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REVIEW

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A survey of second-life batteries based on techno-economic perspective and applications-based analysis

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Abstract

The penetration of electrical vehicles (EVs) is exponentially rising to decarbonize the transport sector resulting in the research problem regarding the future of their retired batteries. Landfill disposal poses an environmental hazard, therefore, recycling or reusing them as second-life batteries (SLBs) are the inevitable options. Reusing the EV batteries with significant remaining useful life in stationary storage applications maximizes the economic benefits while extending the useful lifetime before recycling. Following a critical review of the research in SLBs, the key areas were identified as accurate State of Health (SOH) estimation, optimization of health indicators, battery life cycle assessment including repurposing, End-Of-Life (EOL) extension techniques and significance of first-life degradation data on ageing in second-life applications. The inconsistencies found in the reviewed literature showed that the absence of degradation data from first as well as second life, has a serious impact on accurate remaining useful life (RUL) prediction and SOH estimation. This review, for the first time, critically surveyed the recent studies in the field of identification, selection and control of application-based health indicators in relation to the accurate SOH estimation, offering future research directions in this emerging research area. In addition to the technical challenges, this paper also analyzed the economic perspective of SLBs, highlighting the impact of accuracy in second-life SOH estimation and RUL extension on their projected revenue in stationary storage applications. Lack of standard business model based on future market trends of energy and battery pricing and governing policies for SLBs are identified as urgent research gaps.

Keywords Second life batteries, Energy storage system, Battery degradation, State of Health (SOH) estimation

1 Introduction

Electric vehicles (EVs) with zero emissions are considered to be the best alternative to combustion engine cars reliant on polluting fossil fuels. According to the International Energy Agency's annual report, global EV sales surpassed 2.8 million in 2020, bringing the overall number of EVs to 10.1 million [1]. By 2060, it is expected that this number would reach 1.2 billion [2]. Due to reduced capacity of less than 80% of the rated capacity, also known as End-of-Life, these batteries cannot be used for traction purposes, according to comprehensive research [3, 4]. Remaining usable life (RUL) is the capacity of a retired battery that can be evaluated using state-of-charge (SOC) estimates. To make EVs affordable and alleviate End-of-Life anxiety among EV producers and customers, the probable solution in the literature is to employ these retired batteries for stationary applications [5, 6]. Reuse of these retired batteries provides environmental benefits in addition to economic gains [7]. Hence, the term "second life batteries (SLB)" is introduced in the literature to describe them.

Various techniques are implied for screening, repurposing, and accurate SOH estimation of electrical vehicle retired batteries to enhance the techno-economic

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benefits in second-life applications. Advanced machine learning-based techniques and health indicators for SOH estimation are introduced for improving the accuracy and speed of the process [8–11]. Assessment of opportunities, scopes, challenges, and market trends related to this new technology of EV battery secondary use is gaining hype every passing day and has been reviewed by several fellow researchers. Initial review based on this specific area includes a critical discussion on the overall concept of battery second use. The survey mostly focuses on existing R&D projects involving second-life batteries and closely judges the environmental as well as economic aspects of battery secondary use [12]. Following a review in 2019, the authors tried to cover the gap by proposing potential solutions to challenges posed by economic and environmental adaption of second-life battery reuse [13]. Business models, government policies, market strategies, environmental benefits from repurposing, SLB's modelling techniques, cost analysis of repurposing and installation, and impact on overall cost reduction are proposed and discussed in detail. In addition to stationary storage applications, mobile applications including EV charging stations are accessed both technically and economically [13]. Another review paper later this year combined the economic aspects with social and environmental dimensions hence emphasizing the need for sustainable business models for EV battery second use. Existing business models are discussed and their comparison is made with proposed sustainable models, the results stay uncertain due to lack of empirical research data and ambiguity of possible stakeholder's involvement in the battery second use market but it opens a new horizon of sustainability in future Electrical vehicle battery reuse market [6]. Another review paper sheds light on technical, environmental, and market challenges involved with the reuse process and proposes data and cloud-based technologies to keep a better record of battery historical data and the existing state of the health for future reuse reference [14]. In [3] second life battery market trends are surveyed and challenges faced regarding reuse and recycling of used electrical vehicle batteries are accessed globally. There is a discussion of environmental impacts and economic challenges associated with manufacturing, recycling, and wasting different types of batteries on a global level. A more recent review on second life batteries covers the economic, technical, and environmental aspects of said technology. The technical aspects of battery screening for reuse are highlighted including degradation studies mainly in first use but also after deployment in secondary use to a smaller extent. Battery recycling challenges, reuse applications and business models are also explored. There is an emphasis on further research in this field to make second life batteries a part of mainstream market [15]. The latest survey reviews specifically the technical aspects of the inclusion of second-life batteries in stationary storage applications. It covers the literature regarding battery repurposing, ageing mechanisms, battery management systems for battery optimal sizing, and battery modelling. This review also points out the lack of degradation studies in second use and precise ageing model [16].

Although this review study and the aforementioned articles cover some prospects for electrical vehicle second-life batteries applications, their main targets are economic benefits and market strategies which is no doubt need of the hour. However, these benefits are not achievable if technical aspects are not thoroughly surveyed and the battery is not fully productive during its second use. A discussion about technical prospect of battery reuse after degradation in first use is included in [12, 16], however, there seems an uncertainty in accessing the future trends of this technology in techno-economic point of view. The most important reason of this uncertainty is ignorance of battery degradation history from first use. There is a need to review battery degradation process both in first and more importantly in secondary use as the data from first use plays an important role in determining battery ageing process in secondary use. There is no set methodology yet to record battery degradation history in first use hence most of the studies are based on assumptions and hypothetical data. This predication of remaining useful life is more inevitable during second-life so that it could be extended to a maximum limit. In this paper we try to fill this gap by reviewing the literature focusing on degradation studies of batteries during secondary stationary storage applications. The latest developments in SOH estimation techniques such as identification of health indicators for both battery first and second-life will be examined. Existing battery ageing models and state of health (SOH) estimation techniques will be reviewed and their applicability on battery second-life will be examined closely with references from literature. A critical discussion on existing second-life batteries R&D projects will be included and suggestions will be made to more realistic approaches.

To perform this survey, a systematic research and review method was implemented to analyze the process of battery degradation during second-life applications. To obtain our required results the keywords "Electrical vehicle battery", "battery degradation" and "SOH estimation" were used in the search engine "Google Scholar". This has an authentic scientific peer-reviewed publication containing both journal and conference papers. The following methodology is shown in the Fig. 1. Filtering of literature having above mentioned keywords in their abstract, title, and keywords was performed. All research

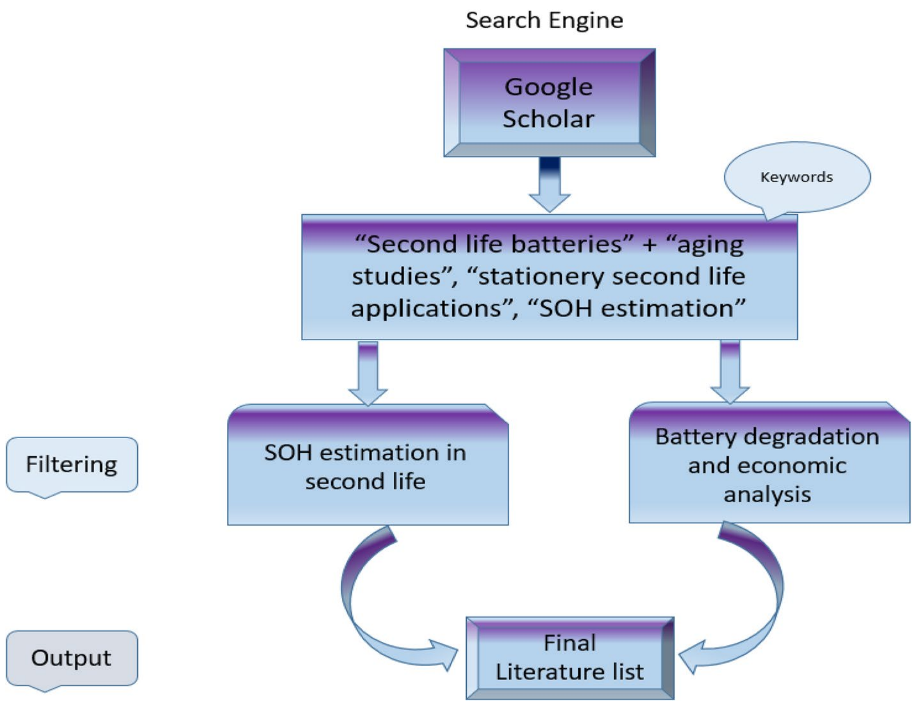

Fig. 1 Literature survey methodology

papers were then further screened by focusing on papers having all keywords together. This resulted in the final list of data used in this literature survey which consists of (several) papers.

The organization of the paper is as follows. Section 2 covers a brief background of the environmental benefits of electrical vehicles' battery second use followed by the history of viable business models. Section 3 is a comprehensive and critical literature survey on existing and ongoing research methodologies for battery second used, keeping in view technical, economic, and applications aspects more importantly the second-life battery life cycle assessment in stationary storage applications. Section 4 includes the discussion on the above section using a heat map and identifying opportunities and challenges in battery second use. Section 5 presents future research directions and objectives.

2 Handling Retired EV batteries

It is predicted that an enormous number of EV batteries will be retired in future years [2]. With this growing number of EV batteries, the issue of how to dispose of retired Lithium-ion batteries is becoming particularly crucial. There are no approved recycling facilities for these batteries, and discarding them without adequate handling can cause greater environmental difficulties than fossil fuels, rendering the entire electric vehicle transition worthless [17]. On the other hand, the high cost of lithium-ion batteries is a key obstacle to the evolution of electric car technology, and it is the reason why these batteries should be handles carefully [18]. Disposal, recycling, and reuse are the most common current solutions for retired batteries [19]. EVs are expected to travel between 120,000 and 240,000 km on average. The most commonly used LIBs is expected to last 8–10 years and have a useable capacity of 70–80% [12, 20].

2.1 Disposal

The disposal of retired EV batteries is not a very suitable option due to many reason, one of them is that an average battery pack weighs 250 kg, then five million LIBs retired from EV waste will weigh 1.25 million tons when they reach the end of life [20]. If they are disposed of, they generate a lot of trash because recyclable and expensive materials are discarded. Heavy metals and electrolytes from these batteries contaminate soil and water, causing irreversible damage to the environment [21, 22]. The majority of discarded electric vehicle batteries end up in landfills, with a few being transferred to waste-to-energy facilities for ignition [23]. The lithium salt $LiPF_6$ is an example of discarded material that is extremely toxic and damaging to the human body, causing damage to the eyes, skin, and lungs in particular [23]. Nonflammable metals such as nickel and cobalt are collected in the bottom of burnt materials with ash and eventually disposed of in landfills, causing harm in the same way as direct landfill disposal does [24].

