Modeling the Demand and Supply of Reconditioned Electric Vehicle Batteries under Consideration of Stakeholder Interests

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Sandra Huster, M.Sc.

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Erster Gutachter: Prof. Dr. Frank Schultmann
Zweiter Gutachter: Prof. Dr. Simon Glöser-Chahoud

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Abstract

The transition to electric mobility is expected to significantly increase the number of electric vehicle batteries (EVBs) reaching end of life (EoL). As EVBs contain critical raw materials and their production is associated with significant environmental impacts, it is essential to manage them in a sustainable manner. Circular EoL strategies include recycling EVBs at the material level, reconditioning them for reuse as spare parts in electric vehicles, and repurposing them for use in non-automotive applications. While recycling and repurposing have received considerable attention in both academia and industry, reconditioning remains insufficiently understood, particularly in terms of its economic viability and its acceptance among key stakeholders. The objective of this thesis is to support EoL decision-making by developing a tool that evaluates how stakeholder decisions and technical developments influence the supply and demand of reconditioned EVBs.

To this end, four studies (A–D) were conducted. Study A presents a simulation model estimating the volume of reusable EVBs as well as the number of electric vehicles requiring battery replacement. The estimation is based on the lifetime mismatch between batteries and vehicles and considers constraints such as battery quality and the age of the host vehicle. Study B investigates consumer demand through a discrete choice experiment. It analyzes how product attributes, such as price, life expectancy, and environmental footprint, affect preferences for replacing a failed EVB with either a new or reconditioned battery, or for retiring the vehicle entirely. Study C integrates the findings from Studies A and B and incorporates additional insights from stakeholder interviews to develop a discrete event and agent-based simulation model. The model includes 49 parameters, reflecting trends in recycling, repurposing and reconditioning costs, battery technology developments, consumer and workshop preferences, and legal requirements such as recycled content targets. The model outputs projections of reconditioned EVB supply and demand up to 2050. Study D addresses the complexity and computational burden of the integrated model by using machine learning methods to approximate its input-output relationships. It shows that different key performance indicators can be predicted with varying accuracy depending on the machine learning approach applied.

The studies show that reconditioning can be a valuable component of a circular battery economy, provided that key technical, economic and collaborative conditions are met. The simulation approach developed in this thesis serves as a flexible tool for exploring future scenarios and supporting strategic decisions by manufacturers and policymakers. Future research could examine additional stakeholder dynamics and technical challenges of reconditioning, and analyze its ecological impacts in greater detail.

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List of Abbreviations

aao	all-at-once (estimation approach)
ABM	Agent-based modelling
ANN	Artificial neural network
ARIMA	Autoregressive integrated moving average
BEV	Battery electric vehicle
BMS	Battery management system
CE	Circular economy
DCE	Discrete-choice experiment
DES	Discrete event simulation
DT	Decision tree
EoL	End-of-life
EV	Electric vehicle
EVB	Electric vehicle battery
GHG	Greenhouse gas
GPR	Gaussian process regression
KPI	Key performance indicator
LCA	Life cycle assessment
LFP	Lithium-iron phosphate (cathode)
LHS	Latin hypercube sampling
LIB	Lithium-ion battery
MSE	Mean square error
NMC	Nickel manganese cobalt (cathode); numbers indicate the ratio of nickel-to-manganese-to cobalt, e.g., NMC622
OEM	Original equipment manufacturer
rec	Recursive (estimation approach)
RF	Random forest
RMSE	Root mean square error
SD	Standard deviation
SoH	State of health
XGB	XGBoost

Part I: Framework

1 Introduction

1.1 Motivation

The global adoption of electric mobility is rising rapidly. According to projections by the International Energy Agency, the global electric vehicle (EV) stock is expected to reach between 525 and 585 million vehicles by 2035, up from approximately 45 million in 2023 (IEA 2024a). While EVs are associated with substantial greenhouse gas (GHG) emission reductions compared to internal combustion engine vehicles (Verma et al. 2022), this environmental benefit is partially offset by the high energy and resource demands linked with the production of electric vehicle batteries (EVBs) (Farzaneh and Jung 2023). For instance, the VW ID.3 Pro is equipped with a 59 kWh battery (Volkswagen 2025a). Producing a battery of this size requires approximately 6.1 kg of lithium, 31.0 kg of nickel, 10.4 kg of cobalt and 9.7 kg of manganese, assuming a cell chemistry with a nickel-manganese-cobalt ratio of 6:2:2 (NMC622), which is common in current EVBs (Maisel et al. 2023; Marie and Gifford 2023). The environmental challenges of sourcing these input materials, combined with the substantial energy required for cell manufacturing, underscore the importance of managing EVBs responsibly across their life cycle.

