 May 2024).
32. Electrive. Ustra Factory Recycles Old eCitaro Batteries. 2021. Available online: <https://www.electrive.com/2021/04/28/ustra-factory-recycles-old-ecitaro-batteries/> (accessed on 9 May 2024).
33. Connected Energy. Battery Energy Storage. Available online: <https://connected-energy.co.uk/news/battery-energy-storage/> (accessed on 9 May 2024).
34. This Dutch Football Stadium Creates Its Own Energy and Stores It in Electric Car Batteries | World Economic Forum. Available online: <https://www.weforum.org/agenda/2018/07/netherlands-football-johan-cruijff-stadium-electric-car-batteries/> (accessed on 24 March 2023).
35. 13 MWh Second-Life Battery Project in Germany. Available online: <https://www.yolegroup.com/industry-news/13-mwh-second-life-battery-project-in-germany/> (accessed on 9 May 2024).
36. Energy Storage News. Bosch, BMW, Vattenfall Resurrect EV Batteries for Second Life as Large-Scale Energy Storage. Available online: <https://www.energy-storage.news/bosch-bmw-vattenfall-resurrect-ev-batteries-for-second-life-as-large-scale-energy-st/> (accessed on 9 May 2024).
37. Birk, C.R.; Frost, D.F.; Bizeray, A.M.; Richardson, R.R.; Howey, D.A. Modular converter system for low-cost off-grid energy storage using second life li-ion batteries. In Proceedings of the IEEE Global Humanitarian Technology Conference (GHTC 2014), San Jose, CA, USA, 10–13 October 2014; pp. 192–199.
38. Nedjalkov, A.; Meyer, J.; Göken, H.; Reimer, M.V.; Schade, W. Blueprint and implementation of rural stand-alone power grids with second-life lithium ion vehicle traction battery systems for resilient energy supply of tropical or remote regions. *Materials* **2019**, *12*, 2642. [CrossRef] [PubMed]
39. Xu, X.; Mi, J.; Fan, M.; Yang, K.; Wang, H.; Liu, J.; Yan, H. Study on the performance evaluation and echelon utilization of retired LiFePO₄ power battery for smart grid. *J. Clean. Prod.* **2019**, *213*, 1080–1086. [CrossRef]
40. White, C.; Thompson, B.; Swan, L.G. Repurposed electric vehicle battery performance in second-life electricity grid frequency regulation service. *J. Energy Storage* **2020**, *28*, 101278. [CrossRef]
41. Stecca, M.; Elizondo, L.R.; Soeiro, T.B.; Bauer, P.; Palensky, P. A Comprehensive Review of the Integration of Battery Energy Storage Systems Into Distribution Networks. *IEEE Open J. Ind. Electron. Soc.* **2020**, *1*, 46–65. [CrossRef]
42. Rahil, A.; Partenie, E.; Bowkett, M.; Nazir, M.H.; Hussain, M.M. Investigating the possibility of using second-life batteries for grid applications. *Battery Energy* **2022**, *1*, 2021001. [CrossRef]
43. Nissan. Nissan Partners with Enel to Launch Innovative Second-Life Storage System for Used Electric Car Batteries. Available online: <https://europe.nissannews.com/en-GB/releases/nissan-partners-with-enel-to-launch-innovative-second-life-storage-system-for-used-electric-car-batteries?selectedTabId=releases> (accessed on 9 May 2024).

44. Jaguar Land Rover. Jaguar Land Rover Gives Second Life to I-PACE Batteries. 2022. Available online: <https://media.jaguarlandrover.com/news/2022/03/jaguar-land-rover-gives-second-life-i-pace-batteries> (accessed on 1 August 2023).