2.2 Recycling

Recycling is another popular option for retired batteries. Using the recycling process, it is possible to recover and return the valuable materials of lithium-ion batteries into the value chain [20, 25, 26]. It has the potential to provide significant economic and environmental benefits. Instead of discarding valuable metals, this method can collect them for reuse, making the acquisition of raw materials easier [22]. Recycling plastic and graphite can also boost the economic value of retired lithium-ion batteries [27, 28]. From an environmental standpoint, disposal is the most unaccepted alternative for dealing with end-of-life EV batteries [29]. For the recycling of valuable elements from end-of-life lithium-ion batteries, standard chemical and physical procedures have been used [21, 30]. However, because battery cathodes are made of a variety of materials, developing a low-cost, environment-friendly recycling method still remains a difficult and debatable issue [29].

2.3 Reusing

On the other hand, Instead of recycling the retired batteries, the smart way is to reuse them to maximize their remaining potential life [31]. Reuse of EV batteries can be defined as the application/treatment of these retired batteries for storing energy in domestic storage systems and as a backup in modern grids that are integrated with renewable energy sources [32]. Two common methods of reusing these EV batteries are repurposing and remanufacturing [33]. The latter entails repairing or renovating used EV battery packs and redeploying them in automotive applications, whereas the former entails reconfiguration of these EV batteries to deploy them in less-demanding secondary applications such as those indicated above [20, 34]. However, prior to secondary usage, batteries may require additional processing such as testing, inspection, disassembly, removal of faulty calls, and replacement [35].

Figure 2 depicts the complete life cycle process at the end of the transportation life of the EV battery. This include battery screening for capacity dispersion among cells, refurbishment and then these repurposed batteries should be implied in storage applications.

There have been numerous studies in the literature that support the reuse of electric vehicle batteries, these are discussed here. In the United States, a cost-effective and carbon emission analysis of installing SLBs against new LIBs for three energy storage applications: (1) domestic energy storage with rooftop PV, (2) utility-level PV firming, and (3) utility-level peak-shaving is conducted [36]. In comparison to new LIBs, SLBs reduced the levelized cost of power by 12–57 percent and carbon emissions by 7–31 per cent. When compared to rooftop PV alone at the residential level, SLBs lower the levelized cost by 15–25 percent and carbon emissions by 22–51 percent, making SLBs attractive to residential users as well [36].

When these three methods of handling retired EV batteries are compared, it is obvious that discarding them after their initial usage is not an acceptable alternative from both an economic and environmental standpoint. While it is self-evident that reused batteries will

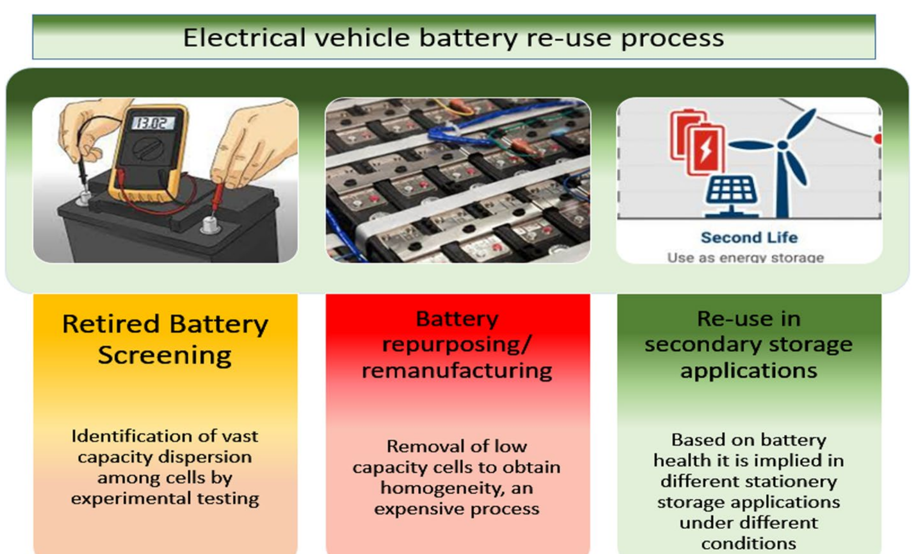

Fig. 2 Electrical vehicle battery at the end of first-life

eventually be recycled, the only practical choice for maximizing financial advantage and optimizing environmental benefit is to reuse them in static applications. It will also facilitate the intermittent renewable electricity supply in the future by implying a controlled life cycle analysis of reused batteries in these stationary storage applications [37].

However, there are still significant obstacles in reusing EV batteries, particularly in terms of estimating remaining life, life cycle evaluation, screening process, regrouping, and, most importantly, safety management of wasted batteries for secondary use [29]. According to [37] repurposing old EV batteries into stationary storage systems can improve the overall environmental sustainability of EVs and residential storage. The environmental implications, in particular, are reduced by a percentage ranging from roughly 4% (in cumulative energy usage) to 17% (in abiotic depletion potential). This will help kick-start the transition towards a low-carbon economy. According to this research, more research is needed to improve the environmental sustainability assessment of used batteries' second lives [37]. The lack of primary data on key energy model factors that affect environmental impact assessments, such as charge/ discharge efficiency, battery capacity degradation, and battery lifetime, as well as methodological assumptions (e.g., allocation strategy), is a major concern in this sector. Introducing proper business models for retired battery use in post-vehicle markets can assist lower the upfront cost of an electric car, producing money, and making them more accessible to the general public, increasing EV penetration in the transportation sector.

3 Second-life battery degradation studies in stationary storage applications

The use of second-life batteries in stationary storage applications has proven to be a better alternative to disposal and recycling [20, 31]. Hence, an accurate estimation of the battery's useful capacity and remaining life in second-life applications should be assessed with utmost attention. There are various variables used for accessing the parameters responsible for battery ageing [38–40]. Battery state-of-health (SOH) is the parameter defining the battery's useful capacity, it is the most widely used notion in battery ageing studies [38, 41]. If it is not measured and predicted precisely this can lead to a misconception about the battery's operational capacity, misjudge any fault condition of the battery as well as can pose serious safety hazards [42, 43].

3.1 Battery SOH estimation and ageing models

Battery SOH is generally predicted by its internal resistance data and capacity fade [44]. Hence, battery degradation/ageing studies play a crucial role in predicting the health of the battery both during first and second-life applications. There are several ageing models proposed for battery SOH estimation but still, the precision is compromised due to factors summarized below.

1. SOH being an internal battery parameter is hard to be sensed directly. It is usually obtained from the integration of other measurable parameters such as current, voltage etc. [45].
2. Using off-line data sets for most prediction methods in the literature, Also, the SOH of a battery depends on environmental factors as well as multiple internal parameters that are strongly dependent on time [45].
3. Due to the high involvement of various internal and external factors, the battery degradation curve is very non-linear which makes SOH predication methods unreliable [45].

Currently, SOH estimation algorithms are based on model-based methods, data-driven methods and the combination of model-based and data-driven methods [46]. There are studies initiated for optimal accurate prediction of the capability of second-life batteries in stationary storage applications by accessing cycle life and estimating battery SOH. The assessment of useful lifetime of a battery in specific applications require practical data, which is not very common practice yet [47, 48]. Figure 3 shows conventional and advanced methods of SOH estimation.

The choice of an appropriate battery ageing model is very important for battery SOH estimation. As SOH is considered an indicator of battery ageing there are various techniques in the literature to estimate battery SOH. In an ageing study for an Electric vehicle battery, an electrical equivalent circuit is used to represent battery performance and ageing in different second-life applications [49]. Some ageing parameters are indicated but there are no demonstrations on how they are involved in controlling battery life. This [50] equivalent circuit model is combined with a reliability model to check stress levels from the battery ageing model to more accurately estimate the remaining useful lifespan of the battery. The battery model is used to calculate SOC and DOD from the battery current and capacity. The reliability of a Li-ion battery on second-life stationary energy storage missions can be assessed using this model. The conventional coulomb counting method compares estimated capacity with rated capacity by continuously measuring current, [51] is a simple technique but has the disadvantage of requiring a complete battery cycle of 100% which is practically not true [52]. A data-driven SOH estimation technique in [53] using autoregressive integrated moving

