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Review

Repurposing Second-Life EV Batteries to Advance Sustainable Development: A Comprehensive Review

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Abstract: While lithium-ion batteries (LIBs) have pushed the progression of electric vehicles (EVs) as a viable commercial option, they introduce their own set of issues regarding sustainable development. This paper investigates how using end-of-life LIBs in stationary applications can bring us closer to meeting the sustainable development goals (SDGs) highlighted by the United Nations. We focus on how this practice can support three of these goals, namely Goal 7: Affordable and Clean Energy, Goal 12: Responsible Consumption and Production, and Goal 13: Climate Action. We present a literature review that details the aging mechanisms of LIBs, namely battery degradation, state of charge, state of health, depth of discharge, remaining useful life, and battery management systems. Then, we thoroughly examine the environmental and economic benefits of using second-life EV batteries in stationary applications and how they align with the SDGs. Our review of the literature summarizes the most relevant research in battery aging, giving a foundation for further research and allowing effective legislation to be written around EVs. Additionally, our examination of the benefits of using second-life batteries motivates initiatives for sustainable practices, helping both corporations and legislators orient their ideals towards the SDGs.

Keywords: sustainable development goals; repurposing; second-life battery; stationary applications; environmental benefits; battery aging mechanism

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1. Introduction

Environmentally clean energy generation and, subsequently, clean energy storage have been significant topics of discussion worldwide. In this paper, we analyze the current literature on the environmental feasibility of using second-life batteries (SLB) extracted from electric vehicles (EVs) as a storage system for clean energy [1]. note that the demand and sales of EVs have risen because of government incentives and initiatives.

Because of the natural process of battery degradation, EV batteries are eventually discarded and recycled for their materials. However, these batteries often have residual capacity that is wasted when disposed of. Thus, there is a potential use for them in other applications. An example of an SLB is found in stationary applications, such as V2G or Transitioning Batteries from Vehicle to Grid. According to [2], the number of discarded batteries is projected to reach 3.4 million by 2025, amounting to approximately 953 GWh capacity.

The threshold for when an EV battery has reached its "end-of-life" is when the battery has degraded to a capacity of 80% of its original capacity and can no longer be used in an EV) [3,4]; thus, requiring its removal and reconfiguration for a secondary application. An LIB used in an EV has an approximate lifespan of 8 years but using it in a stationary second-life application, as our review suggests, can extend it by 10 years [5]. An estimation given by [6] says that these batteries can be used in EVs for up to 12.5 years. [7] constructed a model and found the length of time a second-life EV battery would last in four distinct applications, namely, Self Consumption, Area Regulation, Transmission upgrade Deferral, and Fast EV Charge. They considered the input of expected battery current load in each application, and they continuously calculated a variety of metrics, such as state of health (SOH) change, depth of discharge (DOD), and current rates, each of them is considered an indicator of battery aging. Their results were that in the four applications, an SLB would run for 12 years, 6 years, 12 years, and 30 years, respectively.

Battery degradation is an electrochemical process that increases resistance and decreases battery capacity. This inevitable process prompts the idea of monitoring battery health quantitatively, thus motivating the use of performance factors. The main factors used to model battery aging are state of charge (SOC), remaining useful life (RUL), DOD, and SOH. Furthermore, to accurately model and optimize these factors, a battery management system (BMS) plays a key role [8]. Figure 1 shows the lifecycle of a battery through its various repurposed applications.

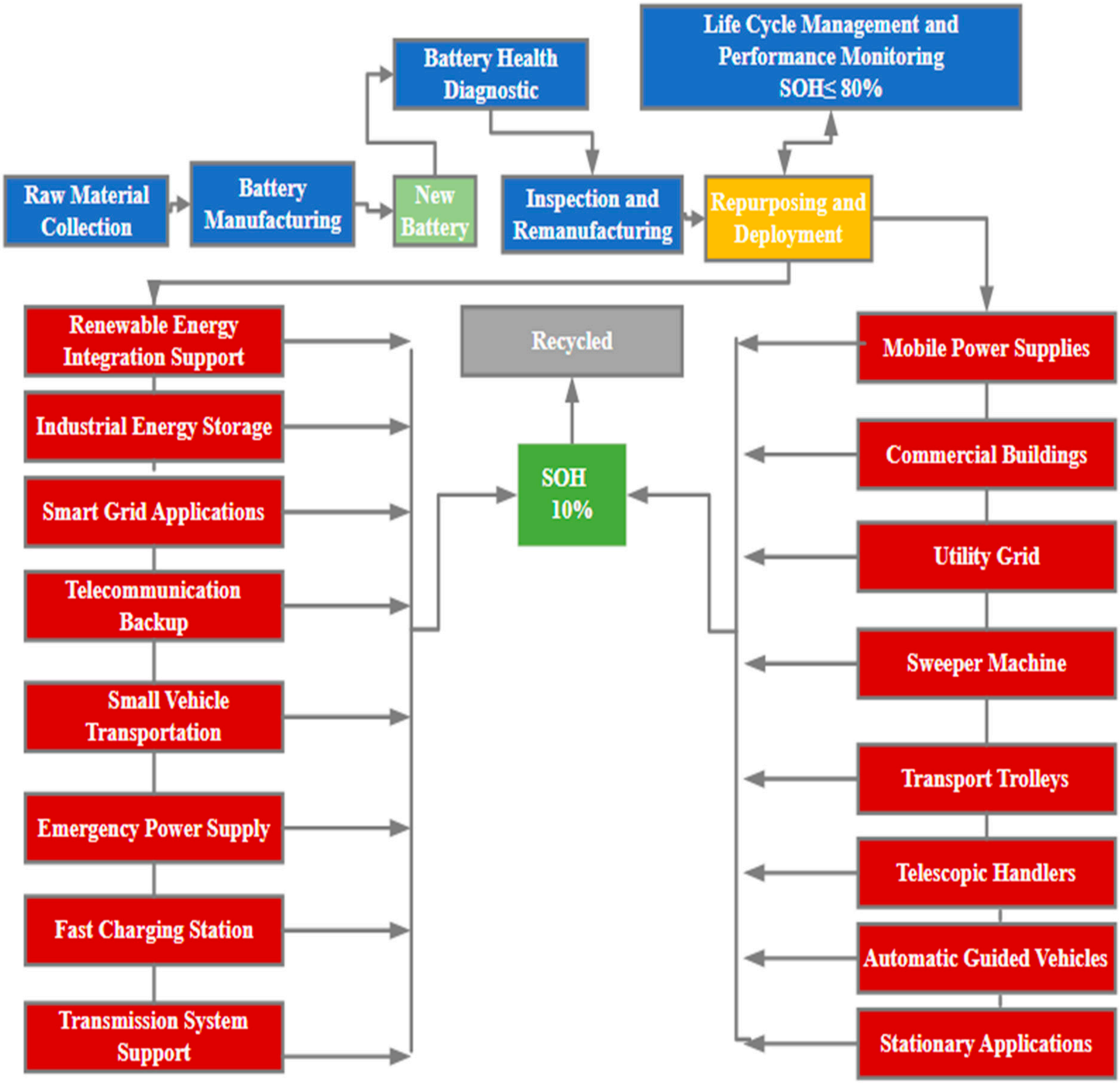

Figure 1. Life cycle of LIB of an EV.

The sustainable development goals (SDGs) consist of seventeen objectives and 169 specific targets established by the UN General Assembly in 2015 to put forth a standard for the countries around the world to strive towards sustainable development [9]. These goals and targets have five cores that help direct their change, namely people, the planet, prosperity, peace, and partnership. The aim of the SDGs is to grow and develop prospering economies, protected environments, and healthy human beings on a global scale, all by 2030.

Repurposing EV batteries can significantly progress the achievement of these SDGs. By prolonging the service period of these batteries, the need for immediate recycling is postponed, which reduces the energy and resources required for battery disposal and new battery production [10]. Therefore, overall energy costs decrease, the economy becomes more circular, and less GHGs are emitted into the atmosphere, aligning directly with SDGs 7, 12, and 13.

The aim of this paper is to offer a literature review on the use of second-life EV batteries in stationary applications and how they impact and progress sustainable development. Readers from academic and industrial backgrounds will be interested in considering the reports and models we have reviewed and studied on EV battery degradation, SOC, SOH, DOD, RUL, BMS, SLB Use in Stationary Applications, and the environmental impact. We will also provide an analysis of how reducing costs and GHG emissions by using batteries in stationary application could improve the achievement of the SDGs.

2. Methodology

The methodology of this literature review involves an organized approach to gather, analyze, and synthesize existing research on the reusing of EV batteries for second-life applications and their alignment with (SDGs). The methodological approach is designed to ensure the comprehensiveness and relevance of the reviewed literature by considering multiple aspects related to battery aging mechanisms, second-life battery (SLB) applications, and their environmental impacts. This section outlines the steps taken to conduct this review, including the selection of sources, the criteria for inclusion, and the classification of topics.

The primary sources of literature for this review were academic articles, conference papers, and books accessed through various electronic databases, including Google Scholar, Scopus, and ScienceDirect. These databases were chosen for their extensive collections of peer-reviewed publications, ensuring a high standard of quality and credibility in the sources selected.

The search strategy involved the use of specific keywords and phrases to retrieve the relevant literature. The key terms included:

- "Use of second-life batteries in stationary applications"
- "Battery degradation"
- "Remaining useful life (RUL)"
- "Environmental impacts of second-life batteries"
- "State of charge (SOC)"
- "State of health (SOH)"
- "Depth of discharge (DOD)"
- "Battery management system (BMS)"

These keywords were used in various combinations to capture a broad spectrum of relevant research. Additionally, references from key articles were examined to identify additional relevant research. To guarantee the importance and quality of the articles included in the review, particular standards were set for choosing the articles:

- **Relevance**: The study must address one or more of the following topics: battery aging mechanisms, second-life applications of EV batteries, environmental impacts, or the alignment of SLBs with SDGs.
- **Quality**: Priority was accorded to articles published in peer-reviewed journals, papers presented at conferences, and chapters from well-respected books.
- **Recency**: Recent studies were selected to make sure the review conveys the contemporary developments and trends in the field; namely, studies written within 5 years were given preference. However, seminal works and foundational studies were also included irrespective of their publication date.

- **Language**: The review process was kept consistent by including only English-published articles.

The initial query revealed a total of 439 results. To assess its relevance, each article's main signifiers, i.e., the title and abstract, were utilized. The articles that passed the first screening test had reviews of the entire text performed for the articles that passed the second screening test. After this rigorous selection process, 212 articles that were judged to be extremely relevant and educational for the subjects addressed in this study were chosen. Table 1 summarizes the number of papers considered in each section of the review.

Table 1. The count of papers in every section.