45. Wu, X.; Ma, J.; Wang, J.; Zhang, X.; Zhou, G.; Liang, Z. Progress, Key Issues, and Future Prospects for Li-Ion Battery Recycling. *Glob. Chall.* **2022**, *6*, 2200067. [CrossRef]
46. Harper, G.; Sommerville, R.; Kendrick, E.; Driscoll, L.; Slater, P.; Stolkin, R.; Walton, A.; Christensen, P.; Heidrich, O.; Lambert, S.; et al. Recycling lithium-ion batteries from electric vehicles. *Nature* **2019**, *575*, 75–86. [CrossRef]
47. Assefi, M.; Maroufi, S.; Yamauchi, Y.; Sahajwalla, V. Pyrometallurgical recycling of Li-ion, Ni-Cd and Ni-MH batteries: A minireview. *Curr. Opin. Green Sustain. Chem.* **2020**, *24*, 26–31. [CrossRef]
48. Larouche, F.; Tedjar, F.; Amouzegar, K.; Houlachi, G.; Bouchard, P.; Demopoulos, G.P.; Zaghib, K. Progress and status of hydrometallurgical and direct recycling of Li-ion batteries and beyond. *Materials* **2020**, *13*, 801. [CrossRef] [PubMed]
49. Baum, Z.J.; Bird, R.E.; Yu, X.; Ma, J. Lithium-ion battery recycling—Overview of techniques and trends. *ACS Energy Lett.* **2022**, *7*, 712–719. [CrossRef]
50. Fan, E.; Li, L.; Wang, Z.; Lin, J.; Huang, Y.; Yao, Y.; Chen, R.; Wu, F. Sustainable recycling technology for Li-ion batteries and beyond: Challenges and future prospects. *Chem. Rev.* **2020**, *120*, 7020–7063. [CrossRef]
51. Lai, X.; Huang, Y.; Gu, H.; Deng, C.; Han, X.; Feng, X.; Zheng, Y. Turning waste into wealth: A systematic review on echelon utilization and material recycling of retired lithium-ion batteries. *Energy Storage Mater.* **2021**, *40*, 96–123. [CrossRef]
52. Mrozik, W.; Rajaeifar, M.A.; Heidrich, O.; Christensen, P. Environmental impacts, pollution sources and pathways of spent lithium-ion batteries. *Energy Environ. Sci.* **2021**, *14*, 6099–6121. [CrossRef]
53. Castro, F.D.; Mehner, E.; Cutaia, L.; Vaccari, M. Life cycle assessment of an innovative lithium-ion battery recycling route: A feasibility study. *J. Clean. Prod.* **2022**, *368*, 133130. [CrossRef]
54. Xiao, J.; Li, J.; Xu, Z. Recycling metals from lithium ion battery by mechanical separation and vacuum metallurgy. *J. Hazard. Mater.* **2017**, *338*, 124–131. [CrossRef]
55. Hantanasirisakul, K.; Sawangphruk, M. Sustainable Reuse and Recycling of Spent Li-Ion batteries from Electric Vehicles: Chemical, Environmental, and Economical Perspectives. *Glob. Chall.* **2023**, *7*, 2200212. [CrossRef] [PubMed]
56. Xu, P.; Yang, Z.; Yu, X.; Holoubek, J.; Gao, H.; Li, M.; Cai, G.; Bloom, I.; Liu, H.; Chen, Y.; et al. Design and optimization of the direct recycling of spent Li-ion battery cathode materials. *ACS Sustain. Chem. Eng.* **2021**, *9*, 4543–4553. [CrossRef]
57. Makuzo, B.; Tian, Q.; Guo, X.; Chattopadhyay, K.; Yu, D. Pyrometallurgical options for recycling spent lithium-ion batteries: A comprehensive review. *J. Power Sources* **2021**, *491*, 229622. [CrossRef]
58. Träger, T.; Friedrich, B.; Weyhe, R. Recovery concept of value metals from automotive lithium-ion batteries. *Chem. Ing. Tech.* **2015**, *87*, 1550–1557. [CrossRef]
59. Jiang, S.; Hua, H.; Zhang, L.; Liu, X.; Wu, H.; Yuan, Z. Environmental impacts of hydrometallurgical recycling and reusing for manufacturing of lithium-ion traction batteries in China. *Sci. Total Environ.* **2022**, *811*, 152224. [CrossRef] [PubMed]
60. Jung, J.C.Y.; Sui, P.C.; Zhang, J. A review of recycling spent lithium-ion battery cathode materials using hydrometallurgical treatments. *J. Energy Storage* **2021**, *35*, 102217. [CrossRef]
61. Yang, Y.; Okonkwo, E.G.; Huang, G.; Xu, S.; Sun, W.; He, Y. On the sustainability of lithium ion battery industry—A review and perspective. *Energy Storage Mater.* **2021**, *36*, 186–212. [CrossRef]
62. Zhang, H.; Sun, C. Cost-effective iron-based aqueous redox flow batteries for large-scale energy storage application: A review. *J. Power Sources* **2021**, *493*, 229445. [CrossRef]
63. Wang, S.; Yu, J.; Okubo, K. Life cycle assessment on the reuse and recycling of the nickel-metal hydride battery: Fleet-based study on hybrid vehicle batteries from Japan. *J. Ind. Ecol.* **2021**, *25*, 1236–1249. [CrossRef]
64. Bergqvist, N.; Talakoob, B. Comparative Life Cycle Assessment of Second Life NMC Batteries. Master’s Thesis, Chalmers University of Technology, Göteborg, Sweden, 2022.
65. Zhang, Y.; Zhou, Z.; Kang, Y.; Zhang, C.; Duan, B. A Quick Screening Approach Based on Fuzzy C-Means Algorithm for the Second Usage of Retired Lithium-Ion Batteries. *IEEE Trans. Transp. Electrif.* **2021**, *7*, 474–484. [CrossRef]
66. Azizighalehsari, S.; Venugopal, P.; Singh, D.P.; Huijben, M.; Popovic, J.; Ferreira, B. High-Performance Lithium Polymer Battery Pack for Real-World Racing Motorcycle; High-Performance Lithium Polymer Battery Pack for Real-World Racing Motorcycle. In Proceedings of the 2021 23rd European Conference on Power Electronics and Applications (EPE’21 ECCE Europe), Ghent, Belgium, 6–10 September 2021.