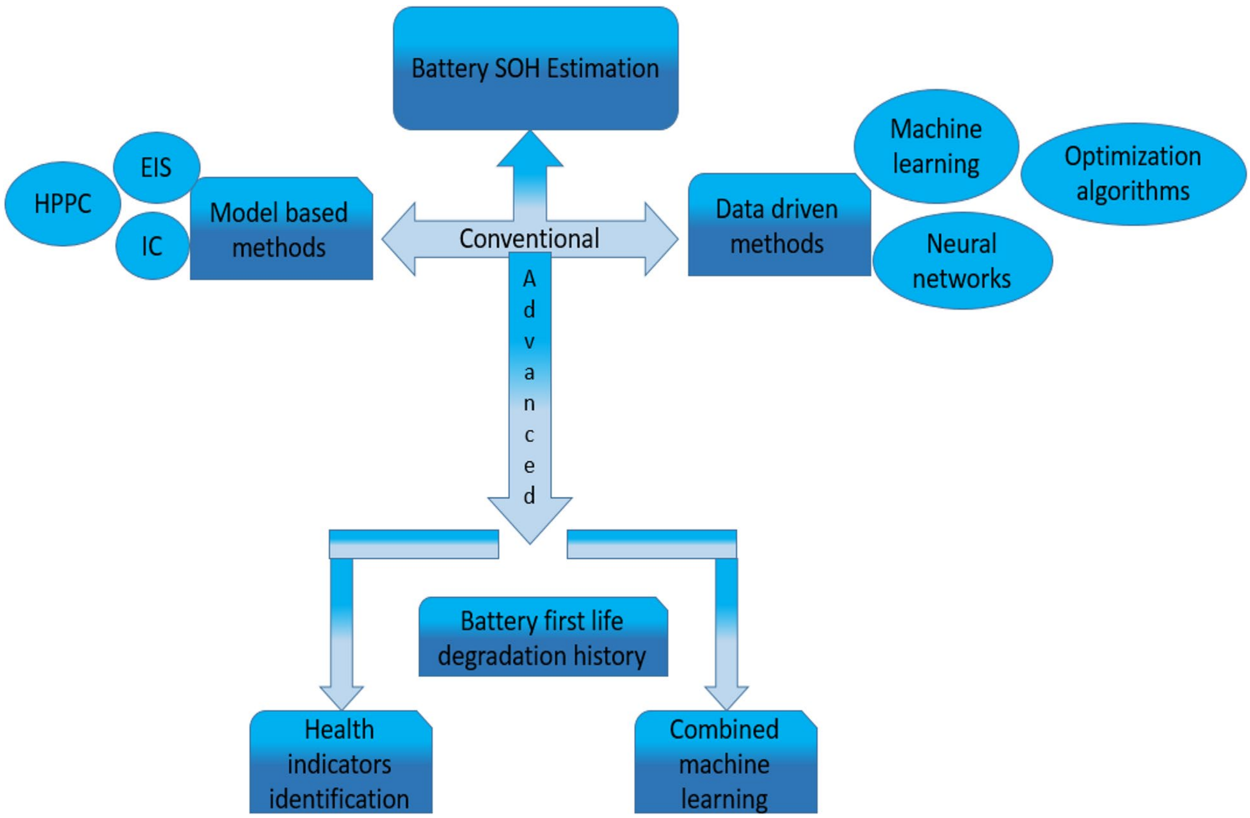

Fig. 3 Battery SOH estimation methods

average (ARIMA) uses a forecasting algorithm to predict second-life battery remaining useful life in stationary applications with less than 3% error. This technique works by initializing a model order and starting a time series model constructed on the past cycle's training data. The combination of this approach with other forecasting algorithms for example neural networks is proposed to handle the non-linearity in components estimating SOH [10]. Another innovative lithium-ion battery ageing model in [54] is based on open circuit voltage analysis using incremental capacity curves. Following these, a bi-stage segmented non-linear regression technique is used here to fit the curves as per peak value. This approach presents a better degree of accuracy to a vast application area of lithium-ion batteries, possibly extendable to second-life applications as well.

In [55] a forecasting model to predict battery capacity estimation both for ageing and regeneration phenomenon is presented. However, this study does not use data from an actual electrical vehicle battery so in the future proposed model can be applied to real-life battery data from different compositions and manufacturers. Table 1 entails a comprehensive survey of literature on degradation studies on second-life batteries including economic analysis and technical aspects like ageing studies method, ageing parameters, control of ageing parameters, health indicators identification, capacity dispersion, specific second-life application and effect of temperature.

3.2 Health indicators for SOH estimation

Recently, the identification of health indicators (HI) for extension of the useful life of these EV batteries in their secondary applications is gaining popularity. It makes SOH estimation more accessible by parameterizing. The internal resistance rise, which is evaluated practically using impedance spectroscopy, capacity fade, which is determined by incremental capacity analysis, as well as current and voltage measurement, are the commonly utilized battery health indicators for SOH estimation [20, 25, 26]. New classes of HIs are being identified and classified based on accuracy under specific second-life applications. This study, in addition to previously stated HIs, identifies two novel indicators of Cpk (Capacitance peak) and Vpk (Voltage at peak Capacitance) for specific battery chemistry (lithium iron phosphate LFP). This technique uses a simple conventional estimation algorithm to obtain an average accuracy for RUL predication (above 97%) and high accuracy capacity prediction (error less

Table 1 Detailed Overview of battery degradation technologies in stationary storage application

Ref	Methodology	Ageing models/SOH estimation	Degradation history from first use	Degradation mechanism based on the specific application	Ageing parameters/ Health Indicators	Ageing parameters control for EOL extension	Experimental data	Real-life application	Heterogeneity among aged cells from first use	Effect of Temperature	Cost analysis
[49, 50, 56, 57]	Ageing and Equivalent model in Simulink	✓,✓,✓,✓	✘,✘,✘,✘	✓,✓,✘,✘	✓/✘,✓/✘,✓/✘,✓/✓	✘,✘,✘,✘	✓,✓,✓,✓	✓,✓,✘,✘	✘,✘,✘,✓	✘,✘,✘,✘	✓,✘,✘,✘
[58]	Pulsed charge regulation and interlacing	✓	✘	✘	✓/✓	✓	✓	✘	✘	✘	✘
[59]	Hybrid pulse power characterization (HPPC), EIS, capacity analysis	✓	✘	✘	✓/✘	✘	✓	✓	✓	✘	✘
[8, 37]	Remaining useful life (RUL) estimation algorithms and novel His	✓,✓	✘,✘	✓,✘	✓/✓,✓	✘,✘	✓,✓	✘,✓	✘,✓	✘	✘
[54]	Two-stage regression algorithm to smooth incremental capacity	✓	✘	✘	✓/✓	✘	✓	✘	✓	✘	✘
[60]	Effective capacity Characterization of used batteries	✘	✘	✓	✓/✘	✘	✓	✘	✓	✘	✘
[61]	A semi-empirical capacity degradation and economic load model	✓	✓	✓	✓,✓	✓	✓	✘	✘	✘	✓
[62]	BESS simulation model SimSES	✓	✘	✓	✓/✘	✘	✓	✓	✓	✘	✓
[63]	Incremental capacity analysis and IC peak area analysis	✓	✘	✓	✓/✓	✘	✓	✘	✘	✘	✘

Table 1 (continued)

Ref	Methodology	Ageing models/SOH estimation	Degradation history from first use	Degradation mechanism based on the specific application	Ageing parameters/ Health Indicators	Ageing parameters control for EOL extension	Experimental data	Real-life application	Heterogeneity among aged cells from first use	Effect of Temperature	Cost analysis
[54]	Capacity dispersion studies experiment	✓	✘	✘	✓/✘	✘	✓	✘	✓	✓	✘
[64]	Battery screening and sorting for Echeloned use	✓	✘	✘	✓/✓	✘	✓	✘	✓	✘	✘
[32, 65, 66]	Life and Residual cycle assessment	✘,✓,✓	✘,✘,✘	✓,✓,✓	✓/✓,✓,✓	✘,✘,✘	✓,✓,✓	✓,✓,✓	✘,✓,✘	✘,✘,✘	✓,✘,✓
[67]	Half-cell and electrochemical voltage spectroscopy test	✓	✘	✓	✓/✘	✘	✓	✓	✓	✓	✘
[36]	ESS analysis using considering battery ageing	✓	✘	✘	✘	✘	✓	✓	✘	✘	✓
[57]	Mixed least square estimator ramp rate compliant (MLSERRC) algorithm	✓	✘	✓	✓/✘	✘	✓	✘	✘	✘	✓
[68–70]	Techno-economic analysis using an Optimization algorithm and Data based model	✓,✓,✓	✘,✘,✘	✓,✓,✓	✓,✓,✓	✘,✘,✘	✓,✓,✓	✓,✓,✓	✘,✘,✘	✘,✘,✘	✓,✓,✓
[71–73]	Electrochemical impedance spectroscopy (EIS), ICA, average Fréchet distance (AFD)	✓,✓,✓	✘,✘,✘	✘,✘,✓	✓/✓,✓,✓	✘,✘,✘	✓,✓,✓	✘,✘,✓	✓,✘,✓	✘,✘,✘	✘,✓,✘

Table 1 (continued)

Ref	Methodology	Ageing models/SOH estimation	Degradation history from first use	Degradation mechanism based on the specific application	Ageing parameters/ Health Indicators	Ageing parameters control for EOL extension	Experimental data	Real-life application	Heterogeneity among aged cells from first use	Effect of Temperature	Cost analysis
[74]	Method of On-board impedance parameters and voltage estimation of Li-ion batteries	✓	✓	✗	✓/✓	✗	✓	✗	✗	✓	✗
[75]	Cloud-connected battery management approach	✓	✗	✗	✓/✓	✗	✓	✓	✗	✗	✓
[76]	Impedance spectroscopy characterization	✓	✗	✗	✓/✓	✗	✓	✗	✓	✗	✗
[9, 10, 53, 55]	Advanced, Combinational and Forecasting Machine learning Techniques	✓,✓,✓,✓	✗,✗,✗,✗	✗,✓,✗,✓	✓/✓,✓,✓,✓	✗,✗,✗,✗	✓,✓,✓,✓	✗,✓,✓,✗	✗,✗,✗,✗	✗,✗,✓,✓	✗,✗,✓,✗
[71]	CdS-based method (Using IES spectrum)	✓	✗	✗	✓/✓	✗	✓	✓	✗	✓	✗
[77]	Multi-Objective Natural Aggregation Algorithm	✓	✗	✓	✓/✗	✗	✓	✓	✗	✗	✓
[78]	Modelling of Battery Energy management system in Simulink Matlab	✗	✗	✗	✗/✗	✗	✗	✓	✓	✓	✗
[10, 11]	SOH estimation based on MIHs, repurposing and SL based on 58 His	✓,✓	✗,✗	✓,✓	✓/✓,✓	✗,✗	✓,✓	✗,✗	✓,✓	✗,✗	✗,✗

Table 1 (continued)

Ref	Methodology	Ageing models/SOH estimation	Degradation history from first use	Degradation mechanism based on the specific application	Ageing parameters/ Health Indicators	Ageing parameters control for EOL extension	Experimental data	Real-life application	Heterogeneity among aged cells from first use	Effect of Temperature	Cost analysis
[79]	Electrochemical impedance spectroscopy and back propagation neural network	✓	✓	✗	✓/✓	✗	✓	✗	✗	✗	✗
[80]	Economic dispatch model based on Semi-Empirical battery degradation model and total battery throughput	✓	✓	✓	✓/✗	✗	✓	✓	✗	✓	✓
[81]	Model predictive control for economic analysis considering dynamic degradation of batteries	✓	✗✗	✓	✓/✗	✗	✓	✓	✗	✗	✓

Table 2 Health indicators identification for SOH estimation

Ref	[8]	[9]	[10]	[11]
Health indicators	Two novel HIs (Cpk and Vpk)	2 Novel HIs (SOHC, SOHE)	6 HIs (R0, Rp and Cp in the ECM, capacity from ICA, two OCV-based HIs)	58 HIs (from ICA, PCM, CC and CV charge stages, and DC internal resistance Measurements)
Estimation Algorithm	Combination of regularized logistic regression (RLR), multivariable linear regression (MLR), multilayer perceptron (MLP)	Combined Machine learning	The Back Propagation Neural Network (BPNN)	Combined machine learning
RUL prediction accuracy	More than 97%	N/A	Error less than 1.31%	N/A
Capacity estimation accuracy	Error less than 1%	N/A	Error less than 1.31%	0.2% root mean square error in the repurposing stage and 2% in second life
Second-life Application	Low-capacity applications	N/A	Low-capacity applications	Repurposing and second-life application

than 1%) [8]. It is also suggested to investigate their applicability to other battery compositions.