Given this environmental intensity, the end-of-life (EoL) treatment of EVBs becomes a critical determinant of their overall sustainability. The optimal EoL strategy, however, remains a subject of ongoing debate. Among the available options, recycling is the most established. It entails the recovery of materials from decommissioned batteries to re-enter production loops. Although still maturing, the EVB recycling sector benefits from prior experience with other battery chemistries, and considerable capacity is expected to be added both in Europe and globally by 2050 (IEA 2024b; Miksad 2024). Regulatory support, such as the EU Battery Regulation adopted in 2024, enforces recovery targets for raw materials and mandates minimum levels of recycled content in new batteries (European Parliament and European Council 2024a). However, the EU waste hierarchy states that "preparation for reuse" should precede material recovery (European Parliament and European Council 2008). For EVBs, reuse can take two forms: The first is repurposing, in which batteries are applied in non-automotive contexts, such as grid-connected stationary storage for renewable energy. Repurposing can involve the use of entire battery systems or selected modules or cells and has been explored in numerous pilot projects (Patel et al. 2024). The second option is preparing the EVB, or parts of it, for reuse in the original application, i.e., in a vehicle. The EU Battery Regulation refers to this under the term "remanufacturing", and requires a minimum state-of-health (SoH) of 90% on a battery system level, and low variance among cells (European Parliament and European Council 2024a). However, in conventional remanufacturing literature, such a definition would not qualify as full remanufacturing, which is defined as restoring a product to at least as-new specifications, including a warranty equivalent to that of a new product (Deutsches Institut für Normung e. V. 2023). As EVBs cannot currently be restored to their original quality (Autocraft Solutions Group 2023), the term “reconditioning”, understood as restoring to a high, yet not new, performance level (Ijomah et al. 2004), appears more accurate. Due to the reduced performance compared to a new EVB, reconditioned batteries are assumed to only be used as spare batteries in older EVs and not for installation in new vehicles. Unlike recycling and repurposing, which are increasingly industrialized, reconditioning is still in a development phase. Only a few firms, such as Mercedes and Stellantis (Mercedes-Benz n.d.; Stellantis 2023), are actively pursuing it, while others like Volkswagen merely mention it as a future option (Volkswagen 2025b).

Despite its potential, reconditioning faces substantial barriers. Technologically, it requires the development of robust, non-destructive disassembly methods and fast SoH diagnostics (Graner et al. 2023). Economically, these efforts are only viable if there is sufficient demand. However, forecasting such demand is complex. Time series methods are ineffective given the novelty of the market, and reconditioning introduces more stakeholders compared to other EoL options that are potentially involved in the decision-making process. Recycling and repurposing are primarily business-to-business transactions involving original equipment manufacturers (OEMs), recyclers or energy providers (Kulkov et al. 2025; Srinivasan et al. 2025). Reconditioning, on the other hand, also involves workshops and end customers. Their decisions may depend not only on price and performance, but also on factors such as trust in the technology or its environmental impact (Huster et al. 2024a, 2024b).

Additionally, the entire EoL landscape for EVBs is subject to high uncertainty. Future EV sales, regulatory shifts, and technological developments in all three EoL pathways—recycling, repurposing, and reconditioning—are difficult to predict. Thus, instead of static forecasting, a flexible, scenario-based approach is needed to assess supply and demand under diverse future conditions, enabling robust strategic planning for sustainable EVB management.

1.2 Research Objectives

The primary objective of this research is to develop a methodology for quantifying both the supply and demand of reconditioned spare EVBs. Such an analysis integrates a product-oriented view, focused on the physical availability of reconditioned EVBs, and a stakeholder-oriented view, addressing the socioeconomic and economic dynamics influencing reconditioning practices. Achieving this objective requires both empirical data collection and analytical models capable of scenario-based evaluation. The overarching aim is to develop a decision-support tool that enables OEMs and policymakers to evaluate the effects of their decisions and of potential developments beyond their control. Accordingly, this research is structured around four interrelated objectives, which are depicted in Figure 1.1 and delineated in the following sections 1.2.1 to 1.2.4.