67. Devie, A.; Baure, G.; Dubarry, M. Intrinsic variability in the degradation of a batch of commercial 18650 lithium-ion cells. *Energies* **2018**, *11*, 1031. [CrossRef]
68. Baumhöfer, T.; Brühl, M.; Rothgang, S.; Sauer, D.U. Production caused variation in capacity aging trend and correlation to initial cell performance. *J. Power Sources* **2014**, *247*, 332–338. [CrossRef]
69. Dubarry, M.; Truchot, C.; Cugnet, M.; Liaw, B.Y.; Gering, K.; Sazhin, S.; Jamison, D.; Michelbacher, C. Evaluation of commercial lithium-ion cells based on composite positive electrode for plug-in hybrid electric vehicle applications. Part I: Initial characterizations. *J. Power Sources* **2011**, *196*, 10328–10335. [CrossRef]
70. Dubarry, M.; Vuillaume, N.; Liaw, B.Y. Origins and accommodation of cell variations in Li-ion battery pack modeling. *Int. J. Energy Res.* **2010**, *34*, 216–231. [CrossRef]
71. Rumpf, K.; Naumann, M.; Jossen, A. Experimental investigation of parametric cell-to-cell variation and correlation based on 1100 commercial lithium-ion cells. *J. Energy Storage* **2017**, *14*, 224–243. [CrossRef]

72. Wang, Q.; Wang, Z.; Zhang, L.; Liu, P.; Zhang, Z. A Novel Consistency Evaluation Method for Series-Connected Battery Systems Based on Real-World Operation Data. *IEEE Trans. Transp. Electrif.* **2021**, *7*, 437–451. [CrossRef]
73. Iraola, U.; Aizpuru, I.; Gorrotxategi, L.; Segade, J.M.C.; Larrazabal, A.E.; Gil, I. Influence of Voltage Balancing on the Temperature Distribution of a Li-Ion Battery Module. *IEEE Trans. Energy Convers.* **2015**, *30*, 507–514. [CrossRef]
74. Werner, D.; Paarmann, S.; Wiebelt, A.; Wetzel, T. Inhomogeneous temperature distribution affecting the cyclic aging of Li-ion cells. Part I: Experimental investigation. *Batteries* **2020**, *6*, 13. [CrossRef]
75. Aguilar Boj, E.; Azizighalehsari, S.; Venugopal, P.; Rietveld, G.; Soeiro, T.B. A Distribution of Relaxation Time Approach on Equivalent Circuit Model Parameterization to Analyse Li-ion Battery Degradation. In Proceedings of the 11th International Conference on Power Electronics-ECCE Asia (ICPE 2023-ECCE Asia), Jeju, Republic of Korea, 22–25 May 2023.
76. Xiong, R.; Pan, Y.; Shen, W.; Li, H.; Sun, F. Lithium-ion battery aging mechanisms and diagnosis method for automotive applications: Recent advances and perspectives. *Renew. Sustain. Energy Rev.* **2020**, *131*, 110048. [CrossRef]
77. Krupp, A.; Ferg, E.; Schuldt, F.; Derendorf, K.; Agert, C. Incremental capacity analysis as a state of health estimation method for lithium-ion battery modules with series-connected cells. *Batteries* **2020**, *7*, 2. [CrossRef]
78. Ansean, D.; Garcia, V.M.; Gonzalez, M.; Blanco-Viejo, C.; Viera, J.C.; Pulido, Y.F.; Sanchez, L. Lithium-Ion Battery Degradation Indicators Via Incremental Capacity Analysis. *IEEE Trans. Ind. Appl.* **2019**, *55*, 2992–3002. [CrossRef]
79. Li, Y.; Abdel-Monem, M.; Gopalakrishnan, R.; Berecibar, M.; Nanini-Maury, E.; Omar, N.; van den Bossche, P.; Van Mierlo, J. A quick on-line state of health estimation method for Li-ion battery with incremental capacity curves processed by Gaussian filter. *J. Power Sources* **2018**, *373*, 40–53. [CrossRef]
80. Riviere, E.; Sari, A.; Venet, P.; Meniere, F.; Bultel, Y. Innovative incremental capacity analysis implementation for c/lifepo 4 cell state-of-health estimation in electrical vehicles. *Batteries* **2019**, *5*, 37. [CrossRef]
81. Lin, C.; Cabrera, J.; Denis, Y.; Yang, F.; Tsui, K. SOH estimation and SOC recalibration of lithium-ion battery with incremental capacity analysis & cubic smoothing spline. *J. Electrochem. Soc.* **2020**, *167*, 090537.
82. Dahn, J. Phase diagram of Li x C 6. *Phys. Rev. B* **1991**, *44*, 9170. [CrossRef]
83. Groot, J. *State-of-Health Estimation of Li-Ion Batteries: Cycle Life Test Methods*; Chalmers Tekniska Hogskola: Göteborg, Sweden, 2012.