As data-driven ageing models based on HIs are getting famous, an innovative combined machine learning approach for accurate estimation that is also faster than standard processes. This scheme is verified on 200 cells of different compositions and under varying operating circumstances [9]. It uses SOH_C (battery current maximum capacity) and SOH_E (battery current maximum energy) as novel initial health indicators. The proposed method is efficient and widely applicable based on a limited data set of measured voltage and current only. Moreover, this study has ranked the data-driven machine learning-based model in [9] as an efficient technique for battery accurate and fast state of health estimation for second-life allocation.

Six health indicators (collectively called multiple health indicators MHIs) are identified and used in [10], combined with a lifetime degradation model (based on a neural network approach) to reduce the dispersion among different battery cells from first-life to be reconfigured for second-life use under different duty cycles. Three of them are based on impedance studies from the battery equivalent circuit model, two from the battery OCV curve and the last one is from the incremental capacity curve. At least 22.9% more accurate results are claimed to be achieved from this MHIs-based system as compared to single HI-based techniques.

The health indicators' identification for degradation studies of batteries suggests that this is the main strategy for cost reduction of second-life batteries both in the repurposing stage and during second-life applications. The authors in [11] have taken a step ahead and identified 58 HIs from different battery internal parameters such as internal resistance, ICA, charging/discharging studies and current /voltage measurements etc. Comparative analysis of these HIs for-battery degradation studies reveals the best HI for both repurposing and second-life use cases. Then using an estimation algorithm battery SOH is predicted based on chosen HI. Table 2 briefs the above description for better and quick understanding.

3.3 Degradation data from first use

Battery degradation history from first use can play a crucial role in determining its ageing trends in second-life. However, there is not much development in this regard to keep a track of the battery's complete history during first use. An initiative has been taken in this aspect and an innovative cloud-connected battery management system is suggested [75]. This system keeps a track of battery data in electrical-thermal from first use continuously on a back-end server. Then a combination of this data and an empirical ageing model is proposed for the correct prediction of battery remaining useful life. The crucial part of this model is the extraordinary requirement of the degree of precision of the electrical and thermal model to compute stress factors for ageing estimation of different cells. The merits of this proposed method above related techniques in literature are economical and reliable state estimation at the end of first-life and remaining useful life during secondary use as well. However, in a real life scenario, there is a requirement for an appropriate ageing model for identical electrochemical cell types and ideally the same cell type for each battery. Brings another parameter into consideration which is battery repurposing which can be an expensive process if not handled and planned according to the existing health conditions and homogeneity among battery cells. Repurposing has a significant effect on battery degradation properties in the second-life in the context of both cost and efficiency [64].

3.4 Second-life Batteries Screening and Repurposing

So there is another highlighted problem is the handling of end-of-life batteries of EVs to repurpose them as stationary energy storage devices. Accelerated cyclic testing is performed in [65] on six cells extracted from the Nissan Leaf battery after reaching end-of-first-life to see whether they might be reused in a stationary application that required low performance. An end-of-life ageing knee is determined for battery second use by using capacity fade and internal resistance rise during cell ageing testing. In a related study in [56], five NMC battery cells, with different states of health for four of them, were tested for their performance from the first end of life. It was concluded that these batteries can be involved in stationary storage applications with relatively lower performance requirement such as frequency services. A low charge/discharge current rate can extend their useful life in second applications. This study was extrapolated to Electrochemical Impedance Spectroscopy (EIS) analysis in [76] for different chemical properties of batteries and their SOH estimation. The influence of ageing on the batteries has been investigated with the parametrization of the battery impedance circuit model.

However, handling EOL batteries and repurposing them may become costly if the capacity dispersion among cells is not taken into account [17]. An intra-modular and inter-module capacity dispersion of battery cells are performed on 10 first-life modules and 32 s-life modules for comparison before repurposing [82]. A proposed method in [60] suggests two-step characterization; initial scanning based on external physical parameters and then sorting the scanned batteries based on their remaining effective capacity. A sophisticated workbench is used for testing the battery in this proposed method. A Smart Batching Management modelling tool is proposed as a cost solution to perform capacity test to find SOH of all used cells on field, this will also ease quick sorting of used cells [17]. Testing of batteries in practical application is postponed for future work and the life cycle of second-life batteries is proposed to be described as a function of energy storage system application. An experiment-based sorting technique categorizes six battery samples for grid connecting applications is proposed in [83]. However, no attention was given to battery degradation and heterogeneity among cells.

To handle heterogeneity among cells, a general energy management system (GEMS) is proposed in [78] to regulate and distribute load demands between varying capacity second-life battery modules under various operating conditions (load profiles, disturbances). Experimental verification of this scheme shows that it successfully manages the performance differences between second-life battery modules of varying sizes, capacities and chemistries in the same application at the same time. However, the initial age of the battery cells should also be taken into account. An automated testing device is built and tested in [84] to handle second-life lithium-ion batteries. For future scenarios, this device can be used to perform multiple accelerated charge/discharge life cycle tests on the batteries and provide real-time data. This data will be helpful in the determination of the feasibility of batteries integrated with grid-tied energy systems. But this testing has been intended for future work and no real-time result/data is available from it to date. There is another retired electrical vehicle batteries repurposing technique presented in [58] for a renewable integrated high-scale battery energy storage system. A hybrid technique to extend the battery ageing process called “Multi-Level Interlaced Pulse Charging (MLIPC)” is developed from two processes, 1. Pulsed charge management and 2. Battery interlacing. This combination allows a single battery pack operated by simultaneous multiple interlaced PWM pulse trains so if applied to multiple batteries can contribute to charge exchange between the cells. This helps in avoiding an unbalance stress on one battery unit/cell. However, no comprehensive economic study was conducted. Further research into the length of the battery’s pulse period is needed to optimize the performance of the system. In another related study with unknown battery history, sorting and prediction studies are conducted to categorize and repurpose batteries for secondary storage applications [59]. The techniques used are called Hybrid Pulse Power Characterization (HPPC), EIS analysis and incremental capacity analysis. Three LMO battery models were tested for SOH estimation of end-of-first-life sorting using all three different techniques. The results are based on comparisons showing that each method has its own merits of looking into specific aspects of degradation studies of batteries.

3.5 Life cycle assessment

The efficient modelling of complete life cycle assessment of second-life batteries in energy storage systems also plays an important role in optimal utilization of second-life batteries in stationary applications hence it is an inevitable part of battery second-life degradation studies. A parametric life cycle system model has been developed and applied to integrate second-life batteries to facilitate the renewable electricity supply and to access the potential of these batteries to be used in second-life applications in California in the future [85]. Different techniques of battery testing to estimate battery SOH has been used in the literature. These include incremental capacity analysis, EIS (Electrochemical Impedance Spectroscopy) and estimation algorithms based on machine learning. The method of EIS in [67] along with half-cell testing is used to study the degradation of two different cells under two grid applications of frequency regulation and energy arbitrage services. Suggestions are made for appropriate cell types in a particular grid service with maximum economic benefits. This poses an opportunity for grid operators and also researchers to manage the life span of second-life batteries by using them under particular conditions and operational time. Nevertheless, the cell compositions cannot be disregarded on the basis of type of application as it can cause instabilities in assessment of life cycle and cost estimations.

A novel method to link SOH with EIS of new and used lead-acid batteries in [71] provides a better and reliable way to predict battery SOH for all values with less than 10% of error and is valid for possible SOC range from 80 to 20 percent. The drawback is an extremely costly workbench for battery testing. The methods of incremental capacity analysis and probability density function are used and compared for battery SOH modelling in [72] for a constant power operating condition. Whether it is the cell or the module, the variation in SOH between different batteries in the BESS is significant. The relative degree of ageing degree for a battery can be determined by grading the HI value on ICA or PDF curves based on actual charging voltage data in the case of an unknown SOH. This study's methodology and findings add to the adoption of online SOH battery evaluation in real-world energy storage systems. The above-mentioned techniques are combined with another method for battery ageing studies called average Frechet distance of battery ageing, and introduced in [73]. The offline SOH is predicted using internal resistance as a health indicator. However, the results drawn here cannot be applied generally to all battery types because this testing has been performed under specific conditions.

As data-driven based SOH estimation techniques are gaining attention due to their robustness and accuracy. A SOH estimation for battery degradation studies uses linear regression with incremental capacity analysis to estimate the remaining useful lifespan in second-life storage applications. Life cycle tests are performed on six lithium-ion battery cells to demonstrate the battery's ageing characteristics for three typical load profiles. Then a quantitative incremental capacity analysis is performed to access ageing mechanisms followed by another systematic ageing analysis to find the similarities and differences under different load conditions. The suggestion is to use a combination of ridge and linear regression with a correlation-based feature to counter the estimation variance with so many inputs [63]. There are some discontinuities in results possibly due to differences in the ageing patterns in EV first operations. As part of the European Second-life battery energy storage system, a novel algorithm called a mixed least square estimator ramp rate compliant (MLSERRC), based generic method is used in [57] to determine the optimal rating of SLBs, power exchange and battery state of charge profiles for an entire operational year. The driver for using SL batteries is the possibility of reducing costs and minimizing the environmental impact by using aged batteries closer to their lower operation performance. The authors claim that the power profiles obtained from this study can later be used for SLB testing, which will allow analyzing the performance capabilities of such batteries, and their ageing.

As previously emphasized, historical data from battery first use can be a game-changer in optimizing the useful life of second-life batteries, this study in [79] aims for total life span prediction of batteries starting from cycle life in first use, second-life application life and then remaining capacity of retired batteries. There is also an investigation of ageing process and SOH estimation for the said life span of batteries. First-life data of a new battery is used to train the second-life battery to predict the interdependence of both. Being a beginner research area, a few deficiencies are also observed in this study, one of them is an online estimation of impedance [74], as impedance is an important deciding factor in SOH estimation, it should be estimated precisely and online. Moreover, as batteries in each stage have different capacity fade ratings, it can result in inconsistent battery system overall ageing behavior hence more investigation is recommended in this regard.

A summary of key research issues in the deployment of lithium-ion batteries includes the estimation of actual capacity, sorting of battery modules based on capacity dispersion, remaining useful life, battery circuit model and SOH algorithms. New methods and models for sorting retired batteries and estimating SOC and RUL of these batteries are put forward [4], which improve the consistency, decrease the degradation and prolong the battery cycle life. In future, these methods should be verified by experiments to attain benefits from them.