Section Number	No. of Papers
1.0 Introduction	16
3.0 Battery Aging Mechanisms 2 Degradation 24 State of Charge (SOC) 23 State of Health (SOH) 22 Depth of Discharge (DOD) 6 Battery Management System (BMS) 15 Remining Useful Life (RUL) 29	121
4.0 Second-Life Batteries in Stationary Applications	51
5.0 Environmental Impact	17
6.0 Discussion	7
Total	212

The selected articles were categorized into thematic areas corresponding to the main topics of the review. The thematic areas included:

1. **Battery Aging Mechanisms**: This section focused on the electrochemical processes and factors influencing battery degradation, including SOC, SOH, DOD, RUL, and battery management system (BMS). Articles in this category provided insights into the technical aspects of battery life and performance.
2. **SLB Use in Stationary Applications**: Studies in this category examined the potential and actual applications of SLBs in stationary contexts, such as grid storage, renewable energy integration, and V2G systems. The analysis included case studies, experimental results, and modeling approaches.
3. **Environmental Impact**: This section reviewed the environmental benefits and challenges of repurposing EV batteries. It included life cycle assessments (LCAs), carbon footprint analyses, and discussions on resource efficiency.

To ensure the reliability of the findings, each article was subjected to a quality assessment. This involved evaluating the methodology, data sources, and conclusions of each study. Articles with robust methodologies and well-supported conclusions were given higher priority in the synthesis process. The synthesis of findings involved integrating results from different studies to provide a thorough understanding of the topics. This process included identifying common themes, contrasting differing viewpoints, and highlighting gaps in the current literature. Visual aids such as tables and figures were used to summarize and present the synthesized data effectively. To provide context on the evolution of research in this field, the number of articles released each year is shown in Figure 2. From 2018 onwards, we have seen a significant increase in research output, highlighting the escalating curiosity and advancements in the study of SLB and their uses. The growing quantity of written works suggests a growing acknowledgment of the significance of SLBs in attaining sustainability objectives and addressing energy storage challenges. This trend underscores the need for continued research and innovation in the field.

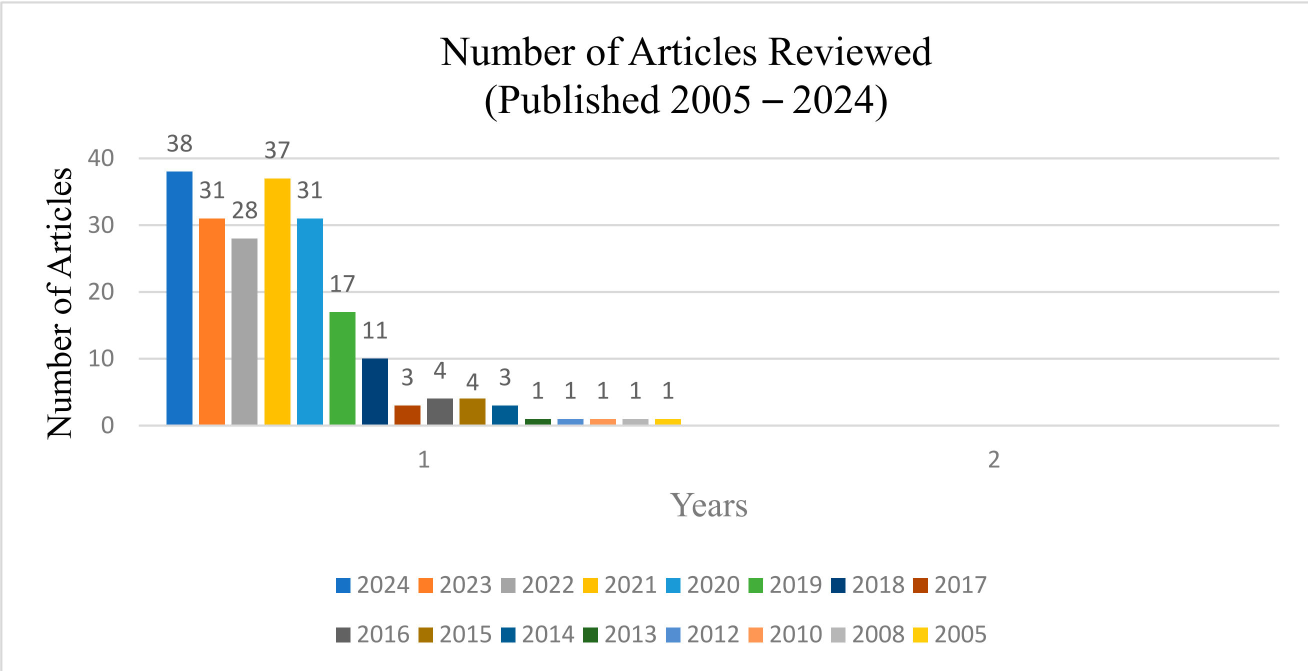

Figure 2. Number of papers in each year.

3. Battery Aging Mechanisms

The aging process of a battery is influenced by a variety of factors that impact its performance and lifecycle. Of these factors are the state of charge (SOC) and depth of discharge (DOD), indicating a battery's remaining capacity at a given time and how much of its capacity has been discharged. Keeping these factors within controlled ranges helps to slow the aging process; however, frequent charging and discharging cycles accelerate wear, which leads to loss of capacity over time. Another important factor is state of health (SOH), which represents the current condition of a battery compared to its original state as a ratio. Charging/discharging cycles change the internal mechanical and chemical processes of a battery, which are reflected in the SOH. A natural phenomenon that all batteries face is degradation, which affects battery electrodes and causes electrolyte decomposition. It reduces overall health, decreasing SOH. Then, a battery's remaining useful life (RUL) estimates how much longer a battery can function before requiring a replacement. To monitor and control these factors, a battery management system (BMS) is crucial. By managing SOC, regulating temperatures, balancing cells, and preventing extreme conditions, a robust BMS can ensure optimal operating conditions for a battery, thus extending its lifespan. In essence, a battery's aging mechanism is encapsulated through SOC, DOD, and SOH, it is impacted by degradation, a time estimate for its remaining life is RUL, and a BMS can manage these parameters to optimize the battery lifespan and performance. This is very important for economic and environmental sustainability [11].

In this section, we will cover the following topics: battery degradation, SOC, SOH, DOD, RUL, and BMS. Figure 3 below describes the EV battery aging mechanism.

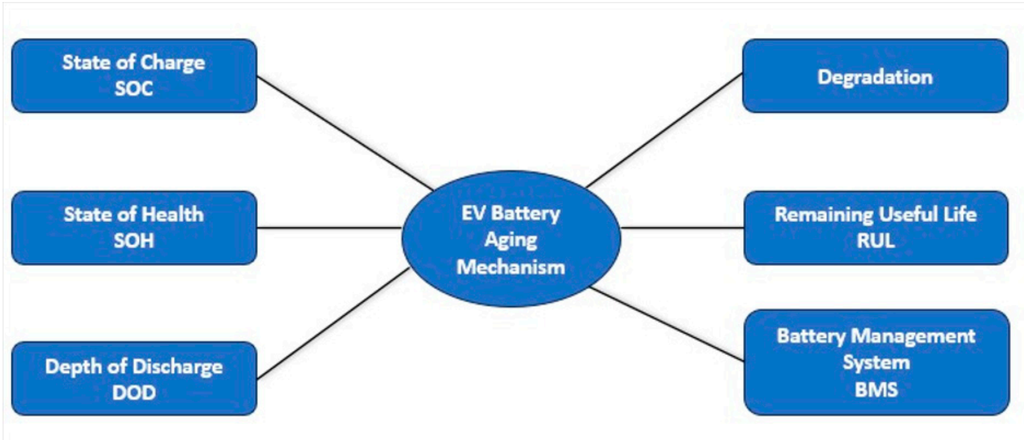

Figure 3. Electric vehicle battery aging mechanism.

3.1. Degradation

There are four main types of EV battery degradation: (i) Cycling Capacity Loss: the loss of cycling capacity due to the growth of the internal Solid Electrolyte Interface layer; Structural degradation of the electrode; (ii) Cyclable Lithium Loss: The loss of cyclable lithium during the charge/discharge process, mainly due to the charge/discharge cycle quantities; (iii) Calendar Capacity Loss: Loss of calendar capacity due to self-discharging and side reactions in the storage period; (iv) Aging Time: due to the aging time of the battery; Ambient temperature: mainly due to high temperatures exposed to the battery [12,13]. Table 2 summarizes the literature reviewed on battery degradation.

Table 2. Battery degradation.

Author	Year	Remarks
Surabhi et al.	2024 [14]	This research work meticulously examines the methodologies employed to mitigate battery degradation in electric vehicles. The findings reveal that the pronounced deterioration of electric batteries commences approximately after 200,000 miles into their lifespan.
Bamdezh and Molaeimanesh	2024 [15]	In this study, an in-depth analysis is conducted on the aging behavior of an electric vehicle battery pack, considering the vehicle's operation under real-world driving conditions, including ambient temperature, humidity, and solar irradiation conditions, over a period of 10 years.
Rahman and Alharbi	2024 [16]	In this article, a thorough examination is conducted to explore the complex process of battery degradation.
Li et al.	2024 [17]	The research introduces a framework for digital twin analysis and prediction of performance degradation in LIBs.
Timilsina et al.	2023 [18]	The battery degradation mechanism is explained in detail in this paper.
Agrawal et al.	2023 [19]	This paper creates a model to calculate EV battery degradation by considering points like travel time, traffic, and temperature.
Wei et al.	2022 [20]	This paper presents the results of a multi-year battery cycling study using commercial 24 Ah pouches with Li $(NiMnCo)O_2$ (NCM) cathode by varying the mean SOC, DOD, and charging rate across 33 values of the conducted experiment.
Ebrahimi et al.	2020 [21]	The proposed model incorporates an in-depth plug-in EV LIBs aging model based on the averages of battery cell surface temperature, current rate, SOC state and depth of discharge depth.
Fermín-Cueto et al.	2020 [22]	This paper suggests a reliable approach to calculate the "knee-point" in capacity fade curves based on capacity degradation data.

Table 2. *Cont.*

Author	Year	Remarks
Ahmadian et al.	2018 [23]	This paper discusses the stochastic approach to smart charging for plug-in electric vehicles.
Saxena et al.	2019 [24]	This paper creates a C-rate capacity fade model for LIBs under several C-rate loading scenarios to convert the performance and deterioration of a battery population under C-rate accelerated conditions to C-rate normal conditions.
Han et al.	2019 [25]	This study shows how batteries degrade over their entire life cycle.
Gao et al.	2018 [26]	This paper looked at battery degradation behaviors and found that degradation below 20% depth of charge is much slower than degradation at 100% depth of charge
Liu et al.	2021 [27]	This study proposes a new battery lifetime estimator based on the multiple health indicators system, which includes six health indicators with different characteristics.
Preger et al.	2020 [28]	This article presents the results of a multi-annual cycling study on commercial $LiFePO_4$ (LFP), $LiNi_xCo_yAl_{1\text{-}x\text{-}y}O_2$ (NCA), and $LiNi_xMn_yCo_{1\text{-}x\text{-}y}O_2$ (NMC) cells.
Jiao et al.	2020 [29]	This study performs a life cycle test to examine the aging feature and structure of $Li(Ni_{0.5}Co_{0.2}Mn_{0.3})$ O_2 batteries.
Atalay et al.	2020 [30]	This study utilized a novel form of aging that incorporates a heterogeneous double layer solid electrolyte intermediate phase (SEI), as well as a lithium-plated ageing mechanism with a porosity assessment.
Farzin et al.	2016 [31]	This paper examines the declining of the LIB of EVs in V2G programs and provides a practical model of wear cost for EV charge scheduling applications.
Dubarry et al.	2012 [32]	In this paper, a new mechanistic model is presented that can be used to facilitate battery diagnosis and prediction.
Sun et al.	2017 [33]	This paper examines the process by which battery capacity is depleted through the application of electrochemical and physical characterization.
Birkl et al.	2017 [34]	This paper provides the first experimental evidence to support the commonly reported degradation pathways by testing coin cells of LIBS.
Darma et al.	2016 [35]	This study explores how cycling temperatures and speeds affects the consistency of the positive electrode within battery systems.