84. Hua, X.; Zhang, T.; Offer, G.J.; Marinescu, M. Towards online tracking of the shuttle effect in lithium sulfur batteries using differential thermal voltammetry. *J. Energy Storage* **2019**, *21*, 765–772. [CrossRef]
85. Merla, Y.; Wu, B.; Yufit, V.; Brandon, N.P.; Martinez-Botas, R.F.; Offer, G.J. Novel application of differential thermal voltammetry as an in-depth state-of-health diagnosis method for lithium-ion batteries. *J. Power Sources* **2016**, *307*, 308–319. [CrossRef]
86. Wang, Z.; Yuan, C.; Li, X. Lithium battery state-of-health estimation via differential thermal voltammetry with Gaussian process regression. *IEEE Trans. Transp. Electrif.* **2020**, *7*, 16–25. [CrossRef]
87. Azizighalehsari, S.; Venugopal, P.; Singh, D.P.; Rietveld, G. Performance Evaluation of Retired Lithium-ion Batteries for Echelon Utilization. In Proceedings of the IECON 2022–48th Annual Conference of the IEEE Industrial Electronics Society, Brussels, Belgium, 17–20 October 2022.
88. Mc Carthy, K.; Gullapalli, H.; Ryan, K.M.; Kennedy, T. Electrochemical impedance correlation analysis for the estimation of Li-ion battery state of charge, state of health and internal temperature. *J. Energy Storage* **2022**, *50*, 104608. [CrossRef]
89. Iurilli, P.; Brivio, C.; Wood, V. On the use of electrochemical impedance spectroscopy to characterize and model the aging phenomena of lithium-ion batteries: A critical review. *J. Power Sources* **2021**, *505*, 229860. [CrossRef]
90. Breazu, B.; Azizighalehsari, S.; Venugopal, P.; Rietveld, G.; Soeiro, T.B. Li-ion Battery Prognostics with Statistical Model and RNN Trained with EIS-Based Features. In Proceedings of the 2023 IEEE Energy Conversion Congress and Exposition (ECCE), Nashville, TN, USA, 29 October–2 November 2023; pp. 1699–1705.
91. Savca, A.; Azizighalehsari, S.; Venugopal, P.; Rietveld, G.; Soeiro, T.B. Feasibility of EIS on Module Level Li-ion Batteries for Echelon Utilization. In Proceedings of the 2023 11th International Conference on Power Electronics and ECCE Asia (ICPE 2023-ECCE Asia), Jeju, Republic of Korea, 22–25 May 2023; pp. 1811–1816.
92. Locorotondo, E.; Pasquali, M.; Cultrera, V.; Andrenacci, N.; Pugi, L.; Lutzemberger, G.; Berzi, L.; Pierini, M. Impedance spectroscopy characterization of lithium batteries with different ages in second life application; Impedance spectroscopy characterization of lithium batteries with different ages in second life application. In Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Madrid, Spain, 9–12 June 2020.
93. Zhang, Q.; Li, X.; Du, Z.; Liao, Q. Aging performance characterization and state-of-health assessment of retired lithium-ion battery modules. *J. Energy Storage* **2021**, *40*, 102743. [CrossRef]
94. Kehl, D.; Jennert, T.; Lienesch, F.; Kurrat, M. Electrical Characterization of Li-Ion Battery Modules for Second-Life Applications. *Batteries* **2021**, *7*, 32 [CrossRef]
95. Tesla Vehicle Safety Report | Tesla. Available online: <https://www.tesla.com/VehicleSafetyReport> (accessed on 9 May 2024).
96. Beyond EVs—Stranded Energy Is a Concern Across All Energy Storage Technologies. Available online: <https://www.nfpa.org/News-and-Research/Publications-and-media/NFPA-Journal/2020/January-February-2020/Features/EV-Stranded-Energy-ESS> (accessed on 9 May 2024).
97. Sun, P.; Huang, X. LLC, part of Springer Nature Manufactured in The United States. *Fire Technol.* **2020**, *56*, 1361–1410. [CrossRef]
98. Hua, Y.; Liu, X.; Zhou, S.; Huang, Y.; Ling, H.; Yang, S. Toward Sustainable Reuse of Retired Lithium-ion Batteries from Electric Vehicles. *Resour. Conserv. Recycl.* **2021**, *168*, 105249. [CrossRef]

99. Bisschop, R.; Willstrand, O.; Amon, F.; Rosengren, M. Fire Safety of Lithium-Ion Batteries in Road Vehicles. 2019. Available online: <https://urn.kb.se/resolve?urn=urn:nbn:se:ri:diva-38873> (accessed on 9 May 2024).