4 Economic Assessment considering battery ageing

There is a lot of ongoing research on this emerging second battery reuse technology. There are some techno-economic studies presented that undertake battery degradation aspects into account for second-use applications, but most of them are based on approximations of battery capacity, efficiency and lack of first-use data [3, 13]. The economic models are either specific for battery type, chemistry or type of application under specific conditions so no generic techno-economic tool is present to date [61, 86]. This topic undertakes all the progress made in battery secondary use degradation studies from the prospect of economic benefits.

Several projects and research works are reviewed in [87] to understand the developments related to second-life batteries. The technical feasibility, economics, and environmental impact of using second-life batteries are also investigated under different applications. The world's first battery energy storage system comprising second-life batteries from BMW i3 sets a cornerstone for future reliable energy storage systems [88]. A combination of estimation techniques for battery SOH and cost analysis tools is required for a comprehensive techno-economic assessment that would also keep in sight the concept of useful lifetime extension of second-life batteries. A real-life case study in [62] considering two different scenarios in Spain analyses the feasibility of second-life battery energy storage but with approximations. An economic model built in MATLAB is later analyzed for expected results using a system called SMEs (small and medium enterprises). Electricity tariff reduction is proposed in an energy storage system with data from market and suitable battery ageing model. A leading electrical vehicle manufacturing company has recently devised a mixed research methodology for said purpose [89]. An application-based analysis of second-use batteries is conducted, and a comparison is made for economic feasibility themselves. The economic evaluation is performed for three different applications of battery repurposing with equally dispersed capacities, refurbishing for use again in electrical vehicles and finally reuse in secondary storage applications. The reuse of batteries in secondary storage applications without any categorization, refurbishing and repurposing is the most economical process of all. There is a need for detailed economic analysis for all three concepts to strengthen the idea of economic gain from the reusing process instead of recycling.

It is also recommended to analyze second-life batteries use in residential systems with solar PV as initial studies. Levelized cost of electricity LCOE is used as an economic analysis tool for a residential energy storage system comprising of PV array and second-life batteries. Carbon emissions are also compared for an added environmental benefit. A research study in [36] suggests grid level scenario as most favorable in terms of total cost reduction if compared on basis of specific application. Results are based on 41 cases including residential rooftop PV using energy storage, PV firming and peak shaving at the grid level. The use of second-life batteries in the residential system in combination with renewable generation reduced the LCOE by 12.57%. This is further investigated in another residential prosumer's storage system in [69] consisting of second-life batteries and solar PV. Sensitivity analysis is used to access the said system in terms of techno-economical aspects second-life battery changing market prices in California. The second-life batteries have variable battery SOH and variable PV generation penetrations. There are supporting results about economic revenue from battery operation hence encouraging the consumers to adopt second-life batteries as a viable option for energy storage.

In a case study in [90], used batteries are deployed in different grid applications including supporting the grid in fast EV charging stations, self-consumption, transmission deferral and area regulation. Great reliability is predicted for a renewable generation as self-consumption results show the endurance of close to 12 years. The economic and environmental evaluation is not very feasible if used batteries are connected to the grid without renewable support. This is verified when a typical rooftop PV in the combination of second-life batteries is evaluated for technical, economic and environmental benefits in the US [91], it predicts a clear cost reduction when the excess electricity from solar arrays is not sold to the main grid. It can be said that the use of net-metering strategies can increase the cost of electricity from PV arrays. There is a need to devise policies for use of second-life batteries in residential energy storage systems and net metering to consider both the economic and environmental benefits. It is further studied in [61], another case of second-life batteries and solar energy-based storage systems, a project in California. A data-driven battery ageing model is included to estimate ageing phenomenon and results are compared with another project with a new battery. A certain control policy is used to minimize battery cycle ageing with different SOC values and the life of the proposed system is calculated. Under these specific conditions, this project has been more long-lasting and economically favourable for use of a second-life battery in place of a new battery with cost benefits. The results presented here are for specific battery types and specific circumstances and loading conditions. Also, with the current battery prices, there remains uncertainty about the proposed economic benefits of this system. More rigorous analysis is required to generalize the presented results. Another research in [92] investigates an analysis of energy exchange between a residential PV array, second-life battery energy storage system and a grid in Southern Europe. The results are presented for 10 years of operation and technical benefits from batteries are confirmed. As far as economic benefits are concerned, large and small repurposed batteries were compared and conclusions verify the payback time of large batteries was greater than smaller but both batteries can provide technical benefits for an evaluated period of ten years. The policymakers should consider these results as a benchmark for future second-life battery projects. The accurate economic assessment is also useful to justify the motive of wide EV-market adoption as well as the use of EV batteries in residential energy storage applications. Table 3 includes studies undertaking battery degradation use into account while performing a techno-economic assessment of second-life batteries-based energy storage systems. The degradation methods are listed along with the type of application and conclusions drawn from surveyed literature.

However, there is no consideration of uncertainty related to battery first use in the determination of its value in second use and for optimal sizing in storage applications yet. A stochastic optimization method should be adopted to counter degradation uncertainties associated with battery and sizing of second-life batteries in the second-life application [97]. This has been proposed in [94] for optimal sizing of second-life batteries in a real-life PV power plant based on a mixed least-squares estimator ramp-rate compliant (MLSERRC) algorithm. A one-year power profile is obtained and applied to second-life batteries in the laboratory for testing and ageing studies. An economic analysis is then performed for the optimal size of SLBs, this applies to other cases too. Another appropriate sizing technique for the battery is presented in [70] based on an updated model of Present Value of Throughput (PVT) estimation. This advanced PVT model also takes care of battery disposal prices. It is based on a case study in Europe but in future could be generalized to different market scenarios.

In [66], another novel techno-economic analysis tool is given for the sizing of PV, second-life Li-Ion battery and power consumers integrated micro-gird as a component of the main grid. This tool is highly conditional and based on many assumptions but works fine for the given scenario by optimal sizing of PV and energy storage system based on the Net Present Value criterion. Results are shown for both cases with and without ageing involved. A cost comparison is done using economic indicators with a case where only the main grid is present. It predicts a microgrid with storage is way more economical than without a storage system. However, Calendar ageing is ignored in this analysis. There is a lot of room for improvement in this tool for the future such as considering power electronic components losses, more optimized battery ageing model during second use, more complex energy management models, battery life cycle assessment due to capacity dispersion among cells in calendar ageing, SOH and resistance values at end of first use depending upon first-life use and also uncertainty in market trends and price inflation impact on economic analysis over long periods.

It is stressed that degradation history at the end of first use can be of great importance in accurate estimation of the used battery's remaining life span hence making economic evaluations more reliable. This economic model in [80] regarding grid-able EVs and second-life batteries undertakes both vehicle and second-life degradation phenomena. It encourages EV owners to decide when to start second life for their EV battery depending on their requirement of revenue margin. Battery degradation is allowed up to 70% in first-life and up to 30% in second-life use and it is concluded that around 19.56% of a battery's upfront cost can be compensated by using this proposed model of degradation considered in both uses. It is suggested that the battery continues to generate revenue for both lives and the vehicle owner can decide about the amount of cost saving by starting the battery's second life and also selling the electricity in addition to the battery's second-life use. A techno-economic evaluation using software called SimSES in [96] investigates the revenues generated by deploying second-life batteries of varying capacities under different applications. This model looks quite detailed taking into account battery characteristics, ageing and operating conditions. However, some limitations seen in the model are neglecting non-linearity in an ageing phenomenon, battery cell unpredictable failures or any unseen technical circumstances.

4.1 Business models and policies

The secondary usage of retired batteries and the creation of new business models in these fields have advanced significantly. However, rather than the environmental and social aspects of this new developing technology, the emphasis is on its commercial advantages. Several car firms have started programs to demonstrate this field in collaboration with energy companies and governments. To evaluate the key players in the battery second use industry and their impact on the development of environmental ecosystems, case study in [98] featuring notable participants in the market must be carefully analyzed. An operational optimization model has been presented in [68] to examine all the conditions in which second-life battery use in stationary energy storage systems is beneficial in China. It is said that if battery initial costs are not considered in future the profit margins will significantly decrease during their use in secondary storage applications.

In an attempt to quantify the importance of policies and business models, rooftop photovoltaics with SLBs in five US cities were analyzed in [91]. The cost of electricity was reduced, hence, excess electricity from photovoltaics was stored in SLBs rather than exporting to the grid. Another study [99] explored sustainable business models (SBMs) evolution for SLBs to create a new

Table 3 Summary of economic assessments of second-life batteries incorporating degradation studies

Ref	Economic analysis tool	Degradation mechanism	Second-life Application	Results	General Comments
[62]	Annual Cost investment, return of Investment (ROI)	Mathematical ageing model	Energy Arbitrage Peak load shaving	ROI:11.33, 18.21 years Cell ageing 12.5, 13 years	Battery degradation plays a crucial role in economic results
[89]	Total cost calculation of investment, payback years, return rate (RR) and profit factors using mathematical formulas	Based on literature	Repurposing, refurbishing for EV, Reusing in storage application	Remanufacturing has the best RR while ESS has the shortest payback time and highest profit	Reusing Energy storage systems without repurposing them is the best economic scenario
[90]	Based on literature	Equivalent electric battery-ageing model	Fast charging EVs, Self-consumption, transmission deferral and area regulation	self-consumption results show the endurance of close to 12 years	Used batteries and renewables should go hand in hand for max economic profits
[93]	The annual cost of electricity ACOE using net present value (NPV)	Residual cycles and available capacity reduction	Fast EV charging and second-life battery energy storage system	Clustered CSs are cheap, ACOE value is less than the 13% average value of the dedicated CS solution. ACOE of II-Life and I-Life ESSs are compared to identify a competitive price of II-Life battery modules	The number of CSs in a cluster with shared ESS could be optimized according to the size of a given EV battery pack. Second-life battery can be an economical choice
[77]	Multi-objective optimization problem, minimizing cost	Mathematical battery model	Centralized charging station with Echelon battery system	The energy purchase cost of the CCS-PV-EBS is reduced in all cases. Controlling charging instances results in reduced depreciation cost	Energy purchase costs can be decreased by deploying retired batteries, and optimization of charge/discharge cycles can result in capacity enhancement and extended lifetime
[81]	Model predictive control	Dynamic degradation model	Second-life batteries-based energy storage system with a practical Wind farm	Not very beneficial with current battery and wind farm prices The second-life battery refurbishment cost makes it expensive	If wind farm prices decrease at a quick rate than second-life batteries then combination may be economically feasible in future
[69]	Sensitivity analysis based on Time of Use (ToU)	Analytical-empirical calendar and cyclic ageing model	A residential PV generation and storage system	Favorable results when solar has the highest penetration, for a certain high solar output, battery optimal value reaches a saturation point	The combination of higher PV output and low-capacity installed battery results in reducing the overall lifespan of the second-life batteries-based storage system
[91]	Levelized cost of electricity LCOE using net present value	Empirical model	A residential PV generation and storage system	Retired batteries produce a reduction in LCOE for all given cases. Carbon footprint is decreased. Grid-level applications show the most favorable results	Results can be combined with market trends, the potential availability of SLB and consumer acceptance to ensure the deployment of second-life batteries more successfully.
[66]	NPV based on the return-on-investment time (ROIT) and the profitability index (PI)	Exchangeable energy ageing model	PV-second-life battery connected microgrid	Second-life battery in a microgrid reduces grid interference and has cost benefits. Some parameters affecting NPV inflation rate, discount rate and purchase price of energy from the grid using sensitivity analysis	Battery degradation should be taken into account for a profound and accurate techno-economic analysis