3.2. State of Charge (SOC)

LIBs are widely utilized as energy storage devices because of their high energy density, extended service life, and low self-discharge rate, as well as their lack of memory effect [36–38]. To achieve optimal working performance of a battery storage system with a well-defined management strategy, it is necessary to accurately monitor the battery state in the BMS. A battery's "state" is an intricate concept that typically encompasses numerous sub-branches, such as the SOC, SOH, state of power. The SOC figures prominently in the estimation of the BMS. The proportion of a batteries current remaining capacity to its maximum value is called the SOC [39–41]. Table 3 summarizes the literature reviewed on battery SOC.

Table 3. State of charge (SOC).

Author	Year	Remarks
Huang et al.	2024 [42]	A novel optimization technique for the estimation of the state of charge (SOC) is introduced. This technique integrates the Levenberg–Marquardt Algorithm (LMA) for the purpose of online parameter identification, alongside the extended Kalman filter (EKF) for SOC estimation.
Lin	2024 [43]	This study addresses important issues in battery management and improves EV efficiency by introducing a novel deep learning-based method for estimating the state of charge (SOC) of EV batteries.
Sulaiman et al.	2024 [44]	This study introduces a deep learning (DL) method by employing Feed-Forward Neural Networks (FFNN) to forecast SOC in an EV.
Liu and Dun	2024 [45]	This study tackles the problem of forecasting the SOC for EV batteries by utilizing a dynamic Kalman neural network model
Fallah et al.	2023 [46]	This paper employs deep, artificial, and gated recurrent unit recurrent neural networks to calculate LIB SOC.
Lazreg et al.	2023 [47]	The paper proposes an estimation algorithm for an SOC with nominal capacity of 20 Ah for an NMC cell, using the basic smooth variable structure filter (SVSF) theory.
Tian et al.	2023 [48]	This paper introduces a sequential-to-sequence network design aimed at achieving an accurate estimation of the SOC by measuring voltage, current, and temperature directly.
Zho et al.	2023 [49]	Technical issues and trends in state estimate of LIB technology are analyzed in this paper.
Xie et al.	2023 [50]	This paper examines the estimation of the SOC of a LIB using a modified Kalman filter algorithm.
Chen et al.	2022 [51]	GRU-AKF is a combination of GRU (gated recurrent unit recurrent neural network) and AKF (adaptive Kalman filter) that is proposed in this paper as a reliable and effective combination of SOC estimation.
Munisamy and Wu	2022 [52]	For discharging Li-S state of charge estimation, this paper describes the sliding mode observer (SMO) and compares it with extended Kalman filter (EKF). The two estimators are based on first order equivalent circuit network (ECN) model (Li-S cell parameters).
Ma et al.	2021 [53]	This research looks at a new data-driven approach that can predict SOC and state of energy at the same time using a deep neural network called a “long short” term memory (LSTM).
Liu et al.	2021 [54]	This research investigates how to use an LSTM recurrent neural network and transfer learning to calculate the SOC of an LIB.
Chandran et al.	2021 [55]	This paper uses six machine learning algorithms to estimate SOC in LIB.
Hanan et al.	2020 [56]	This research proposes a deep learning transformer model trained with Self-supervised Learning (SSL) for the estimation of total SOC without the need for feature engineering and adaptive filtering.
Liu et al.	2022 [40]	This paper developed a cubic particle filter approach for estimating the SOC of an LIB.
Fasahat and Manthouri	2020 [57]	This paper proposes a high-precision estimation of SOC of an LIB using a combination of autoencoder and LSTM neural networks.
How et al.	2020 [58]	This article presents a model for the estimation of SOC of LIB utilizing a refined deep neural network approach.
Wei et al.	2018 [59]	This paper provides a systematic comparison of three different methods for co-estimating the online SOC of an LIB.

3.3. State of Health (SOH)

The SOH is defined as the proportion of the real parameter to the rated one, like the battery’s capacity or resistance. There are different types of SOH estimation methods, like the empirical, physical, and data-driven methods. The empirical model is the most popular method for estimating SOH for second-life batteries (SLBs). It is an empirical equation that looks at temperature, the state of charge rate, and how many cycles the battery has been in use as independent variables. It is pretty accurate for certain conditions, but it is not very good at generalizing to different batteries and conditions [60]. Table 4 presents the summary of the work related to the SOH.

Table 4. Battery state of health (SOH).

Author	Year	Remarks
Nakano et al.	2024 [61]	To estimate the SOH, this study presents SOH-TEC, a transformer encoder-based model that analyzes raw time-series battery and vehicle-related data from a single EV trip.
Nasimov et al.	2024 [62]	In this paper, a novel approach combining advanced particle swarm optimization (APSO) and bidirectional long short-term memory (Bi-LSTM) is developed to effectively address the problem of accurate SOH estimation.
Sun et al.	2024 [63]	This research created an advanced deep learning system for estimating battery SOH without any prior understanding of battery capacity degradation.
Safavi	2024 [64]	This study introduces an innovative data pre-processing framework to automatically extract health-associated characteristics from battery discharge data for the calculation of SOH.
Fan et al.	2023 [65]	The LIBs electrochemical impedance spectroscopy (EIS) properties were analyzed under various charge and health conditions in this research work.
Xing et al.	2023 [66]	This study proposes a SOH estimation approach that is based on the use of Improved Aquila Optimizer (IAO) and support vector regression (SVR) to obtain a precise estimation of SOH.
Shen et al.	2023 [67]	The charging voltage prediction and the machine learning-based estimation are used in this paper to provide accurate estimation.
Bülow and Meisen	2023 [68]	The goal of this study is to motivate and define the most important criteria for SOH forecasting models based on how they can be applied from the user's point of view, from fleet managers to battery designers.
Lee et al.	2023 [69]	A convolution neural network model is proposed in this study to predict LIBs SOH value in the early stages of qualification testing.
Li et al.	2023 [70]	The suggested Co-Estimation method is based on segment data of Constant Current Charge (CCC), SOH, and RUL.
Wang et al.	2023 [71]	This paper focuses on the extraction and fine-tuning of health indicators (HIs) for a highly accurate SOH prediction using the Gaussian process regression (GPR) model.
Lin et al.	2023 [72]	This paper introduces a novel procedure to approximate SOH values using a generalized additive model for LIB.
Gismero et al.	2023 [73]	The purpose of the research is to identify the condition and to evaluate the ability of the incremental capacity analysis (ICA) to determine SOH of actual EVs.
Wu et al.	2022 [74]	This paper provides a methodology for estimating SOH based on real-world EV data.
Lin et al.	2022 [75]	This paper proposes a multi-feature-based multi-model fusion method for the SOH estimation of LIBs.
Li et al.	2022 [76]	This paper compares the accuracy and robustness of SOH estimation of three neural networks and their various configurations.
Deng et al.	2022 [77]	This study looks at how battery early aging data can be used to help identify degradation patterns and transfer learning, which can help improve the battery's health estimation accuracy.
Yao et al.	2021 [78]	This article provides an overview of the battery degradation process and primary SOH definitions.
Vichard et al.	2021 [79]	This paper utilized an experimental database derived from three years of tracking a fleet of ten postal vehicles to simulate the battery's performance in real-world conditions.
Chen et al.	2021 [80]	This paper proposes a new MELM (metabolic extreme learning machine) model for SOH prediction.

Table 4. *Cont.*

Author	Year	Remarks
Tang and Yuan	2021 [81]	This research proposes the development of a new enhanced extreme learning machine algorithm to train models and forecast health indicators associated with battery aging.
Tian et al.	2020 [82]	This study discusses the age-related causes of LIBs, presents the status of health prediction method according to the classification framework and discusses the key advantages and disadvantages of each method.

3.4. Depth of Discharge (DOD)

The DOD is the amount of battery used between charges. A DOD of 80 kWh equals 80% of the total capacity of a 100-kWh battery. Battery health, including battery lifetime, battery capacity, and battery power, can be maintained by using a lower depth of discharge [83]. Table 5 summarizes the paper reviewed for DOD.

Table 5. Depth of discharge.

Author	Year	Remarks
Qahtani et al.	2024 [84]	This document offers perspectives on enhancing the functionality of batteries utilized in electricity markets to improve their economic viability. Different values of depth of discharge (DOD) are examined and assessed.
Weber	2024 [85]	In this research, a cycle-discharge curve alongside an undetermined exponential capacity-degradation curve is used to determine an optimal robust depth of discharge.
Park et al.	2023 [86]	In this research, the battery's energy efficiency and safety were enhanced by regulating the DOD according to battery SOH.
Khizbullin et al.	2022 [87]	This study shows the behavior related to parameters such as: depth of charge, battery capacity, battery state of charge, and battery voltage cycles during charging and discharge.
Eldesoky et al.	2022 [88]	This study investigated the effects of temperature, upper cut-off voltage (UCV), C-rate, depth of discharge (DOD), and AG (artificial graphite) single-crystal cells of battery lifetime.

3.5. Battery Management System (BMS)

The BMS handles all the energy storage, transmission, control, and management related to electric vehicles, as well as charge equalizer, voltage control for the battery cells, voltage controls for the input/output voltage, protection, diagnosing and error detection. It also looks at the charging characteristics and status of the battery, the charge and discharge of the battery, and the load demand for the battery pack [89–91]. Table 6 summarizes the paper reviewed for BMS.

Table 6. Battery management system.

Author	Year	Remarks
Suganya et al.	2024 [92]	This review provides an in-depth examination of different algorithms employed for parameter estimation in battery management systems (BMS), highlighting their benefits, drawbacks, and real-world applications.
Krishna et al.	2024 [93]	This document explores the hardware components of battery management systems (BMS) utilized in electric vehicles and stationary applications. It provides a comprehensive overview of the current concepts in advanced systems, assisting readers in evaluating the critical factors necessary for BMS design across different applications.
Tapaskar et al.	2024 [94]	This study introduces model of a 4S3P LIBs system created with MATLAB R2023b, aimed at enhancing battery management system (BMS) functions using mathematical modeling and computational intelligence.