100. Huang, W.; Attia, P.M.; Wang, H.; Renfrew, S.E.; Jin, N.; Das, S.; Zhang, Z.; Boyle, D.T.; Li, Y.; Bazant, M.Z.; et al. Evolution of the Solid—Electrolyte Interphase on Carbonaceous Anodes Visualized by Atomic-Resolution Cryogenic Electron Microscopy. *Nano Lett.* **2019**, *19*, 5148. [CrossRef]
101. Montoya-Bedoya, S.; Sabogal-Moncada, L.A.; Garcia-Tamayo, E.; Martínez-Tejada, H. A Circular Economy of Electrochemical Energy Storage Systems: Critical Review of SOH/RUL Estimation Methods for Second-Life Batteries. In *Green Energy and Environment, Chapter 4*; IntechOpen: London, UK, 2020. [CrossRef]
102. Atalay, S.; Sheikh, M.; Mariani, A.; Merla, Y.; Bower, E.; Widanage, W.D. Theory of battery ageing in a lithium-ion battery: Capacity fade, nonlinear ageing and lifetime prediction. *J. Power Sources* **2020**, *478*, 229026. [CrossRef]
103. Xie, S.; Ren, L.; Yang, X.; Wang, H.; Sun, Q.; Chen, X.; He, Y. Influence of cycling aging and ambient pressure on the thermal safety features of lithium-ion battery. *J. Power Sources* **2020**, *448*, 227425. [CrossRef]
104. Gabbar, H.A.; Othman, A.M.; Abdussami, M.R. Review of Battery Management Systems (BMS) Development and Industrial Standards. *Technologies* **2021**, *9*, 28 [CrossRef]
105. Zheng, L. Development of Lithium-Ion Battery State Estimation Techniques for Battery Management Systems. Doctoral Dissertation, School of Electrical and Data Engineering, University of Technology Sydney, Sydney, Australia, 2018.
106. Report on Boeing 787 Dreamliner Battery Flaws Finds Lapses at Multiple Points-The New York Times. Available online: <https://www.nytimes.com/2014/12/02/business/report-on-boeing-787-dreamliner-batteries-assigns-some-blame-for-flaws.html> (accessed on 24 March 2023).
107. Samsung Confirms Battery Faults as Cause of Note 7 Fires-BBC News. Available online: <https://www.bbc.com/news/business-38714461> (accessed on 9 May 2024).
108. Belgium Li-Ion ESS Fire Cause Still Unknown Two Months Later-Energy Storage Journal. Available online: <https://www.energystoragejournal.com/belgiums-li-ion-ess-fire-cause-still-unknown-two-months-later/> (accessed on 9 May 2024).
109. Frequent Fire Raising Concerns over Safety of Solar Energy. Available online: https://www.koreatimes.co.kr/www/tech/2018/12/133_260560.html (accessed on 9 May 2024).
110. APS Says Runaway Thermal Event Caused 2019 Battery Explosion, Outlines 4 Steps to Avoid a Repeat! Utility Dive. Available online: <https://www.utilitydive.com/news/aps-says-runaway-thermal-event-caused-2019-battery-explosion-outlines-4-st/582475/> (accessed on 9 May 2024).
111. Tesla Says Single Battery Module Caused Car Fire in Shanghai, Has Changed Vehicle Settings | Reuters. Available online: <https://www.reuters.com/article/us-tesla-china-safety-idUSKCN1TT154> (accessed on 9 May 2024).
112. BMW i8 Catches Fire in Europe Dealership, Gets Dropped in Huge Bath-Motor Illustrated. Available online: <https://motorillustrated.com/bmw-i8-catches-fire-in-europe-dealership-gets-dropped-in-huge-bath/23440/> (accessed on 9 May 2024).
113. Kabir, M.; Demirocak, D.E. Degradation mechanisms in Li-ion batteries: A state-of-the-art review. *Int. J. Energy Res.* **2017**, *41*, 1963–1986. [CrossRef]
114. Guo, J.; Li, Y.; Pedersen, K.; Stroe, D.I. Lithium-ion battery operation, degradation, and aging mechanism in electric vehicles: An overview. *Energies* **2021**, *14*, 5220. [CrossRef]
115. Braco, E.; San Martín, I.; Berrueta, A.; Sanchis, P.; Ursúa, A. Experimental assessment of cycling ageing of lithium-ion second-life batteries from electric vehicles. *J. Energy Storage* **2020**, *32*, 101695. [CrossRef]
116. Waldmann, T.; Hogg, B.I.; Wohlfahrt-Mehrens, M. Li plating as unwanted side reaction in commercial Li-ion cells—A review. *J. Power Sources* **2018**, *384*, 107–124. [CrossRef]
117. Schuster, S.F.; Bach, T.; Fleder, E.; Müller, J.; Brand, M.; Sextl, G.; Jossen, A. Nonlinear aging characteristics of lithium-ion cells under different operational conditions. *J. Energy Storage* **2015**, *1*, 44–53. [CrossRef]
118. Fan, W.; Zhu, J.; Qiao, D.; Jiang, B.; Wang, X.; Wei, X.; Dai, H. Prediction of nonlinear degradation knee-point and remaining useful life for lithium-ion batteries using relaxation voltage. *Energy* **2024**, *394*, 130900. [CrossRef]
119. Martinez-Laserna, E.; Sarasketa-Zabala, E.; Villarreal Sarria, I.; Stroe, D.I.; Swierczynski, M.; Warnecke, A.; Timmermans, J.M.; Goutam, S.; Omar, N.; Rodriguez, P. Technical Viability of Battery Second Life: A Study from the Ageing Perspective. *IEEE Trans. Ind. Appl.* **2018**, *54*, 2703–2713. [CrossRef]