Table 3 (continued)

Ref	Economic analysis tool	Degradation mechanism	Second-life Application	Results	General Comments
[80]	Total Revenue calculation based on the optimization problem	Cyclic and calendar ageing in charge/discharge cycles both first and second-life	SLBs of Grid-able vehicles in smart grid	Initial battery purchase cost can be compensated by19.56% considering degradation in both the first and second-life, the cycle's number show that the battery continues to earn revenue in both lives	This is the best platform for EV owners to choose when to start their battery's second-life based on the required revenue. Energy can also be sold in addition to second-life use to increase the range of revenue
[61]	Benefit–cost ratio calculation	semi-empirical data-based degradation model	PV-second-life battery connected to the utility grid	By controlling battery cyclic degradation, a second-life battery-based storage system looks economically feasible and the project life span is increased by 16 years if SOC is kept in the range of 15–65%. Costs are also reduced to less than 80% as compared to new batteries	With the current battery prices, there remains uncertainty about proposed economic benefits. More rigorous analysis is required to generalize economic benefits from the deployment of second-life batteries
[94]	Optimization technique	Mathematical ageing model	PV power plant	Annual power profile obtained using a mixed least-squares estimator ramp-rate compliant (MLSERRC) algorithm and testing of SL batteries in for ageing and sizing studies along with cost calculations	Second-life battery analysis is important for looking into their performance and will facilitate degradation studies evaluation when used with integrated renewables smoothing applications
[92]	Time-of-Use tariff, NPV and payback period	Degradation model in MATLAB-Simulink	Residential building with a photovoltaic system	Both small and large batteries stay technically feasible even after 10 years of operation. The payback period of a large battery is 9.53 years higher than a small rating battery	This type of study could offer results as a benchmark for policymakers for future second-life battery projects
[36]	Life cycle cost assessment using Levelized cost of electricity (Homer Pro and SimaPro software)	Not considered	Grid, SLB, and PV	The lifespan of the second-life battery found shorter than a new battery and replacement is needed after 10 years. SLBs reduce the cost and carbon emissions	There is a strong need for new and faster-charging infrastructure which can increase grid power demand
[70]	Present Value of Throughput (PVT) estimation	Capacity fade	SLBESS	A business plan can be set if company costs and yearly revenue is considered along with present value of throughput of batteries plus battery repurposing expenses	Such kind of analysis could be generalized and provide good strategies for this potentially growing market of second-life batteries.
[95]	NPV, feed-in Tariff	-	Different possible future second-life battery investments	Second-life battery has a cost advantage over the new battery if its future price is considered a lot less. Germany, at present, seems most economically favourable for these investments but profits can be extended to other countries in future	This economic analysis based on electricity prices and Feed-In Tariff schemes can provide a list of economic challenges and facilitators to second-life battery future investments

Table 3 (continued)

Ref	Economic analysis tool	Degradation mechanism	Second-life Application	Results	General Comments
[96]	SimSES	Empirical ageing model	Photovoltaic (PV) home storage, intraday market (IDM) and primary control reserve (PCR)	Combined applications case is most economical but technically least favourable due to the highest degradation. The SOH should be more than a minimum value of 50% otherwise these battery packs should be replaced	A comprehensive techno-economic analysis should be done before deploying varying capacities of second-life batteries in any specific application

concept of business models for sustainability in the EV B2U market. In [100] a sustainable innovation business model (SIBM) framework for the EV B2U industry is proposed that includes shared sustainable value creations which in turn drive forward business performance and sustainability at the same time. These findings show that if a second-life market can be successfully formed, EV adoption rates can be enhanced. The energy storage systems developed using the SLBs, their applications, and impacts require business strategies and policies. Current barriers to this technology such as smart grid flexibility and demand-side management and their potential solution of energy storage for future power systems required to make SLB businesses sustainable are discussed in [13]. Additionally, multiple concerns such as economic ambiguity about B2U being a cost-effective solution for customers; liability associated with SLBs; and a lack of data on the effectiveness of batteries in their first and second lives create roadblocks that obstruct the usage of retired batteries [101]. Tax rebates and other financial incentives for SLBs can help to attract additional private investors to help prove and realize the concept. The government's policies will have a significant impact on the implementation of SLBs and their determination can drive policymakers and automakers to create a new B2U business model that will benefit both [102].

The global market for second-life batteries is evolving rapidly. There is a need for general regulations, business strategies and policies. A survey of possible battery future investments is accessed economically in [95] using Net Present Value to look for challenges posed to the second-life battery market. The projects are residential level PV-battery systems or only battery, industrial PV-battery systems and primary reserve battery systems. Currently, these used battery projects seem to be economically favorable in countries like Germany but hope to see them grow in other countries as well. This only seems true if future prices of used batteries are way less than new batteries. The second-life battery reuse is also gaining popularity in developing countries. A case study of rural electrification is accessed in [103] economically for reusing second-life components in an energy storage system. All components of energy storage systems are retired including battery units (lead-acid battery) and solar PV arrays. There are economic and environmental benefits reported by reusing components, especially batteries according to sensitivity analysis results. In future, lithium-ion batteries should be considered in place of previously used lead-acid batteries.

Another factor considered in the deployment of used batteries in secondary storage applications is charging infrastructure and renewable integrated micro-grids. There is a strong need to design an infrastructure for an electricity grid based on fast charging stations for EVs and second-life battery energy storage systems for boosting economic benefits. Both issues are addressed in the proposed energy storage system in [104] using second-life battery energy for EV fast-charging systems. Life cycle cost and carbon emission assessment are compared for new and second-life battery-based systems in five U.S cities. Second-life batteries seem more favorable for fast charging stations reducing the levelized cost of electricity (LCOE) by $12-41\%$. The addition of renewable like solar can increase these cost benefits. However, the number of retired batteries can be affected as fast charging can cause fast degradation of an EV battery. Hence understanding of battery degradation is recommended during fast charging techniques adoption. [105] An economic assessment of the solution to this problem is using clustered charging stations for the sizing of energy storage systems comprising second-life batteries [93].

Degradation studies based on residual cycles and capacity fade are adding reliability to this assessment. A comparison of new and second-life batteries for proposed ESS is also done, so this could be a reasonable alternative to conventional charging stations as the proposed model shows 13% less annual cost of electricity when accessed economically using net present value. However, the sizing of the second-life battery for a given number of CSs (Charging Stations) remains ambiguous. A centralized charging station (CCS) can be another solution when used integrated with second-life batteries-based energy storage system (Echelon battery system) and PV arrays [77]. A multi objective based optimization problem is solved using rolling horizon strategy for calculating battery demand values. Integration of retired batteries results in lowering the energy prices and if charging/discharging cycles are optimal, the capacity of these SLBs can be enhanced resulting in life extension. There are certain approximations in this evaluation such as ignoring second-life battery previous data and keeping battery degradation a linear function.

A dynamic battery degradation model with different battery SOH, variable temperature etc. could be another option when it comes to comparing the cost benefits of using new or second-life batteries in practical system. A model predictive approach in [81] is used to optimize maximum economic value of this wind farm considering two real life case studies in USA and Denmark. The optimal sizing of fresh and second-life batteries is performed considering battery degradation under various operating conditions. The findings are not very convincing at present due to high cost of wind farms, refurbishment cost of retired battery and high upfront cost of new battery. However if future cost reductions are expected, a quicker

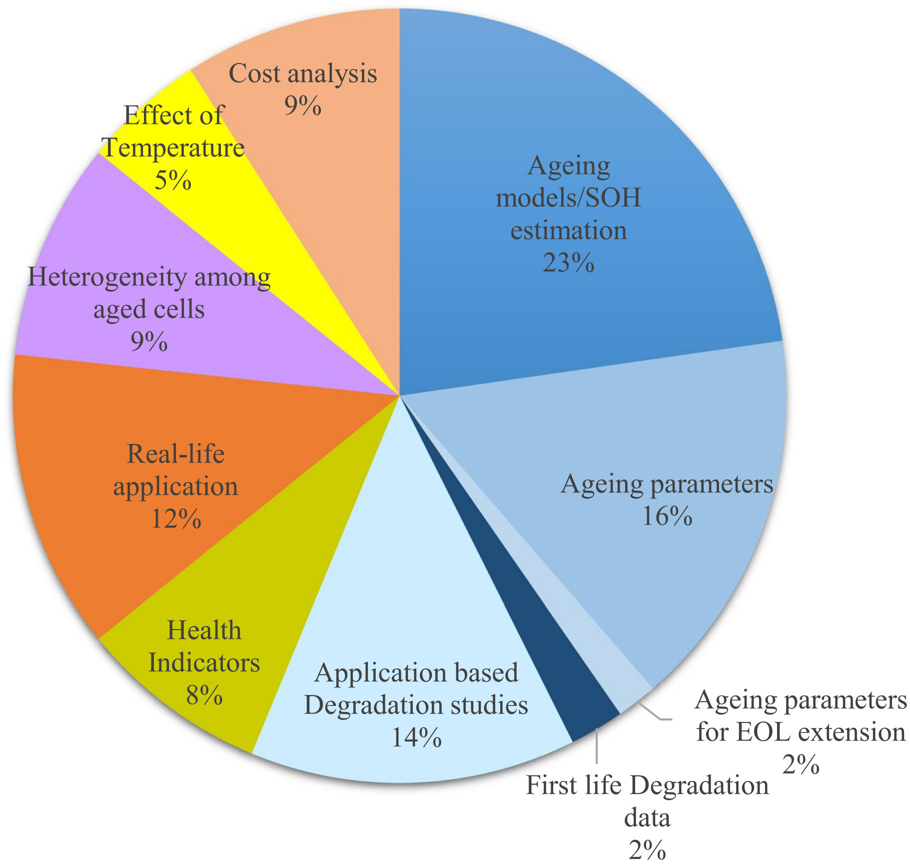

Fig. 4 Categorization of the reviewed application areas in the field of SLBs

cut for wind farm as compared to SL batteries can be favorable to proposed system.