Table 6. *Cont.*

Author	Year	Remarks
Habib et al.	2023 [95]	This article discusses the issues, challenges, and solutions associated with batteries. It also describes the different variants of cell balancing circuit, their parts, voltage and current loads, control performance, power consumption, performance, size, and price, as well as their advantages and disadvantages.
Yang et al.	2023 [96]	In this study, two new battery thermal management systems (BTMS) are selected: Z-type and U-type.
Kummitha	2023 [97]	This study develops a model to achieve a consistent temperature distribution within the battery module, thereby reducing the maximum temperature achievable within the battery cells.
See et al.	2022 [98]	This paper studies the intricacies of BMS for large scale energy storage systems and transportation, especially in hazardous environments.
Tran et al.	2022 [99]	This research examines the design and functionality of cloud-based intelligent BMS, offering some insights into their capabilities and usability, along with the advantages they offer for future battery-related applications.
Ramkumar et al.	2022 [91]	This paper explains how electric vehicles' battery management system works.
Hasain et al.	2021 [100]	This review paper covers a wide range of topics, including EVs EMS, challenges, and issues.
Lee et al.	2021 [90]	This study presents an algorithm for accurately determining the battery state using the proposed SOC and SOH calculations.
Wang et al.	2020 [101]	This paper provides a detailed overview of the most popular battery modeling techniques and state estimation techniques for BMS.

3.6. Remaining Useful Life (RUL)

LIBs are becoming more popular in energy storage systems (ESS). They have many advantages, like high energy density, light weight, easy to use, less maintenance, high electromotive power, wide operating temperatures [102]. These batteries find applications in electric bikes, golf carts, autonomous machines, smart grids, and renewable energy sectors, boasting an extended lifespan. But when charging and discharging, the battery starts to degrade, which limits how long they can last. It is a complicated process, and it can lead to different levels of performance degradation and cost savings depending on the operating conditions [83]. So, it is important to look at the battery's health prognosis, or RUL, to ensure it is within design limits and can last as long as possible [103]. Table 7 below summarizes the papers on remaining useful life.

Table 7. Remaining useful life.

Author	Year	Remarks
Liu et al.	2024 [104]	This research introduces an innovative approach that combines sequence decomposition algorithms with an enhanced neural network. In particular, the Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm is utilized to break down the raw capacity data, thereby significantly reducing the noise associated with capacity regeneration.
Safavi et al.	2024 [105]	This study performs a comparative evaluation to determine the efficacy of various machine learning (ML) models in forecasting the capacity degradation and remaining useful life (RUL) of lithium-ion batteries
Mou et al.	2024 [106]	This paper presents a novel approach that integrates a one-dimensional convolutional neural network (1D CNN) with a two-layer long short-term memory (BLSTM) neural network to compute the (RUL).
Hasib et al.	2024 [107]	This study proposes an innovative method that merges the explainability of convolutional neural networks (CNNs) with the efficiency of Bat-based optimizers.
Nunus et al.	2023 [108]	This study proposes a way to perform online estimation of RUL of SLBs by using unscented Kalman filters (UKFs) and degradation curve model.
Song et al.	2023 [109]	To calculate the useful life of LIBs, a Temporal Transformer Network (TTN) is suggested in this research.

Table 7. *Cont.*

Author	Year	Remarks
Wu et al.	2023 [110]	The PSO-RF (Partial Swarm Optimization-Random Forest) prediction method is proposed in this study to improve the accuracy of RUL forecasts.
Lin et al.	2022 [111]	This study suggests a technique to estimate the SOH of a battery by looking at constant current charging time (CCCT). It considers the difficulty of extracting features, the amount of time needed, and the complexity of the model/calculation.
Ge et al.	2021 [112]	This study aggregated four public battery datasets. The estimates of SOH and prognostic estimates of RUL of LIBs are examined through the analysis of research status.
Li et al.	2021 [113]	This paper talks about how to use fusion methodology, a multi-model framework with a particle filter, and a support vector regression to make predictions about battery capacity and how long batteries will last.
Pan et al.	2021 [114]	To make the prediction more accurate, this study uses a particle filter that has residual resampling to make up for the shortage of particles diversity, this will affect the accuracy of the condition assessment.
Hasib et al.	2021 [115]	This work focuses primarily on battery data acquisition with Li-ion dataset information (both commercially and free), estimation of state of battery with BMS, and estimation of battery RUL.
Ardeshiri and Ma	2021 [116]	This study proposes to use a gated recurrent unit (GRU) and recurrent neural network (RNN) as a deep learning solution to predict the RUL of a lithium-ion battery.
Tong et al.	2021 [117]	This study uses an algorithm called Adaptive Dropout Long Short-Term Memory or ADLSTM, and it combines ADLSTM with Monte Carlo simulation to calculate RUL.
Wang et al.	2021 [118]	This paper discusses, evaluates, categorizes, and compares various adaptive mathematical models for RUL prediction using deep learning algorithms.
Wei et al.	2021 [119]	This research suggests a method to identify the range of uncertainty associated with the RUL forecast and to prevent the overfitting effect.
Xu et al.	2021 [120]	In this study, a novel prediction method was used to calculate the RUL of LIBs under different temperature conditions over time.
Zraibi et al.	2021 [121]	This article presents a combination of deep, convolutional, and LSTM neural networks for estimating the RUL.
Chen et al.	2020 [122]	This study presents a better method for predicting RUL, based on a combination of LORPF (linear optimized resampling particle filter) and SGM (Sliding Window Gray Model).
Park et al.	2020 [123]	This study suggests some new ways to predict RULs based on LSTM (long-term memory).
Cong et al.	2020 [124]	This paper suggests a better way to predict how long LIBs will last with a new cathode Li (NiMnCo) O_2 that uses a better unscented particulate filter (UPF), in terms of capacity decline in the capacity degradation curve over time
Hong et al.	2020 [125]	This research presents the first complete deep learning framework for predicting how long a lithium-ion battery will last.
Jiao et al.	2020 [29]	This work suggests a new particle filter (PF) framework based on the Conditional Variable Auto Encoder (CVAE) and Re-weighting Strategy to predict RUL of batteries
Xue et al.	2020 [126]	This study recommends an integrated algorithm to address the issue of inaccuracy in predicting the RUL of LIBs.
Zhou et al.	2020 [127]	This study proposes a temporal convolutional network (TCN) based SOH model for the LIBS.
Ahwiadi et al.	2019 [128]	This study suggests an advanced mutated particle filter (AMPF) based approach to enhance the capability of particle filters (PFs).

Energy storage systems (ESS) are vital for modern energy solutions, such as grid stabilization, renewable energy integration, stationary applications, and electric mobility. However, these systems face several aging mechanisms that degrade their performance over time. Key aging mechanisms include electrical, mechanical, thermal, and chemical degradation, which contribute to the overall deterioration of ESS capacity, efficiency, and lifespan.

3.6.1. Chemical Aging

Chemical aging is primarily driven by reactions occurring within the electrolytes and electrodes of the energy storage system. These reactions result in the formation of undesirable by-products, such as solid electrolyte interphase (SEI) layers, the evolution of gasses, or dendritic growth within the container of the storage system. Over time, these by-products alter the internal composition of the battery, reducing efficiency and capacity. As an example, in LIBs, electrolyte decomposition and the side reactions at the electrode surface are major contributors to capacity fading. Some recommended strategies can be applied to mitigate chemical aging such as incorporating electrolyte additives, using stable electrode materials, and maintaining optimized charging protocols [129].

3.6.2. Thermal Aging

Thermal aging refers to the degradation caused by excessive heat generation within the ESS. Heat is typically produced during charging, discharging, and prolonged cycling due to internal resistance. High temperatures not only accelerate chemical reactions causing further chemical aging, but also degrade electrode materials leading to reduced performance and potential safety hazards such as thermal runaway. Operating temperatures above 50 °C can in fact double the degradation rate. In order to alleviate the thermal effects, the utilization of phase-change materials and thermal monitoring sensors is essential for reducing the impact of thermal aging [11].

3.6.3. Mechanical Aging

Mechanical aging involves the wear and deformation of the physical components of an ESS due to stress over time. There is a pronounced connection between thermal and mechanical aging, especially during charge and discharge cycles, as high thermals lead to increased stress, and deformation causes inefficient thermal management. The part of an ESS that is most affected by mechanical aging is its electrodes, resulting from battery volume expansion and shrinkage [129].

3.6.4. Electrical Aging

Electrical aging is defined as the deterioration of a battery due to overcharging and discharging which lead to capacity fade and makes the system more inefficient and dangerous to use. When the electrode material used in a battery is inevitably affected by electrical aging, the battery's lifespan is reduced [130], so extra care is required when charging and discharging large clusters of batteries, which is ultimately the burden of the BMS.

3.6.5. Environmental Factors

Environmental factors are largely external factors such as humidity and other weather conditions that are harsh for electrical systems. To alleviate these in an ESS, highly optimized design, proper and safe casing, and regular maintenance prove essential [131]. Figure 4 shows the various aging mechanisms along with their causes and solutions, and Table 8 presents causes and mitigation methods of the aging mechanism.

Table 8. Causes and mitigation methods of the aging mechanism.

Mechanism	Cause	Impact on Battery Performance	Example Study	Gap Identified	References
Chemical	Electrolyte decomposition along with the SEI formation	Reduced capacity, increased resistance	A physics-based aging model for LIBs coupled with chemical/mechanical degradation mechanisms.	Limited understanding of SEI growth dynamics.	Dong and Wei, 2021 [129]
Thermal	High operating temperatures	Reduced lifespan	LIB first and second-life aging, validated battery models, lifetime modeling and aging assessment of thermal parameters.	More dynamic models can be presented considering the various parameters.	Hoog et al., 2020 [132]

Table 8. *Cont.*

Mechanism	Cause	Impact on Battery Performance	Example Study	Gap Identified	References
Mechanical	Electrode fractures	Capacity fade	A physics-based aging model for lithium-ion batteries coupled with chemical/mechanical degradation mechanisms.	Physical deformation saving model can be presented.	Dong and Wei, 2021 [129]
Electrical	High current or voltage stress	Increased resistance	Understanding battery aging in grid ESS.	Modeling of charging and discharging impact reduction.	Kumtepeli and Howey, 2020 [133]
Environmental	Exposure to humidity, temperature extremes	Corrosion, degradation	Study of ESS and environmental challenges of batteries.	Various factors impact reduction mechanism.	Tharumalingam et al., 2019, [131]

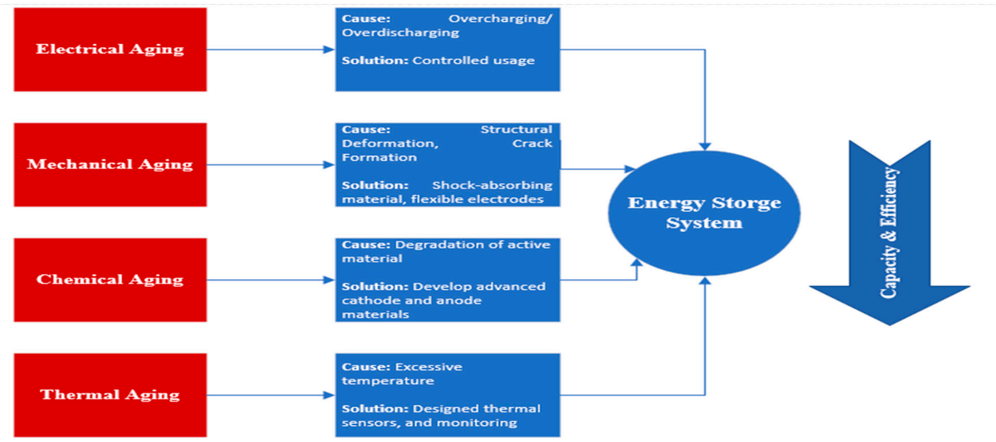

Figure 4. Causes and solutions of the aging mechanism.