1. *Evaluation of the product flow of reconditioned EVBs*

Understanding the flow of reconditioned EVBs is essential for assessing the feasibility of reconditioning as an EoL strategy within a circular economy framework. However, robust estimates of how many batteries may be available and suitable for reconditioning remain limited. Existing research has predominantly focused on recycling- and repurposing-oriented material flow models (e.g., Ai et al., 2019; Sanclemente Crespo et al., 2022), while reconditioning has often been addressed only through static assumptions, such as applying a fixed reconditioning share to the total amount of EoL batteries (e.g., Bobba et al., 2019; Standridge et al., 2014). These approaches typically disregard the uneven aging of vehicles and batteries as well as the stochastic nature of vehicle and battery failures. As a result, they overlook whether there is an actual demand for reconditioned units. Reconditioning is only viable if a vehicle experiences a battery failure prior to reaching end-of-life, and if a suitable replacement battery is available, both temporally and technologically. Without capturing these dependencies, existing models cannot realistically represent the conditions under which reconditioning can occur.

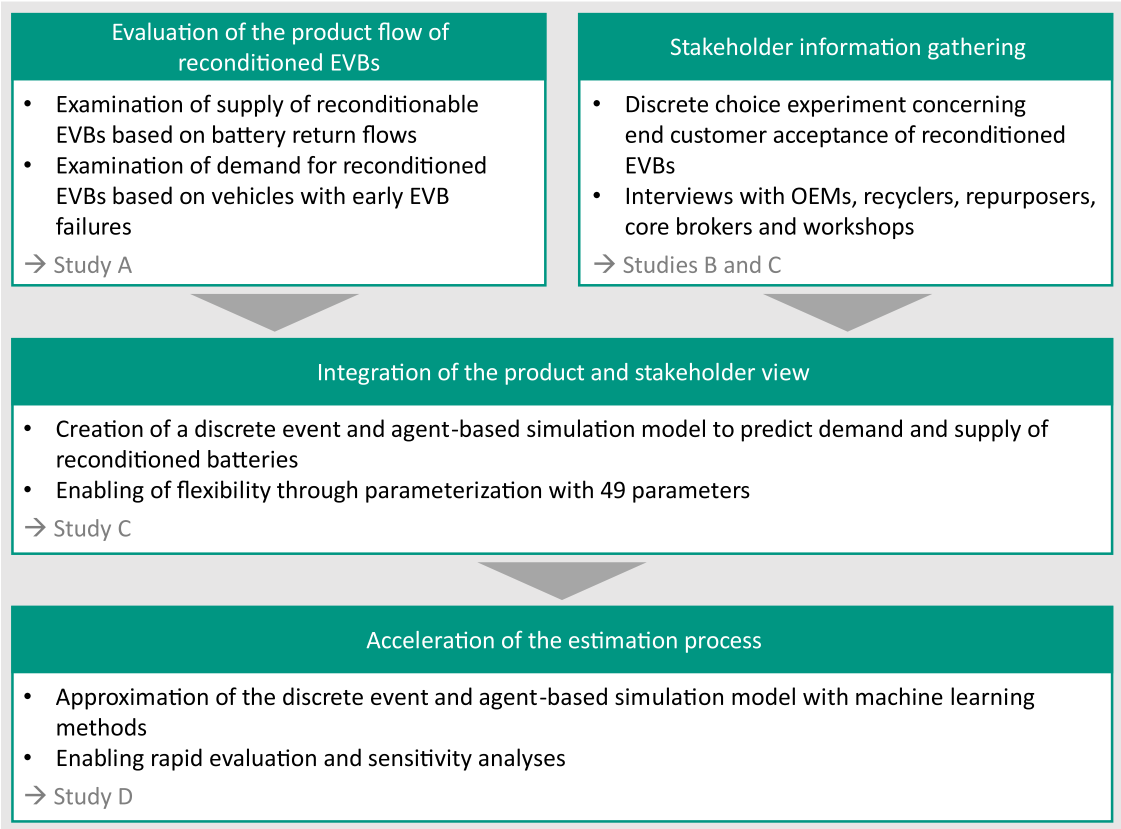


Figure 1.1: Overview of the research objectives and the corresponding studies

This gap is addressed in Study A. A discrete-event simulation model is developed that distinguishes between battery and vehicle life cycles and explicitly integrates both supply and demand mechanisms. Battery failures generate replacement demand, which is met by either new or reconditioned units, depending on their availability and technical compatibility. This allows for a time-resolved estimation of reconditioned battery flows that reflects replacement needs arising from lifetime mismatches. The objective is to quantify these flows under varying assumptions concerning battery and vehicle longevity, as well as replacement policies. The product flow modeling serves as the basis for subsequent analyses of the battery EoL system in Study C.