120. Wang, T.; Jiang, Y.; Kang, L.; Liu, Y. Determination of retirement points by using a multi-objective optimization to compromise the first and second life of electric vehicle batteries. *J. Clean. Prod.* **2020**, *275*, 123128. [CrossRef]
121. Casals, L.C.; García, B.A.; Canal, C. Second life batteries lifespan: Rest of useful life and environmental analysis. *J. Environ. Manag.* **2019**, *232*, 354–363. [CrossRef]
122. Hu, X.; Xu, L.; Lin, X.; Pecht, M. Battery Lifetime Prognostics. *Joule* **2020**, *4*, 310–346. [CrossRef]
123. Chen, C.F.; Barai, P.; Mukherjee, P.P. An overview of degradation phenomena modeling in lithium-ion battery electrodes. *Curr. Opin. Chem. Eng.* **2016**, *13*, 82–90. [CrossRef]
124. Azizighalehsari, S.; Popovic, J.; Venugopal, P.; Ferreira, B. A Review of Lithium-ion Batteries Diagnostics and Prognostics Challenges; A Review of Lithium-ion Batteries Diagnostics and Prognostics Challenges. In Proceedings of the IECON 2021—47th Annual Conference of the IEEE Industrial Electronics Society, Toronto, ON, Canada, 13–16 October 2021. [CrossRef]

125. Zubi, G.; Spertino, F.; Carvalho, M.; Adhikari, R.S.; Khatib, T. Development and assessment of a solar home system to cover cooking and lighting needs in developing regions as a better alternative for existing practices. *Sol. Energy* **2017**, *155*, 7–17. [CrossRef]
126. Li, Y.; Liu, K.; Foley, A.M.; Zülke, A.; Berecibar, M.; Nanini-Maury, E.; Van Mierlo, J.; Hoster, H.E. Data-driven health estimation and lifetime prediction of lithium-ion batteries: A review. *Renew. Sustain. Energy Rev.* **2019**, *113*, 109254. [CrossRef]
127. The ‘Battery Passport’ and the Future of the Auto Industry-Everledger. Available online: <https://everledger.io/the-battery-passport-and-the-future-of-the-auto-industry/> (accessed on 9 May 2024).
128. Battery Passport. Available online: <https://www.globalbattery.org/battery-passport/> (accessed on 9 May 2024).
129. Thangavel, S.; Mohanraj, D.; Girijaprasanna, T.; Raju, S.; Dhanamjayulu, C.; Muyeen, S.M. A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors. *IEEE Access* **2023**, *11*, 20994–21019. [CrossRef]
130. See, K.; Wang, G.; Zhang, Y.; Wang, Y.; Meng, L.; Gu, X.; Zhang, N.; Lim, K.; Zhao, L.; Xie, B. Critical review and functional safety of a battery management system for large-scale lithium-ion battery pack technologies. *Int. J. Coal Sci. Technol.* **2022**, *9*, 36. [CrossRef]
131. Ning, Z.; Deng, Z.; Li, J.; Liu, H.; Guo, W. Co-estimation of state of charge and state of health for 48 V battery system based on cubature Kalman filter and H-infinity. *J. Energy Storage* **2022**, *56*, 106052. [CrossRef]
132. Yu, Q.Q.; Xiong, R.; Wang, L.Y.; Lin, C. A comparative study on open circuit voltage models for lithium-ion batteries. *Chin. J. Mech. Eng.* **2018**, *31*, 65. [CrossRef]
133. Lee, J.; Won, J. Enhanced coulomb counting method for SoC and SoH estimation based on coulombic efficiency. *IEEE Access* **2023**, *11*, 15449–15459. [CrossRef]
134. How, D.N.; Hannan, M.; Lipu, M.H.; Ker, P.J. State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review. *IEEE Access* **2019**, *7*, 136116–136136. [CrossRef]
135. Lipu, M.H.; Hannan, M.; Hussain, A.; Ayob, A.; Saad, M.H.; Karim, T.F.; How, D.N. Data-driven state of charge estimation of lithium-ion batteries: Algorithms, implementation factors, limitations and future trends. *J. Clean. Prod.* **2020**, *277*, 124110. [CrossRef]
136. Misyris, G.S.; Doukas, D.I.; Papadopoulos, T.A.; Labridis, D.P.; Agelidis, V.G. State-of-charge estimation for li-ion batteries: A more accurate hybrid approach. *IEEE Trans. Energy Convers.* **2018**, *34*, 109–119. [CrossRef]
137. Cui, Z.; Kang, L.; Li, L.; Wang, L.; Wang, K. A hybrid neural network model with improved input for state of charge estimation of lithium-ion battery at low temperatures. *Renew. Energy* **2022**, *198*, 1328–1340. [CrossRef]
138. Zhang, R.; Li, X.; Sun, C.; Yang, S.; Tian, Y.; Tian, J. State of charge and temperature joint estimation based on ultrasonic reflection waves for lithium-ion battery applications. *Batteries* **2023**, *9*, 335. [CrossRef]
139. Ning, Z.; Azizighalehsari, S.; Venugopal, P.; Rietveld, G.; Soeiro, T.B. Towards Real-Time Estimation of Li-ion Battery Characteristics for BMS with Storage-Limited Processors. In Proceedings of the 2023 IEEE 8th Southern Power Electronics Conference (SPEC), Florianopolis, Brazil, 26–29 November 2023; pp. 1–7.