4. Second-Life Battery Use in Stationary Applications

The main purpose of this section is to explore the specific practical usage of second-life batteries for stationary applications. Then, the challenges of using SLBs are also explored, such as distributed (residential, community) versus centralized (utility-scale) energy storage systems, hybrid energy systems (solar PV, wind, and hydropower), and energy management systems (optimal energy usage) [134].

Several European vehicle manufacturers, especially the leading players in the EV market, have introduced second-life battery alternatives in a variety of energy storage applications, from small-scale home energy storage to containerized SLB solutions in distributed energy systems [135]. An ESS based on Nissan Leaf EVs is used by the University of California, Davis, and alongside the Rochester Institute of Technology, they have undertaken research projects on SLB applications [136]. Table 9 presents the papers reviewed for SLB use in stationary applications.

Table 9. SLB use in stationary applications.

Author	Year	Remarks	Results
Bai et al.	2024 [137]	This study addresses isolated microgrids and uses SLBs for economic analysis. Stochastic programming is used to solve the optimization problem.	A comparison of SLBs and new batteries is carried out, and it is deduced that SLBs with a price of \$100/kWh are more cost effective than new batteries priced at \$200/kWh for microgrid applications and with 3% true under supply rate (TUR).
Kostenco	2024 [138]	Second-life battery internal degradation index model is studied accounting for cyclic aging factors in battery health monitoring.	The analysis found that the parameters that minimize battery stress and extend lifespan are a DOD of 20–60%, SOC between 40 and 80%, and a C-rate of C/10.
Hussini and Redondo-iglesias	2024 [139]	This report studies SLB passports, digital records for batteries in the market, and it carries out a feasibility analysis for mobile applications.	Various experiments are performed to check the health of battery cells. The analysis based on SOH showed that an SLB's life can be extended to 11 years when under a temperature of 25 °C.

Table 9. *Cont.*

Author	Year	Remarks	Results
Rustamkon et al.	2024 [140]	This study introduces second-life battery applications for energy storage systems.	By analyzing their degradation, lifespans, and various other nuances, the study affirms that SLBs are a feasible means of energy storage in a repurposed application. They also highlight the ability of SLBs to balance grid demands, adapt to renewable energy, maintain performance, optimize costs, and stay within legal bounds.
Blixt	2024 [141]	In this work, the author analyzed the applications and benefits of SLBs with respect to a residential system in a Swedish area.	Detailed work on the various parameters of the batteries, such as ancillary services, battery degradation model, and peak shaving at different rating of the battery are analyzed. The cost and sensitivity analysis revealed that SLBs are beneficial for grid services, and they reduce the rate of carbon emission.
Alamri	2024 [142]	In this work, the state of health of SLBs is analyzed for grid applications.	The analysis revealed the optimal parameters to prolong the life of batteries.
Ali et al.	2024 [143]	This study presents a model that leverages a certain energy management system to optimize over various energy sources	They found operational costs reduced by 18.26% and 14.88% when using LIBs and lead acid batteries, respectively.
Lieskokoski et al.	2024 [144]	The feasibility of repurposing Tesla Model S/X batteries is discussed in this article.	The results showed that the SLB business can pay back its initial costs in 5 years.
Kebier et al.	2023 [145]	This article looked at the potential of using SLB and solar PV to deliver cheap energy to primary school in Kenya.	SLBs reduce electricity costs by 5.6% to 35.3% when compared to the systems with new batteries and 41.9% to 64.5% when compared to the same energy service from the utility grid.
Shi et al.	2023 [146]	A ring-based, multi-agent microgrid cluster energy management plan is proposed in this paper.	The results show the cluster's interaction with the distribution network is minimized, and it significantly increases the rate of use and local absorption of distributed energy.
Al-Alawi et al.	2022 [147]	This study examines the latest modeling and experimental research on how SLBs can be used in secondary applications.	According to the results, retired EV batteries are performing well in the grid services.
Sharma et al.	2022 [148]	This study provides an analysis of a utility grid that is connected to solar, wind, and hydroelectric systems.	The solar, wind, hydro network connected to the utility grid is the best network with a minimum levelized cost of energy of $0.056/kWh.
Fei et al.	2022 [149]	This paper examines the utilization of renewable energy sources and storage in demand response strategies, including real-time prices, key peak prices, and time-to-use rates.	Real-time pricing results demonstrate a 58% saving compared to the Combined Purchase Price (CPP) and Time of Use Critical Peak Pricing of various schemes.
Han et al.	2022 [150]	A techno-economic optimization model is recommended to access the cost effectiveness of PV battery systems for various residential customer segments in Switzerland.	The results demonstrate that when PV is combined with batteries, the net present values are higher, when PV is used on its own for residential customers.
Muqeet et al.	2022 [151]	This research utilizes a university campus as an example to illustrate the potential for energy cost reduction.	The smart resource–load–storage co-ordination is planned on the current campus, resulting in a cost-effective solution.
Motjoadi et al.	2022 [152]	This research examines the utilization of renewable energy sources in conjunction with battery systems to sustain the grid during power outages and interruptions.	The finding of this research shows a reduction in net present cost, lower energy cost, and less operating cost R6,583,640, R0.1511, R2,919, respectively, in South Africa.
Vahedipour-Dahraie et al.	2022 [153]	This paper provides a flexible, stochastic scheduling methodology to assess the short-term dependability and cost-effectiveness of island microgrids under various demand response incentive schemes.	The results show that the microgrid operator's profit is expected to go up by around 4% and by 2.7%, and the reliability indicator has gone up by 60% and by 56%, respectively.
Jalilian et al.	2022 [154]	This study suggests an integrated scheduling model to obtain the most out of the water-cooled power, gas, and water-powered microgrid.	By using an energy storage system, hydro power, and a demand response program and evaluating how that impacts costs of the energy-water microgrid proposal, the simulation confirms benefits.
Bhatt et al.	2022 [155]	This research utilizes the Homer-Pro to evaluate the cost savings by using SLBs in the grid.	The Homer-Pro grid using SLBs decreases costs as compared to new LIBs by 36% and 35% for net present and energy costs, respectively.
Estebsari et al.	2022 [156]	In this report, a real-time management system based on IoT solutions is presented.	Using two algorithms for a variety of scenarios, they show the benefits of real-time network control in cost reduction and power quality.
Colarullo and Thakur	2022 [157]	This research presents a techno-economic study to evaluate how SLBs can improve the energy self-sufficiency of communities.	The results demonstrate the power of local energy systems, showing lower energy costs and more advantages when paired with a storage solution for solar power.
Fallah and Fitzpatrick	2022 [158]	Battery degradation in various types of second-life applications is examined in a financial analysis.	Grid services were identified as the most suitable reuse candidate for the grid-based stationary application use of SLB.

Table 9. *Cont.*

Author	Year	Remarks	Results
Ellabban and Alassi	2021 [159]	This article suggests an optimal economic microgrid sizing framework, which helps to analyze the profitability of off-grid hybrid microgrids that use renewable energy sources in the mining industry in a systematic and integrated way.	The findings provide an in-the-field analysis of how economically viable hybrid microgrid solutions are in mining applications.
Steckel et al.	2021 [10]	This study provides a levelized cost estimate for storage for SLB storage systems, considering both spent and new batteries by creating a model.	Second-life BESS results are strongly correlated with factors such as discount rate, DOD, and module reuse costs.
Nesamalar et al.	2021 [160]	This paper provides a techno-economic look at a Hybrid Energy System design that was created at Kamaraj college of engineering and technology, India.	By calculating the net present cost of the system under various architectures, a cost of $7.66 million has been achieved.
Ma et al.	2021 [161]	This paper provides a sustainable approach to electrification in the Persian Gulf Island and evaluates the feasibility of separate hybrid power options.	The result shows that the capital cost is $300k when considering load following more than cycling charge (CC), but this controller's salvage cost is expected to be lower than in CC mode.
Muqeet et al.	2021 [162]	This paper analyzes how campus microgrids manage energy.	The key to success is to invest in smart grids that transform traditional microgrids into smart microgrids.
Nasir et al.	2021 [163]	A PV system on a university campus that uses ESS and EVs is proposed in this paper.	The suggested energy management system provides a constant power supply and reduces energy costs by almost 45%.
Mehmood et al.	2021 [164]	This paper offers an in-depth analysis of smart grid systems, which are based on IoT and edge computing.	The findings strongly motivate the implementation of edge computing IoT based smart grid systems, providing major concerns and feasible opportunities
Ahmadzadeh et al.	2021 [165]	This paper examines the capabilities of smart grid to manage demand response (DRM).	This study investigates and analyzes the 5G IoT applications along with computational and analysis algorithms used for the implementation of DRM programs in smart grid.
Elmorshedy et al.	2021 [166]	This article talks about a techno-economy design and dynamic rules-based power management system for a solar-wind hybrid off-grid renewable energy system.	Based on the design, the best option for renewable energy is a system that combines solar, wind, lead-acid batteries, and converters. The net present and energy costs $232,423.3 and $0.3458 per kWh, are, respectively, obtained.
Rochd et al.	2021 [167]	This paper recommends a design that can be used in smart home energy management systems in residential buildings.	Results show that by using the recommended algorithm, the use of photovoltaic (PV) energy increases for self-use and cuts down on electricity costs.
Falk et al.	2020 [168]	This study presents how to electrify a small island in Lake Victoria, Tanzania, by using photovoltaics and an 85 kWh SLB as a hybrid off-grid system.	An economic and environmental analysis shows that using SLBs is more optimal than using a traditional diesel generator.
Aemro et al.	2020 [169]	This research looks at how a small DC microgrid could be used to provide power to a school in a rural area of Ethiopia.	The system cost analysis shows that high-efficiency appliances are 51% more economical.
Rinaldi et al.	2020 [170]	The most suitable techno-economic configuration of PV–wind–diesel hybrid systems for off-grid electricity in Peru is identified.	Three considered scenarios had net present and energy costs of $227,335, $183,851, $146,583, and $0.478/kWh, $0.460/kWh, $0.504/kWh, respectively.
Amir and Azimian	2020 [171]	The economic feasibility of deploying multiple carrier microgrids is assessed in this paper.	Numerical simulations demonstrate that the proposed strategy for expanding the microgrid is feasible from a financial, environmental, and technical standpoint.
Al-Badi et al.	2020 [172]	This paper discusses the different types of smart grid systems, such as virtual power plants and active demand on consumer networks. It then discusses what is driving and planning for smart grids around the world.	This study projects the evolution of smart grids worldwide and provides insights into the development and establishment of the Smart Grid Solution in Oman.
Abuelrub	2020 [173]	A scenario aggregation-based optimization procedure is presented in this study.	The outcome of this scenario aggregation results in an ideal system configuration, lowering the system's annual expenditure.
Buonomano	2020 [174]	This paper looks at the energy and cost implications of ($V2B^2$) (Building to Vehicle to Building).	The numerical evidence suggests that off-site renewable power generation is a highly effective use of ($V2B^2$), utilizing the grid to significantly reduce the use of fossil fuels.
Jahangir et al.	2020 [175]	A wave converter/PV/wind turbine/battery hybrid energy system designed to power 3000 residences in Iran is examined in this paper.	All solar, wind, and battery energy is implemented in the system, resulting in independent energy costs of $0.219, $0.233, and $0.242 per kWh for Jask, Genaveh, and Anzali, respectively.
Hossain et al.	2019 [3]	Considering the cost of battery degradation resulting from charging and discharging cycles, this article suggests scheduling battery power 24 h in advance.	The findings were that the proposed methodology can lead to a cost reduction of approximately 40% in operational costs.