5 Critical outlook

This review examines the various techniques used for second-life batteries. Figure 4 below quantifies the percentage of the articles according to different approaches. It is clear that the most intensively explored topics in this area is the selection of ageing parameters and ageing model development. The applicability of these characteristics/methods is called into question because the same models were used in the second-life applications. The retired batteries form EVs usually do not have any degradation data from its first use which is significantly important in analyzing the repurposing for reuse of EV batteries. Also, the ageing parameters data can help in extension of end of life for these batteries in stationary storage applications. This review reveals that despite their significance in determining the future of second-life batteries, these two objectives (lack of first use data and ageing parameters control) are the least studied. Another significant finding from this research is that none of these goals stand alone in determining the future of these retired batteries. Consequently, it may be suggested that the best framework for implementing these batteries in stationary storage applications should be a multi-objective procedure that simultaneously considers all the elements/objectives in the figure below. In an ideal scenario, the proposed framework should have the following attributes;

- A practical ageing model that incorporates the accurate SOH estimation during online operation based on specific applications.
- It should optimize the application based selection of ageing parameters/health indicators to extend the remaining useful life.
- It should also be economically feasible and the proposed solution may need to compensate between cost optimization and degradation control.
- The proposed ageing model can adopt to its best performance by incorporating the degradation data from its first use, as multiple reports [53, 75] proposed a cloud based data storage during primary application in EVs.

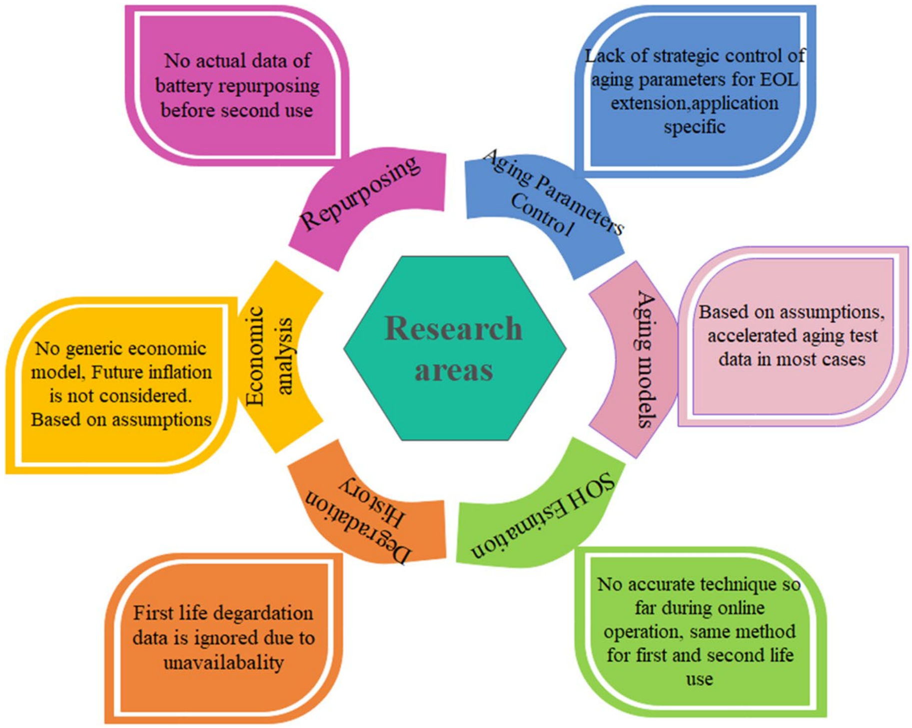

Fig. 5 Research gaps and corresponding shortcomings in existing literature on SLBs

5.1 Discussion

The integration of renewables into utility grids has become increasingly important, and energy storage systems are the key solution to this challenge. Hence, the use of second-life batteries in stationary storage applications has evolved as an emerging market, but it faces various technical, economic, and social challenges [4, 6, 12, 13, 15]. Despite the fact that the idea of integrating these batteries into the electrical grid and storage applications are receiving attention at a global scale, there are still barriers that prevent the adoption of EVs and their retired batteries, especially in developing countries. Some of these problems include lack of infrastructure in existing power system [106, 107], lack of smart energy management systems for retired batteries [14], lack of user incentives and business policies [3, 12], lack of charging stations, and accurate SOH estimation [12, 16, 31]. Fast charging stations with auxiliary batteries are one potential solution to the lack of charging stations, as described in [105], but the expensive cost of these batteries and charging stations is a significant problem.

The analysis of reviewed literature reveals that accurate estimate of the battery's functional capacity and remaining useful life in second-life applications is a primary concern. Lack of first-use data and efficient ageing parameter control during these applications contribute to the problem's ambiguity. As shown in [Fig. 5], the accuracy of SOH estimation of second-life batteries is the most researched topic. A thorough review of both traditional SOH estimation methodologies and cutting-edge data-driven methods using machine learning algorithms is presented in Fig. 3. The majority of the literature on battery ageing in second-life applications focuses on first-use in EVs [7, 32, 37, 49, 50, 56, 57, 61–63, 65, 66, 68–70, 74, 78], which is why it is still a relatively new issue. Only a small number of studies [36, 61, 80, 81, 89, 95, 96] have specifically looked at battery ageing during primary and secondary usage, also, almost all of these studies employ the same ageing models created for first-use. The ability to accurately conduct battery health estimation during second-life applications, which is essential for extending the battery's usable life, is currently lacking.

Estimating battery state of health (SOH) is a crucial problem for the battery management in second-life, because it affects the technical performance and lifespan of batteries. Several techniques, including the traditional coulomb counting approach [51, 52], HPPC, EIS [59, 67, 73, 74, 76, 79], incremental capacity analysis [54, 59, 63, 71] and empirical or semi-empirical battery ageing models [49, 50, 56, 57, 61] have been proposed in recent years for the calculation of battery SOH. EIS method is considered most common after coulomb counting but it is still unreliable due to requirement of excessive experimental data. ICA method has been used in combination with other techniques [73] for online SOH estimation but results are subjected to battery compositions and working conditions. These techniques do have some drawbacks, though, including lengthy experimental times, uncertainty brought on by accelerated ageing testing, and presumptions regarding the internal resistance of the battery at the beginning of a second use. Furthermore, these techniques' dependability is in question since they fail to account for the battery degradation curves' extreme nonlinearity. It can be seen from this review that researchers have now developed data-driven methods using machine learning algorithms including neural networks [9, 38, 79], advanced forecasting algorithms [8, 9, 53, 55] and also, linear and non-linear regression techniques [54, 79] for handling this non-linearity. The bi-staged non-linear regression technique [54] seems to give approximately accurate results but this study only discussed a battery with above 80% SOH, the results are not applicable to second-life battery. Although these methods alone and in combination with model based conventional techniques such as EIS, HPPC and ICA can produce more accurate results, they still have limitations such as needing practical battery test data [9, 38, 54, 79], heavy calculations [8, 9] and applicability on second-life batteries.

The identification of battery ageing factors, which serve as health indicators, is another critical component of battery's accurate SOH estimation. The initial ageing parameters considered were capacity fade [44] and battery internal resistance growth [38–40]. The most recent developments in the subject, however, have led to the introduction of different health indicators and their classification according to particular uses. These health indicators are combined with robust estimate and RUL prediction algorithms in data-driven model-based techniques [7–10] for more precise and effective battery SOH estimation under particular operating conditions. The latest advancement in this area is the meticulous identification of health indicators for battery ageing studies that are evaluated for their precision and impact on SOH calculation. There is a limited applicability of these health indicators on second-life batteries as well [7, 9, 10], but in the proposed methods their accuracy is compromised due to dependence on available information, specific cell characteristics and ignoring the effect of temperature and current. Still, it could be a good starting point for this emerging technique of multiple health indicators and can act as a future of SOH estimation during battery second use.

Limited availability of degradation data from its first use adds to the ambiguity in determining the degradation and hence SOH in second life. Cloud connected technology to store degradation data in primary application (reported in [75]) can help in increasing the precision and accuracy in selecting the optimal parameters for SOH estimation. Hence, this review suggests that, there is a critical need of data storage techniques to keep a record of the complete ageing profile of batteries from transportation to end-of-life.

Battery repurposing is another significant component in understanding battery degradation and efficiency throughout its second-life uses. The development of this technology, while still in its infancy, depends on the availability of used batteries and consumer demand [108]. The market for recycling used electrical car batteries is anticipated to have a big impact on the world's transportation sector and help the world reach its goal of having no greenhouse gas emissions [87, 90, 109]. In contrast to fresh batteries, used battery packs have a tendency to have a more distributed and inconsistent capacity, which presents a number of difficulties in accurately describing them in addition to cost effectiveness of these used batteries [109]. To access the capacity dispersion of each cell inside a module, measurements of internal parameters such temperature rise [54], capacity fading [60, 63, 83], and internal resistance rise [58, 60, 63] are necessary. Only a few studies to date have used battery interlacing [58] and pulse power characterization [54] techniques to calculate capacity dispersion. The multi-level interlaced pulse charging system [58] is capable of repurposing retired batteries too but the bi-directional power electronics used in this technique needs further insight to be completely applicable. These studies have further limitations, such as the low number of cells that can be characterized [82, 83] and the very high cost of experimental workbenches [17]. An optimal battery energy management system in its first use could also help identify heterogeneity among cells in battery modules and the repurposing cost needs to be carefully controlled for increasing interest in used EV batteries.

The technical and economic viability of these batteries is highly dependent on battery degradation studies and the availability of data. This review suggests that, the majority of economic or techno-economic studies ignore the capacity dispersion among repurposed second-life battery cells. Additionally, fast and uncontrolled battery degradation in secondary use presents hazards to environmental benefits [110, 111]. As, the environmental benefit of postponing battery recycling and disposal is the prime motivation of employing used batteries in stationary storage applications, these issues of lack of policies and cost-incentive for repurposing and refurbishment of used battery packs should be addressed. The effective use of this technology requires a roadmap for future research, standards, and regulatory services.

As discussed earlier, global zero and cost effectiveness are main objectives of incorporating second-life batteries.