140. Faraji-Niri, M.; Rashid, M.; Sansom, J.; Sheikh, M.; Widanage, D.; Marco, J. Accelerated state of health estimation of second life lithium-ion batteries via electrochemical impedance spectroscopy tests and machine learning techniques. *J. Energy Storage* **2023**, *58*, 106295. [CrossRef]
141. Nunes, T.S.; Moura, J.J.; Prado, O.G.; Camboim, M.M.; de Fatima N. Rosolem, M.; Beck, R.F.; Omae, C.; Ding, H. An online unscented Kalman filter remaining useful life prediction method applied to second-life lithium-ion batteries. *Electr. Eng.* **2023**, *105*, 3481–3492. [CrossRef]
142. Jiang, Y.; Jiang, J.; Zhang, C.; Zhang, W.; Gao, Y.; Li, N. State of health estimation of second-life LiFePO₄ batteries for energy storage applications. *J. Clean. Prod.* **2018**, *205*, 754–762. [CrossRef]
143. Xiong, W.; Mo, Y.; Yan, C. Online state-of-health estimation for second-use lithium-ion batteries based on weighted least squares support vector machine. *IEEE Access* **2020**, *9*, 1870–1881. [CrossRef]
144. Zhang, S.; Zhai, B.; Guo, X.; Wang, K.; Peng, N.; Zhang, X. Synchronous estimation of state of health and remaining useful lifetime for lithium-ion battery using the incremental capacity and artificial neural networks. *J. Energy Storage* **2019**, *26*, 100951. [CrossRef]
145. Braco, E.; San Martín, I.; Sanchis, P.; Ursúa, A.; Stroe, D.I. State of health estimation of second-life lithium-ion batteries under real profile operation. *Appl. Energy* **2022**, *326*, 119992. [CrossRef]
146. Paul, S.; Diegelmann, C.; Kabza, H.; Tillmetz, W. Analysis of ageing inhomogeneities in lithium-ion battery systems. *J. Power Sources* **2013**, *239*, 642–650. [CrossRef]
147. Eskandari, R.; Venugopal, P.; Rietveld, G. Advanced Battery Management Systems with Integrated Battery Electronics. In Proceedings of the 2022 IEEE 20th International Power Electronics and Motion Control Conference (PEMC), Brasov, Romania, 25–28 September 2022; pp. 55–61.
148. Shahjalal, M.; Shams, T.; Islam, M.E.; Alam, W.; Modak, M.; Hossain, S.B.; Ramadesigan, V.; Ahmed, M.R.; Ahmed, H.; Iqbal, A. A review of thermal management for Li-ion batteries: Prospects, challenges, and issues. *J. Energy Storage* **2021**, *39*, 102518. [CrossRef]
149. Liu, H.; Wei, Z.; He, W.; Zhao, J. Thermal issues about Li-ion batteries and recent progress in battery thermal management systems: A review. *Energy Convers. Manag.* **2017**, *150*, 304–330. [CrossRef]
150. Gou, B.; Xu, Y.; Feng, X. State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-Ion Battery Using a Hybrid Data-Driven Method. *IEEE Trans. Veh. Technol.* **2020**, *69*, 10854–10867. [CrossRef]

151. Escobar, L.A.; Meeker, W.Q. A review of accelerated test models. *Stat. Sci.* **2006**, *21*, 552–577. [[CrossRef](#)]
152. Hasib, S.A.; Islam, S.; Chakrabortty, R.K.; Ryan, M.J.; Saha, D.K.; Ahmed, M.H.; Moyeen, S.I.; Das, S.K.; Ali, M.F.; Islam, M.R.; et al. A Comprehensive Review of Available Battery Datasets, RUL Prediction Approaches, and Advanced Battery Management. *IEEE Access* **2021**, *9*, 86166–86193. [[CrossRef](#)]
153. Wikner, E.; Thiringer, T. Extending battery lifetime by avoiding high SOC. *Appl. Sci.* **2018**, *8*, 1825. [[CrossRef](#)]
154. Cui, Y.; Du, C.; Yin, G.; Gao, Y.; Zhang, L.; Guan, T.; Yang, L.; Wang, F. Multi-stress factor model for cycle lifetime prediction of lithium ion batteries with shallow-depth discharge. *J. Power Sources* **2015**, *279*, 123–132. [[CrossRef](#)]
155. Zhao, Y.; Pohl, O.; Bhatt, A.I.; Collis, G.E.; Mahon, P.J.; Rüther, T.; Hollenkamp, A.F. A review on battery market trends, second-life reuse, and recycling. *Sustain. Chem.* **2021**, *2*, 167–205. [[CrossRef](#)]
156. Cready, E.; Lippert, J.; Pihl, J.; Weinstock, I.; Symons, P. *Technical and Economic Feasibility of Applying Used EV Batteries in Stationary Applications*; Technical Report; Sandia National Lab. (SNL-NM): Albuquerque, NM, USA, 2003.