Table 9. *Cont.*

Author	Year	Remarks	Results
Javed et al.	2019 [176]	Assessing over a remote island, a mathematical model generated by a genetic algorithm is used to optimize a solar–wind hybrid energy system with battery storage.	The initial capital cost is reduced by 25 to 30%, and the operating cost is reduced by 15 to 17% when considering the probability of a power supply failure.
Casals et al.	2019b [177]	This work provides an economic and qualitative analysis of SLBS aging performance in the building.	The results suggest that even though SLBs have an extra four years of life, they may not be the most cost-effective way to reuse them for homes.
Fodhil et al.	2019 [178]	This paper provides an optimization and sensitivity analysis methodology for an autonomous hybrid photovoltaic, diesel-electric, and BES.	The best solution can provide energy without any unmet demand. The lowest energy cost is $0.37 per kWh with 93% renewable energy.
Astaneh et al.	2018 [179]	This work suggests a novel approach to identify the system architecture and energy management approach for off-grid LIBs with the highest cost-effectiveness based on renewable energy systems.	The cost of energy went down by 9.7%, and the battery life went up by 48.6%.
Ghorbani et al.	2018 [180]	A hybrid genetic algorithm and particle swarm optimization are used to determine the ideal size for an off-grid residence with solar panels, wind turbines, and a battery.	Based on the findings, it appears that the energy levelized cost of 0.502 for the PV/WT/battery system is the most optimal based on the comparison methods.

After a review of different studies and applications of SLBs in residential contexts, utility grids, and campus energy storage, the use of these batteries presents many benefits as well as challenges. By using SLBs in hybrid energy storage systems, for instance, many institutions can move towards the adoption of greener energy, as the entry barrier is lower. Regarding the benefits, SLBs can reduce operational costs, reduce carbon footprints, and enhance grid reliability while providing a more affordable energy storage option than new batteries in certain applications. For instance, [155] found that SLBs decreased energy costs by 35% in their particular use case, and [181] achieved a minimum CO_2 emission reduction of 20% when contrasting SLBs with lead-acid batteries. As for challenges, a study based on data from Finland, Malaysia, and Sweden revealed various issues when using SLBs, such as their degradation model and their lifespans. The internal degradation of SLBs, as detailed by [138], requires careful management of factors like depth of discharge (DOD), state of charge (SOC), and temperature to avoid accelerated wear, being that they have already experienced symptoms of extended use. These constraints can limit SLB applications to settings where these parameters can be reliably controlled. Further, the decentralized nature of residential and community-level SLB installations presents further logistical and economic issues compared to centralized, utility-scale implementations. Table 10 presents the categorization and summarization of the SLBs at various levels, and Figure 5 displays the various applications of battery energy storage in four sectors.

Table 10. Categorization and summarization of the second-life batteries aspects.

Application Type	Study	Objective	Methodology	Key Findings	Trend Observed
Microgrid	Sarker et al., 2024 [181]	Life cycle analysis of SLB	Simulation-based analysis	Reduced environmental impact	Growing focus on sustainability
Residential	Blixt, 2024 [141]	Analysis of applications of SLB in electricity market.	Cost–benefit analysis	SLB reduced the emission and operational cost	Increasing cost-effectiveness
Residential	Ali et al., 2024 [143]	Comparison of different energy storage cost analysis	Energy management system	Cost reduced	Stochastic modeling of load and other parameters can be addressed
School building, Kenya	Kebir et al., 2023 [145]	Comparison of new and fresh batteries applications	Cost-analysis based	SLBs reduced the energy cost	Comparison of different energy storage system is ignored

Table 10. *Cont.*

Application Type	Study	Objective	Methodology	Key Findings	Trend Observed
University campus	Fei et al., 2023 [149]	Static and mobile energy storage are considered	MATLAB and linear programming	Scheduling of ESS reduced the cost	Stochastic load modeling was ignored
Grid	Bhatt et al., 2022 [155]	Cost analysis using SLBs	HOMER Pro	SLBs is cost- effective	Some economic and environmental constraints were ignored

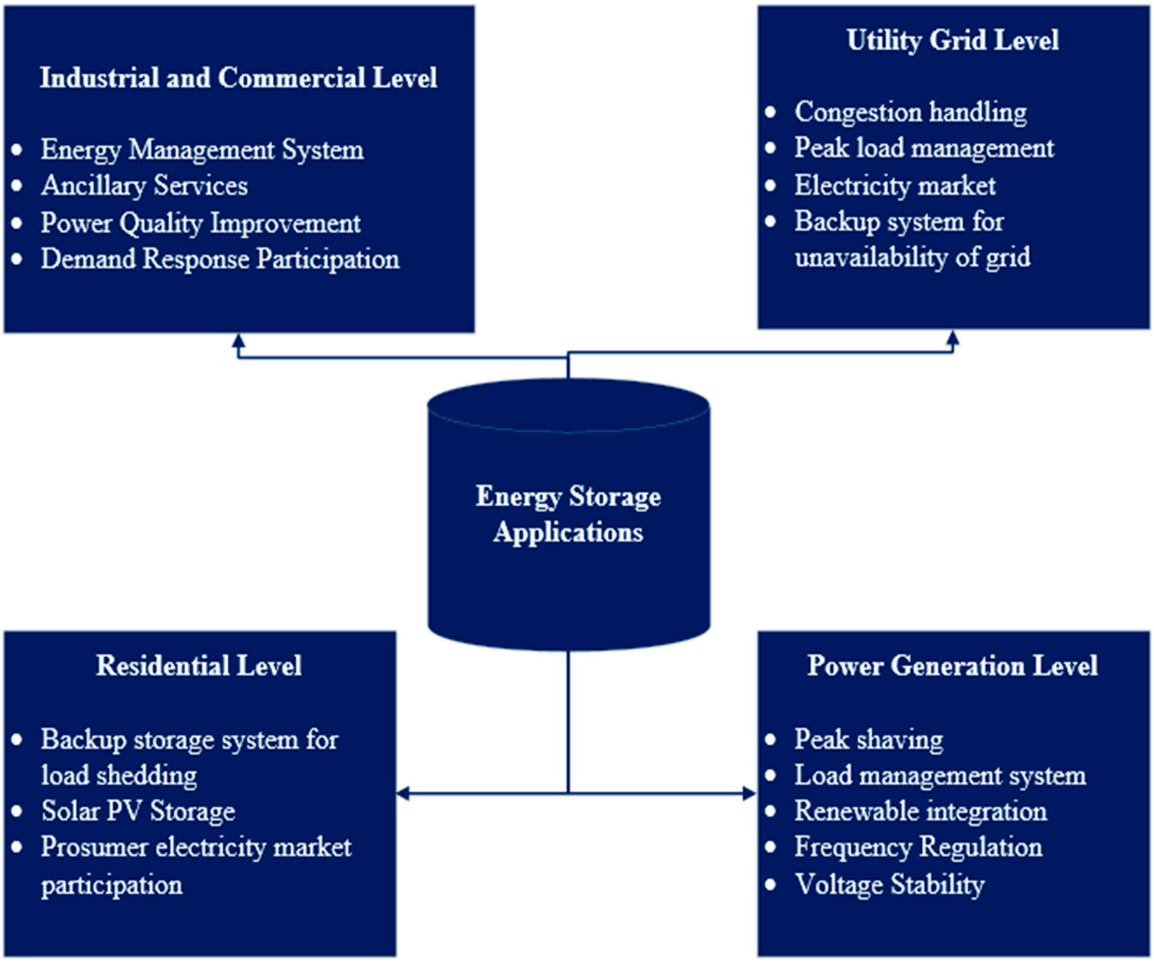

Figure 5. Battery applications at various levels.

Pros and Cons of SLB Uses in Stationary Applications

A primary advantage of SLBs is their cost-effectiveness. They present a low-cost alternative (relative to new batteries) to applications that demand lower battery usage, such as home energy storage, backup systems, and microgrids. When used in residential sectors, SLBs can reduce electricity costs by around 42% to 64% when contrasted with buying energy from a grid [145]. As such, a larger scope of users can make use of this kind of storage, allowing for more decentralized systems which reduce the overall expenses of renewable energy integration. Furthermore, SLBs are vital in promoting sustainability. The environmental and ethical impacts of battery material harvesting, production, and disposal are all reduced by keeping these used batteries in circulation [11,182] find that reusing an EV battery for clean energy storage can achieve a CO_2 emission reduction of up to 56%, benefiting both environmental and sustainable endeavors. Consequently, SLBs promote circularity in the economy, which lowers raw resource demand and decreases carbon emissions involved in the production-consumption line of a new battery.

However, there exist non-negligible technical and operational challenges associated with SLBs [183]. One such issue is the variability of SLB conditions, in that various batteries come from different first-use applications, and therefore may have non-uniform levels of health. As such, standardizing performance or reliably integrating them into energy systems is not straightforward even for smaller scale applications. With that, SLBs usually degrade faster than new batteries, making a long-term application with SLBs more challenging. A well-engineered BMS can help optimize a battery's condition over time to help solve these problems. Another such problem that arises with SLB uses is the policies and legislation that must be followed. Since battery repurposing and recycling is a relatively novel area of study, the regulations surrounding them are at their beginning stages and not well established, thus potentially hindering the widespread adoption of SLBs. To address this, standardizing and reporting on SLB use metrics must be carried out to provide grounds for a beneficial regulatory framework. Additional pros and cons for SLB uses in specific applications are shown in Figure 6.