Energy storage technologies are the key to overcoming the difficulty of integrating renewable energy sources (to achieve global zero) into utility networks [109, 112, 113]. Hence, it is crucial to conduct accurate and reliable assessments of their economic benefits incorporating a full process of repurposing and reusing, for stationary storage applications in real-life scenarios. It is recommended that researchers and stakeholders conduct cost analysis of battery screening, refurbishment, and repurposing for specific applications. There have been various techno-economic tools reported in the literature, such as Return on Investment [62, 66, 96], Return Rate on annual basis [89], Levelized Cost of Energy [36, 91] and Levelized annual Cost of Energy using Net Present Value [93, 95], Benefit–cost Ratio [61], and cost-optimization algorithms [77, 80, 94] for economic analysis, but these are based on several assumptions and are applicable only for specific battery compositions and controlled grid-connected applications [61, 66, 80, 90]. These economic studies have mostly confirmed the cost benefits of second-life batteries over new batteries in terms of decrease in LCOE [91, 93], increased annual revenue [36, 61, 70, 92] and operating as well as payback years [89, 90, 92] but it should be noted that these results cannot be generalized. There are many uncertainties like unpredictable battery prices [92, 96] and application based benefits and controlled conditions [61, 69, 89, 90, 93]. It is recommended to take into account future battery and energy prices inflation for more reliable results. The importance of first-life degradation data and control of particular health indicators/ageing parameters has not been adequately discussed in previous review papers on second-life batteries in stationary storage applications. Further research is needed to conduct an up-to-date economic assessment [114] along with accurate battery capacity management for optimal and feasible control of stationary energy storage systems.

There are only a few comprehensive studies of EV battery secondary usage (B2U) as a new market apart from some initiatives [3]. This new market is distinctive in that it is the first of its kind to bring together significant stakeholders from diverse industries on a single platform, including energy firms, the automotive industry, and government. The use of batteries as a storage component in addition to renewable energy sources has the ability to simultaneously eliminate significant obstacles in the transportation, energy, and waste management sectors [87]. Battery reuse conserves resources and lowers the amount of waste produced in the environment by slowing down the recycling process. It is also suggested to overview the second-life battery market prices and policies to attain a notable adoption of electrical vehicles. This demonstrates an opportunity to improvise the policy making on domestic energy storage [115] and net metering rules by considering both economic and environmental benefits. These regulations for the SLB market are intended to look into the various aspects of using second-hand batteries, particularly concerning renewable energy systems, such as economic, environmental, and regulatory factors. The recommended approaches will be useful in delivering smart grid flexibility and improved demand-side management, as energy storage is a game changer for future power systems.

Multiple concerns have been raised about policymakers' ability to approve legislation and business models for SLBs [115]. Improved and broader analyses of the financial benefits of SLBs will eliminate economic uncertainty. More funding for second-life battery demonstration projects, as well as lowering administrative barriers to execution of the aforementioned, will help to execute this plan quickly. To assist them in overcoming the obstacles to B2U market spread, this review offers the following recommendations for B2U ecosystem players:

- Collaboration with battery manufacturers to avoid new battery competition
- A creative business model to minimize customer risks
- Collaborative efforts by regulators, key OEMs, and research institutes to set standards, demonstrations, and education for customers.

Based on the analysis presented in this review, Fig. 5 highlights the inconsistencies that exist within the literature concerning second-life battery applications and their degradation. Battery ageing modelling, optimizing aging parameters, and accurate State of Health (SOH) estimation are the most researched areas as depicted in Fig. 4. However, this review identifies the significant shortcomings in these areas, such as the application of battery first-life ageing models on second-life batteries, the absence of an accurate and online SOH estimation mechanism in secondary applications. The inability to accurately optimize aging parameters for useful life extension, and assumptions regarding battery first-life data are also lacking in this field. Approximately 65% of battery second-life studies as shown in Fig. 4 focus on degradation studies, including aging models, SOH estimation techniques, and health indicators/aging parameters. However, only 4% of the total studies address the control of these aging parameters and the impact of first-life data on battery degradation, highlighting another significant research gap. It is also identified that in comparison to the rising number of retired batteries, repurposing before reuse is falling behind significantly. This is primarily due to unavailability of the primary use data and high cost of refurbishment and repurposing of these used batteries. The economic aspect of second-life batteries has a major saying in the future of this technique. However, only 8% of second-life battery studies have performed cost analysis, and even fewer have taken into account the impact of battery degradation and battery future market prices. Additionally, no universal economic model for second-life batteries could be found in the literature, revealing a significant inconsistency (gap) in studies on the techno-economics of second-life batteries.

5.2 Future research directions 2

The extensive review of recently developed approaches for the said purpose reveals that future research in the area of battery SOH estimate has a lot of potential, including the creation of cutting-edge estimation algorithms for RUL estimation and battery cell characterization using cutting-edge health indicators. To maximize environmental benefits and to establish a future direction for selecting and assessing reliable health indicators for battery ageing research under various operating conditions, it is advised to incorporate the suggested parameters into practical repurposing and reusing applications. While the traditional approaches only produce approximations, data-driven strategies based on machine learning algorithms have the potential to produce outcomes that are more precise. A list of future research directions is included below:

- Technical challenges: Battery screening and repurposing and the need for a smart energy storage and management system during reuse applications still prevail as technical challenges. There is a lot of research scope in battery capacity dispersion studies and repurposing field.
- Accurate SOH estimation: There is still uncertainty in estimating the SOH of batteries during second-life applications, and researchers should work on developing accurate estimation techniques combining conventional and advanced machine learning methods.
- Economic and business model: There is ambiguity in quantifying the revenue/benefits available to customers and electrical vehicle manufacturers from battery second use. The existing economic models are mostly based on assumptions and specific applications/regions. A standard economic model is required that considers net present value, future battery prices, inflation, and the impact of first-use degradation history and health indicators.
- Identification and control of ageing parameters/health indicators: Health indicators/ageing parameters affecting battery ageing during second-life are being identified, and there is a need for more insight into controlling these health indicators for maximum techno-economic benefits. There are latest developments in this regard in [11], this can be used a baseline for future work.
- Impact of first-use data on second-life degradation and EOL extension: The impact of battery first-use degradation history on second life is a commonly overlooked research area that requires attention. Methods to record this data during vehicle life should be researched to determine its impact on battery ageing during second life. The initiative has been taken in [75].
- Policy making for second-life battery stationary storage applications: There are no governing rules for battery reuse in stationary storage applications, and researchers should explore consumer and environmentally-friendly policies in collaboration with other stakeholders, such as the government and EV battery manufacturers.

6 Conclusion

Due to the global increase in the penetration of EVs in transportation sector, the number of retired batteries is going to increase abruptly in the coming years. Hence, the research on reuse of these batteries for other storage applications has gained popularity. There are still many technical and economic challenges to adaptability of this reuse technology into stationery storage applications. In this paper an extensive review of second life battery degradation studies in stationary storage applications is carried out focusing on technical, economic, business models and policy recommendations prospects. The key technical areas like SOH estimation techniques, battery life cycle assessment including repurposing and methods for End-Of-Life extension of these batteries are analyzed in detail.

This paper critically examined the identification, selection and control of battery health indicators for specific applications and their impact on battery accurate ageing studies. The lack of battery first-life degradation history has a serious impact on useful lifetime estimation of these batteries in stationary storage applications. The cloud connected based storage technologies are recommended for keeping a track of battery ageing during complete life cycle. The conventional model based and data driven SOH estimation techniques are also thoroughly reviewed. This review reveals that absence of a second life battery aging model (adopting first-life ageing model; a common practice) results in uncertainties for accurate SOH estimation. Moreover, an ideal second life ageing model is also recommended based on this review which should be capable of controlling the aging parameters / health indicators for accurate SOH estimation. This ideal model should also be capable of balancing between technical and economic perspectives of second life batteries and can also accommodate battery first-life data, end of life extension.

Critical analysis of economic studies related to application of second life batteries in stationery storage applications reveals that multiple ambiguities exist in the available economic models. Cost effectiveness of these batteries (compared to new ones), price inflation over long time periods and lack of a generic business model are the major hurdles highlighted in this article. Therefore, it is suggested that the future price inflation, accurate battery market prices and net-metering rates should be paid attention for a generic economic model development. This review also reflects that only a limited number of studies have considered the impact of battery's degradation on battery economic studies. Battery degradation studies incorporating a complete life cycle analysis (including first and second life) is of immense importance for optimal techno-economic evaluation. Also, lack of incentives and policies for users and stakeholders like electric cars and battery manufacturers has caused hindrances to adopt this technology. Introduction of government policies regarding market scenarios such as low cost of second life battery in comparison to new battery, attractive net metering rates for second life batteries' users and controlled inflation in second life battery prices are suggested. As stated previously, the combined techno-economic benefits like projected future business revenues and RUL extension by accurate SOH estimation methods are expected to tackle the growing number of retired batteries from EVs by increasing the feasibility of their reuse in stationary storage applications.

Abbreviations

EV	Electric Vehicles
SLB	Second Life Batteries
LIBs	Li-ion Batteries
PV	PhotoVoltaic
B2U	Battery Secondary Usage
SIBM	Sustainable Innovation Business Model
OEMs	Original Equipment Manufacturer
ICA	Incremental capacity analysis
AFD	Average Fréchet Distance
MLSERRC	Mixed Least Square Estimator Ramp Rate Compliant
EIS	Electrochemical Impedance Spectroscopy
RUL	Remaining Useful Life
HPPC	Hybrid Pulse Power Characterization
MONAA	Multi-Objective Natural Aggregation Algorithm
SOH	State of Health
SOC	State of Charge
GV	Gridable Vehicles
R&D	Research and Development
BESS	Battery Energy Storage System
ARIMA	Autoregressive Integrated Moving Average
HI	Health Indicator
V_{pk}	Peak Voltage
C_{pk}	Peak Capacitance
LFP	Lithium Iron Phosphate
MHIs	Multiple Health Indicators
DC	Direct Current
RLR	Regularized Logistic Regression
BPNN	Back Propagation Neural Network
OCV	Open Circuit Voltage
CC	Common Current
CV	Common Voltage
AC	Alternating Current
MLR	Multivariable Linear Regression
MLP	Multilayer Perceptron
PCM	Power-Train Control Module
EOL	End of life
GEMS	General Energy Management System
MLIPC	Multi-Level Interlaced Pulse Charging
HPPC	Hybrid Pulse Power Characterization
LMO	Lithium-Ion Manganese Oxide
PSUs	Power Supply Units
PDF	Probability Density Function
SMEs	Small and Medium Enterprises
ROI	Return Of Investment
RR	Return Rate
ESS	Energy storage system
NPV	Net Present Value
ACOE	Annual cost of Electricity
ToU	Time of use
ROIT	Return-On-Investment Time
PI	Profitability Index
PVT	Present Value of Throughput
CCS	Centralized Charging Station
LCOE	Levelized Cost Of Electricity
GHG	Greenhouse Gas

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