157. Shahjalal, M.; Roy, P.K.; Shams, T.; Fly, A.; Chowdhury, J.I.; Ahmed, M.R.; Liu, K. A review on second-life of Li-ion batteries: Prospects, challenges, and issues. *Energy* **2022**, *241*, 122881. [[CrossRef](#)]
158. Haram, M.H.S.M.; Lee, J.W.; Ramasamy, G.; Ngu, E.E.; Thiagarajah, S.P.; Lee, Y.H. Feasibility of utilising second life EV batteries: Applications, lifespan, economics, environmental impact, assessment, and challenges. *Alex. Eng. J.* **2021**, *60*, 4517–4536. [[CrossRef](#)]
159. Lee, J.W.; Haram, M.H.S.M.; Ramasamy, G.; Thiagarajah, S.P.; Ngu, E.E.; Lee, Y.H. Technical feasibility and economics of repurposed electric vehicles batteries for power peak shaving. *J. Energy Storage* **2021**, *40*, 102752. [[CrossRef](#)]
160. Cusenza, M.A.; Guarino, F.; Longo, S.; Ferraro, M.; Cellura, M. Energy and environmental benefits of circular economy strategies: The case study of reusing used batteries from electric vehicles. *J. Energy Storage* **2019**, *25*, 100845. [[CrossRef](#)]
161. Ioakimidis, C.S.; Murillo-Marrodán, A.; Bagheri, A.; Thomas, D.; Genikomsakis, K.N. Life Cycle Assessment of a Lithium Iron Phosphate (LFP) Electric Vehicle Battery in Second Life Application Scenarios. *Sustainability* **2019**, *11*, 2527. [[CrossRef](#)]
162. Bhatt, A.; Ongsakul, W.; Madhu M., N. Optimal techno-economic feasibility study of net-zero carbon emission microgrid integrating second-life battery energy storage system. *Energy Convers. Manag.* **2022**, *266*, 115825. [[CrossRef](#)]
163. Electric Vehicles, Second Life Batteries, and Their Effect on the Power Sector | McKinsey. Available online: <https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/second-life-ev-batteries-the-newest-value-pool-in-energy-storage> (accessed on 9 May 2024).
164. Bobba, S.; Podias, A.; Di Persio, F.; Messagie, M.; Tecchio, P.; Cusenza, M.A.; Eynard, U.; Mathieu, F.; Pfrang, A. Sustainability Assessment of Second Life Application of Automotive Batteries (SASLAB). In *JRC Exploratory Research (2016–2017), Final Report*; European Union: Maastricht, The Netherlands, 2018; p. 140. [[CrossRef](#)]
165. Canals Casals, L.; Barbero, M.; Corchero, C. Reused second life batteries for aggregated demand response services. *J. Clean. Prod.* **2019**, *212*, 99–108. [[CrossRef](#)]
166. Reinhardt, R.; Christodoulou, I.; Gassó-Domingo, S.; Amante García, B. Towards sustainable business models for electric vehicle battery second use: A critical review. *J. Environ. Manag.* **2019**, *245*, 432–446. [[CrossRef](#)]
167. Kebir, N.; Leonard, A.; Downey, M.; Jones, B.; Rabie, K.; Bhagavathy, S.M.; Hirmer, S.A. Second-life battery systems for affordable energy access in Kenyan primary schools. *Sci. Rep.* **2023**, *13*, 1374. [[CrossRef](#)]
168. Kebede, A.A. Comprehensive Lifetime Investigation of First and Second Life Lithium-ion Batteries: A Study from Mobility and Stationary Application Perspectives. Ph.D. Thesis, Faculty of Engineering, Vrije Universiteit Brussel, Brussel, Belgium, 2023.
169. Liebreich, M. Bloomberg new energy finance summit. In *London: Bloomberg New Energy Finance*; 2013; pp. 1–10. Available online: https://thecoalhub.com/wp-content/uploads/attach_328.pdf (accessed on 9 May 2024).
170. Melin, H.E. *The Lithium-Ion Battery End-of-Life Market—A Baseline Study*; WEF: World Economic Forum: Colonie, Switzerland, 2018.
171. RWE Commissions Second Life Energy Storage System in Germany. Available online: <https://www.electrive.com/2022/01/03/rwe-opens-second-life-energy-storage-system-in-germany/> (accessed on 9 May 2024).

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