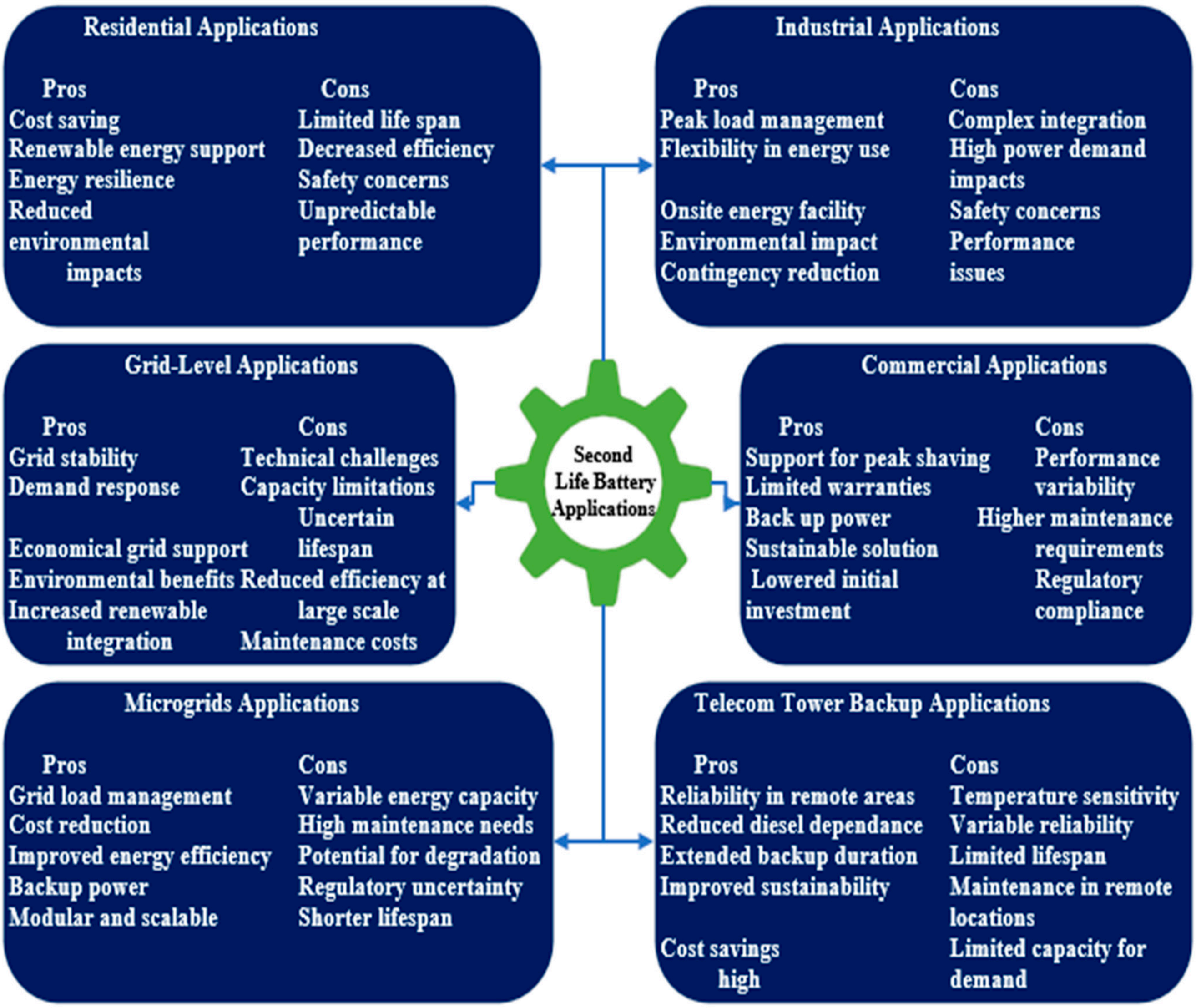

Figure 6. Pros and cons of SLBs using in various stationary applications.

5. Environmental Impact

From an environmental perspective, the second-life batteries' main advantage is that it eliminates the need for manufacturing new batteries, but this comes with various other environmental issues. Firstly, it takes either 250 tons of Spodumene (a mineral ore) or 750 tons of brine rich in minerals to manufacture a single ton of lithium-ion [184]. Mining and processing these raw materials on such a large scale is very damaging to the environment [185]. Secondly, it would require a large amount of water. For every one ton of lithium-ion, 1900 tons of water would need to be produced [186]. Lithium-ion mining in Chile, for example, uses 65% of all the water in the region (Salar de Atacama) [186]. Thirdly, there are the electricity costs associated with manufacturing LIBs. To produce 1 kWh LIB, 50 to 65 kWh of electricity is needed, this is coupled with a CO_2 emission of 55 kg if produced by coal [187]. Table 11 shows the papers reviewed on environmental impact.

Table 11. Environmental impact.

Author	Year	Remarks	Results
Sarker et al.	2024 [181]	This research explores the transformative potential SLB when integrated into residential photovoltaic (PV) systems.	The utilization of the SLB system results in a minimum reduction of 20% in CO_2 emissions when contrasted with conventional lead-acid battery
Akindeji and Ewim	2023 [188]	This research looks at how to optimize the performance of a microgrid that has been set up for the University of KwaZulu-Natal, South Africa.	The result shows an annual CO_2 reduction of 51%.
Wralsen and Born	2023 [8]	This study shows how the circular economy business models for LIBs are better for the environment than traditional business models.	An SLB prevents more than 16% of the manufacturing of new batteries, demonstrating the environmental benefits and downsides of circular economy businesses.
Raza et al.	2022 [189]	This paper assesses the social, economic, and environmental impacts of high-efficiency PV irrigation systems.	This leads to a decrease of CO_2 emissions by 17,622 tons per year, as well as a 41% decrease in water consumption.
Philippot et al.	2022 [190]	An LCA approach is employed to evaluate a nickel manganese cobalt lithium titanate oxide battery.	The result shows that the environmental benefits of reusing and repurposing of EV batteries are 0.27 $kgCO_2eq/kWh$ and 0.22 $kgCO_2eq/kWh$, respectively.
Javeed et al.	2021 [191]	This article suggests an EMS architecture for an on-campus microgrid to minimize operational expenses and GHG.	Rooftop solar power has been shown to reduce GHG emissions by 365.34 kg CO_2/day with 1000 kW installation and by 700.68 kg/day with 2000 kW installation.
Schulz-Mönninghof et al.	2021 [192]	This paper suggests a new LCA framework that manufacturers can use to evaluate various instances of LIB re-utilization.	From the energy consumer's perspective, the climate change benefits of having multiple uses are 10–22% less than when you have just one use.
Kamath et al.	2020 [193]	This paper looks at the electricity prices and carbon dioxide emissions associated with SLB in the US.	Second-life batteries reduce costs and emissions across their lifespans. Utility-level applications saw a cost reduction of 12% to 57%, and emissions reductions of 7% to 31%. For residential applications, cost reductions were 15% to 25% and emissions reductions were 22% to 51%.

Table 11. *Cont.*

Author	Year	Remarks	Results
Kamath et al.	2020 [194]	This work proposes a fast-charging infrastructure, along with end-of life battery management and SLB storage for EV fast charging systems.	When compared with newly manufactured batteries, SLBs decreased electricity levelized costs by 12–41% and global warming potential by 7–77%.
Cusenza et al.	2019 [195]	This research figures out how sustainable a SLB is if used in stationary applications.	The findings indicate that the environmental impact decreases by approximately −4% in terms of cumulative energy demand and −17% in terms of abiotic depletion potential.
Richa et al.	2017 [196]	This research looks at the environmental impacts of SLB when used in stationary energy storage system.	SLB usage for stationary energy storage can cut CO_2 emissions and global warming by 15% by conservative estimates and up to 70% in ideal conditions for refurbishment and re-use.
Sathre et al.	2015 [197]	This study looks at second-life plug-in EV batteries and how they can help expand intermittent renewable electricity in California through 2050.	By using SLBs, electricity produced by greenhouse gas emitting sources would be cut by about 7 million Mt CO_2e per annum in 2050.
Ahmadi et al.	2014 [182]	This paper looks at how EV batteries can be reused at their EOL in stationary applications.	When an EV battery is re-used to store clean electricity to meet peak demand, it can cut CO_2 emissions by up to 56%.

The environmental benefits of using SLBs are substantial, particularly when compared to using newly manufactured LIBs. The CO_2 emissions caused by repurposing an LIB when compared to manufacturing a new LIB is 70–110 kg CO_2/kWh vs. 25–40 kg CO_2/kWh, respectively. Reusing 1 ton worth of LIBs can save approximately 15 MWh of energy, significantly reducing the overall environmental footprint [198]. Furthermore, adopting SLBs can reduce electricity costs by 30–50% for users at various load levels, making it a cost-effective alternative [145]. SLB usage has a wide range of potential benefits when considering CO_2 emissions. A lower bound of 15% and an ideal metric of 70% of emissions can be cut when a battery is repurposed and used in stationary energy storage applications [196], and one such example in practice was conducted by [188] who found a 51% reduction when using SLBs for a South African university microgrid. In this way, it is a more attractive and optimal choice for grid stability along with renewable integration.

5.1. Benefits of Reusing Batteries

The use of SLBs can bring about many environmental benefits by reducing the environmental footprint of ESSs themselves and encouraging sustainable practices among consumers and producers.

5.1.1. Reduction in Raw Material Mining

The materials required for battery production are lithium, cobalt, and nickel, and extracting these materials is both resource intensive and environmentally detrimental. For instance, manufacturing a new lithium nickel-cobalt-aluminum oxide (NCA) battery with a rating of 100 kWh involves 10 kg of lithium, ~13 kg of cobalt, and 67 kg of nickel [199], implying that repurposing such batteries can drastically decrease resource demands.

5.1.2. Prevention of Landfill Contamination

When disposing batteries that have reached end-of-life, risks of toxic materials such as cobalt, nickel, and cadmium contaminating groundwater, polluting soil, and damaging other parts of ecosystems are among the concerns expressed when these used batteries reach landfills.

As such, delaying the disposal of batteries by employing them in a second-life application helps to alleviate strain on waste management and reduces the cause of the concerns.

5.1.3. Support for Sustainable Energy Shifts

A consumer of electricity depends entirely on the supply of the grid from which they buy their electricity. This may motivate both consumers and producers to employ renewable energy, namely solar PV and wind, thus reducing overall costs. SLBs can aid shifting towards these energy sources since they are a cost-effective means of energy storage. They can be used to store surplus energy harnessed during daylight for use during the night. Thus, not only would a consumer be more inclined to adopt this cheaper means of energy, but a producer could use SLBs to balance supply and demand during a 24 h period, thus reducing the reliance on environmentally harmful means of energy like fossil fuels. For a particular instance, [163] propose a PV energy management system for a campus that could reduce costs by close to 45%, making it an appropriate investment.

5.2. Challenges of Reusing Batteries

To provide a holistic understanding of the use of SLBs, it is vital to discuss the challenges of using them and what measures we can take to keep them environmentally and economically feasible.

5.2.1. Limited Recycling Efficiency

LIB recycling is a relatively novel topic and therefore suffers from inefficiencies. While reusing batteries provides substantial environmental benefits, the processes involved in battery recycling are themselves energy-demanding, which may reduce the overall benefit to the environment. Also, the global adoption of recycling practices is currently difficult due to unstandardized battery designs, compositions, and processes, further reducing the efficiency of battery recycling.

5.2.2. Potential Leakage of Toxic Chemicals

LIBs are prone to thermal runaway which causes the release of various gasses. [200] found that carbon monoxide, methane, ethylene, ethane, and hydrogen cyanide are among the gasses that can be released in relatively high volumes during such a process, increasing in concentration for batteries with higher cell capacity. As such, when repurposing or recycling an end-of-life battery, there is cause for concern that dangerous substances may contaminate the surrounding environment if handled improperly.

5.2.3. Degradation and Performance Unpredictability

As per [201], batteries generally do not have uniform SOH when they reach their end-of-life. Thus, when used in second-life applications, their performance and lifespans are also variable. This then requires robust testing and monitoring to optimize their use and effectiveness.

6. Discussion

Energy firms, automotive corporations, and policy makers all hold a stake in this newly emerging market of SLBs. Repurposing end-of-life EV batteries as a means of storage greatly reduces the resource demand and waste production from the transportation and energy sectors. This then subsequently brings the potential for high environmental benefit, as we can drastically decrease the harm caused by raw material extraction, battery production, and disposal of waste. With this potential for economic and environmental optimization, policy writers can be motivated to pass legislation that encourages or mandates the use of SLB in energy storage applications, thus allowing corporations to move towards this more efficient option. Below, we elaborate further on the stakeholders and what role they play in potentially integrating SLB reuse in various applications.

6.1. Energy Firms

Energy firms play a key role in the integration of SLBs into the energy market, especially for applications involving grid-scale scope and renewable sources. They are responsible for infrastructure development, R&D, and market stimulation, each of which can incorporate the adoption of SLBs into their metrics to improve integration, performance, and costs. In turn, these modifications can improve grid stability, and they allow for a more environmentally and economically beneficial system.

6.2. Automotive Corporations

Automotive companies, service providers, and manufacturers are all involved with the development of ESSs and BMSs. As such, they provide battery collection and monitoring services which can help evaluate case-by-case the feasibility of spent batteries in certain second-life applications. One way to improve the integration of SLBs is by partnering with energy firms to provide them with spent batteries more seamlessly, thus increasing the lifespans of said batteries and providing another revenue stream to encourage widespread practice.

6.3. Policy Makers

The role of policy makers is to define the regulations and laws regarding the integration of SLBs into various applications. They are responsible for providing incentives and subsidies to encourage adoption, establishing standards for SLB testing and certification to garner trust in their use, and enact policies that prioritize reuse to motivate sustainable practices. With these, they can allow the market to accept SLBs confidently, allow for better resource management and usage, and ultimately move regions towards increased sustainability.

Addressing the roles and responsibilities of stakeholders such as those mentioned above can develop the SLB industry. Collaboration among these stakeholders can foster innovation, decrease energy storage costs, and drive reliability and sustainability in Canada's energy and automotive sectors. Table 12 summarizes the discussion above.

Table 12. Stakeholder contributions and challenges in second-life battery adoption.

Stakeholder	Contribution	Challenges Faced	Proposed Solution
Energy Firms	Integration of SLB systems	High initial costs for infrastructure	Provide subsidies and financial offers
	Utilizing SLBs for grid stabilization	Uncertainty about long-term reliability of SLBs	Implement the BMS
Automotive Companies	Providing EOL battery data and recycling support	High costs of battery collection	Optimize collection networks and hub
	Partnering with energy firms for stationary storage solutions	Variation in battery state of health	Standardize AI-based SOH evaluating protocols
Policymakers	Developing regulations and incentives for SLB	Lack of standardized testing and certification	Establish international certification SLBs (e.g., IEC or ISO)
	Setting environmental and safety standards	Balancing incentives for both, i.e., recycling versus reuse	Create balanced policies for both factors

6.4. Comparison of Energy Storage Technologies

In Section 4, we present the current literature regarding the use of SLBs in ESSs. A subsequent question would be if there are other means of energy storage that supersede SLBs in effectiveness, cost, efficiency, lifespan, and environmental impact. Table 13 presents a summary of the comparison of such other means of storage.

Table 13. Comparison of energy storage technologies.

Storage Technology	Cost	Efficiency	Lifespan	Environmental Impact	References
Second-Life Batteries	Low	70–80%	5–10 years	Significant reduction in e-waste	Casals et al., 2019 [7]
Newly Manufactured Batteries	High	~90%	10–15 years	High CO_2 emissions in production	Tang and Wang, 2023 [202]
Pumped Hydro Storage	High (initial cost)	70–85%	50+ years	Minimal during operation	Mongird et al., 2019 [203]
Redox Flow Batteries	High	~80%	10–20 years	Environmentally friendly materials possible	Mongird et al., 2019 [203]
Flywheels	High	85–90%	20 years	Low CO_2 Emission	Mongird et al., 2019 [203]
Lead-Acid Batteries	Low	95%	20 years	Low CO_2 Emission	Mongird et al., 2019 [203]

As per the comparison above, SLBs offer a cost-effective and environmentally friendly option to energy storage when contrasted with other alternatives. However, while SLBs excel in these metrics, they are best suited for low-demand applications. Higher performance and large-scale applications may need to leverage the more costly flow batteries and hydrogen storage. This comparison provides insight into the optimal use cases for each option, making the choice of the best option dependent on situational requirements.

6.5. Challenges and Their Mitigation

While using SLBs in ESSs shows benefits, their implementation gives rise to technical, financial, and regulatory challenges that must be addressed [204].

6.5.1. Technical Challenges

Because the batteries in question are given a second life, they have already gone through capacity fade and degradation which may be quantified as poor SOH, and their decreased efficiency may lead to thermal instability. As such, rigorous testing and evaluation can help alleviate the variability of performance, addressing concerns of reliability and the lifespans of ESSs.

6.5.2. Financial Challenges

The costs involved with refurbishing used batteries such as collection, transportation, disassembly, and evaluation all contribute to the hesitance that stakeholders may have to wholly adopt SLB use [144]. Mitigating these factors falls on refurbishers to optimize the processes to minimize expenses and governments to enact policies and provide subsidies to stimulate the SLB market.

6.5.3. Regulatory Challenges

Ref. [205] report that users and manufacturers are uncertain about the feasibility of SLB use due to the lack of legal guidelines for certifications for SLBs, i.e., a user cannot fully trust the reliability of an SLB without assurance from a trustworthy entity. Solving this is in the hands of judiciaries, but more robust research in the field can help shift the views of policy makers to enact appropriate regulations. Table 14 below presents the barriers and mitigation in adopting the second-life batteries.

Table 14. Barriers and mitigation in adopting second-life batteries.

Barrier	Description	Mitigation Strategy	Example
Technical Challenges	SOH evaluation complexity	AI-based predictive models	Accelerating AI-Based Battery management System (Nagarale, and Patil, 2023) [206]
	Irregularity in battery health	Standardized analyzing protocols	Lithium-ion SLB pathways, challenges and outlook (Patel et al., 2024) [205]
	Fast deterioration in high-demand purposes	Advanced Battery Management Systems (BMS)	Challenges and opportunities for SLBs. (Gu et al., 2024) [207]

Table 14. *Cont.*

Barrier	Description	Mitigation Strategy	Example
Financial Challenges	High costs of battery refurbishment	Subsidies for repurpose and refurbishment	Maximizing Canada's EV battery repurposing and recycling ecosystem (Action Canada, 2024) [208]
Regulatory Challenges	Lack of policies for SLB applications	Prepare comprehensive legal frameworks	Sustainability rules for batteries and waste batteries Regulation (EU) (European Union, 2023) [209]
	Absence of standard documentations	Prepare SLB-specific certifications	Batteries in electricity markets: Economic planning and operations (Xu, 2018) [210]

The Zero-Emission Vehicle Infrastructure Program is a Canadian policy that mandates that all new light-duty vehicle sales must be zero-emission by 2035 [211], which incentivizes the adoption of EVs, repurposing of spent batteries, and recycling of batteries when they lose most of their capacity. The EU Battery Directive is an EU based policy that provides a framework to regulate battery production, use, and end-of-life management. One such feature is that new batteries must comprise 65% of recycled materials by 2030 [208]. Both the Canadian ZEV Act and the EU Battery Directive demonstrate strong commitments to sustainable energy and battery lifecycle management.

As we mentioned prior, the impetus for our investigation into second-life EV batteries was the SDGs, and below we highlight the contributions they bring to each of Goal 7, 12, and 13.

6.6. Contribution to SDG 7

With the high demand for clean and affordable energy, an effective storage means is crucial. An immediate benefit of implementing repurposing initiatives for second-life batteries is a reduction in energy storage costs, and indirectly, the demand for newly manufactured storage units would decrease; thus, making the overall use of energy cleaner. Further, this cheaper alternative can be utilized in underserved and off-grid regions, allowing more people to leverage produced energy and improve their quality of life. This ultimately accelerates progress for Goal 7 and widens the reach of the benefit it brings.

6.7. Contribution to SDG 12

A direct progression for SDG 12 is circularizing production lines, one of which is EV battery production; we can close the loop through battery repurposing and recycling, thus optimizing resource consumption and reducing waste. As such, various strategies to extend operation lifespans (such as second-life applications), tailoring battery designs for recycling, and recovering precious materials all promote circularity and reduce raw material demands, leading to better production-consumption lines and reduced environmental harm via battery production and disposal [212].

6.8. Contribution to SDG 13

A major contributor to the emission of greenhouse gasses is raw material extraction and refinement. To combat this, implementing battery recycling and other circular practices can drastically lower our need for materials, reducing the impact of the problem and pushing us towards the completion of SDG 13. Through the adoption of such practices, industries can transition to more sustainable models, aligning with global climate goals and driving systemic change towards carbon neutrality.

7. Future Work

While we provide a comprehensive glimpse into the current literature and research on second-life battery technologies and applications, there still exists potential for additional work. The following are some research routes that have yet to be studied. As of now, the topic of battery degradation primarily considers batteries in their first life, that is, prior to their end-of-life. SLB degradation, however, has relatively scarce research and information, and thus gives an avenue for further study. There also are few studies of business models connecting primary battery manufacturers and ESS integrators, which presents the possibility of economically optimized systems taking advantage of the ideas presented in this literature review. Further, efficient, and autonomous sorting and reassembly of batteries into their second-life forms has clear economic advantages and can be the topic of additional research. Finally, work can be conducted to assess the effectiveness of applying a reverse logistics supply chain mechanism to the battery collection process to further improve economic and environmental viability.

8. Conclusions

Nearly every developed nation is currently striving towards the most economically optimal and environmentally friendly methods of energy generation. Subsequently, a look into energy storage systems and improvements can provide an indirect push towards these efforts. We consider how out-of-commission batteries can grant noticeable impacts. As with many technologies currently, utility grids require renewable or circular components, and one such insertion is the implementation of stationary energy storage systems using SLBs. While regular storage systems that use newly extracted materials are the default option, using such repurposed components has the potential to significantly improve the economy and environment, if proven to be feasible. As such, assessments regarding these modified ESS are essential.

This research work presents a literature review of the current SLB usage in stationary applications, as well as the related economic and environmental benefits. Furthermore, we investigated the aging mechanism of LIBs in EVs by providing a detailed analysis of battery degradation, SOH, SOC, DOD, BMS, and RUL. In examining the economic effects, there was a high consensus across a variety of studies that second-life battery uses in stationary applications show significant benefits, such as cost reduction from decreasing raw material extraction and producing new batteries. We also investigated the environmental impacts of partaking in these endeavors and found benefits across many of the overseen reports and investigations.

We focused on how these endeavors and initiatives can aid in the progression of the SDGs. As we have looked at the economic benefits of such SLBs in stationary applications (which can be used in renewable energy technologies), these benefits can greatly progress Goal 7: Clean and Affordable Energy. Likewise, looking at the significant environmental impacts, Goal 13: Climate Action can see a major push forward. Furthermore, with the added circularity of implementing repurposed batteries in various second-life applications, we see a decrease in the amount of materials we harvest and the products we manufacture that ultimately become disposed of, thus significantly benefiting the achievement of Goal 12: Responsible Consumption and Production. There exists an abundance of literature reviews on the topic of SLB applications, but we present a report with the perspective of the progression and attainment of the SDGs.

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