2. Stakeholder information gathering

The reconditioning of EVBs involves a wide range of stakeholders whose decisions directly affect the viability of this EoL strategy. Beyond technical feasibility, its implementation depends on consumer acceptance and the decisions of actors such as OEMs, recyclers, repurposers, and workshops. Stakeholder interests regarding reconditioning have been explored in relation to automotive parts in general (Kalverkamp and Raabe 2018) and to EVBs in particular (Slattery et al. 2024; Wrålsen et al. 2021). However, these studies primarily examine the functional roles stakeholders play in process chains and material flows, rather than how their decisions actively shape these flows. Furthermore, current research on reconditioned EVBs predominantly emphasizes industrial stakeholders, with limited attention to consumer perspectives. Belbağ & Belbağ (2023) reviewed existing literature on consumers' perspectives on remanufactured parts in general and found out that most studies employed structural equation modelling, regression analysis or discrete-choice experiments (DCEs). While DCEs have been widely applied in the EV domain to investigate adoption and willingness-to-pay for specific attributes (Han and Sun 2024; Liao et al. 2018), applications to *reconditioned* EVBs remain scarce. Existing studies in the EVB reconditioning domain have examined willingness-to-pay or acceptance at a more aggregated level, without differentiating between consumer segments or systematically quantifying preferences for specific attributes of reconditioned EVBs such as cost or lifespan (Chinen et al. 2022; Tondolo et al. 2021). Moreover, they omit realistic alternatives, such as scrapping the entire vehicle instead of replacing the battery.

This dissertation addresses these gaps through empirical investigations targeting both demand and supply side perspectives. Study B employs a discrete choice experiment to examine how consumers weigh trade-offs between cost, lifetime, and environmental benefits of reconditioned EVBs. The design includes realistic alternatives to replacing a failed EVB with a reconditioned one to reflect actual decision-making contexts and enables examining preference heterogeneity across demographic groups. This allows for the identification of key drivers and barriers to acceptance among different consumer segments. Study C complements these insights with qualitative findings from expert interviews conducted with stakeholders involved in the EoL EVB value chain, including OEMs, recyclers, repurposers and workshops. The interviews provide insights into strategic considerations and perceived obstacles. Together, these studies offer the stakeholder-specific information required to inform model assumptions and scenario development in the subsequent simulation-based analyses.

3. Integration of the product and stakeholder view

Reliable forecasts of the supply and demand of reconditioned EVBs require the integration of both technical flows and stakeholder behavior. Existing studies have predominantly approached reconditioning from a technical perspective, focusing on the supply side through material flow analyses (Abdelbaky et al. 2020; Kastanaki and Giannis 2023). These models often estimate the reconditioning supply as a fixed percentage of returning batteries, either across all EoL batteries (Bobba et al. 2019), those within warranty (Abdelbaky et al. 2020), or those under a specific age threshold (Kastanaki and Giannis 2023). While useful for technical feasibility estimates, these methods lack sensitivity to behavioral, economic, and policy-driven factors. Only a few studies to date have attempted to model both supply and demand for reconditioned EVBs in an integrated framework. When demand is included, it is often based on simplified assumptions, such as a fixed share of consumers opting for reconditioned batteries (Tao et al. 2022), or the assumption that reconditioned and new batteries are perfect substitutes (Duarte Castro et al. 2021). These approaches do not account for how consumer preferences vary with product attributes or how stakeholder decisions, such as those of OEMs, workshops, and recyclers, shape both supply and demand. In most cases, stakeholder behavior is not explicitly modeled, but rather implied through fixed parameters. As a result, the interactive effects of economic developments, policy measures, and consumer interests within the reconditioning network remain underexplored.

These limitations are addressed in Study C, where a flexible simulation model is developed based on Studies A and B. The simulation model integrates both the product flow and stakeholder perspectives to predict the supply and demand of reconditioned EVBs. The model combines discrete event and agent-based elements to capture the time-dependent availability of reconditioned EVBs, stochastic failure events, and the influence of key stakeholder decisions. Flexibility is achieved through parametrization with 49 parameters, allowing the model to simulate a broad range of future scenarios, considering policy interventions and business strategies.

4. *Acceleration of the estimation process*

The simulation model developed in Study C enables a comprehensive analysis of the reconditioning system. However, while runtimes remain moderate for single evaluations, they accumulate quickly when multiple runs are required, particularly given the model's 49 input parameters. This limits its applicability for large-scale sensitivity analyses or optimization tasks. To support more efficient decision-making, the final objective of this thesis is to accelerate the evaluation process by approximating the model's outputs using machine learning techniques.

Previous research has explored the use of surrogate models to approximate simulation outputs, particularly in the context of agent-based and discrete event simulations (Angione et al. 2022; Hürkamp et al. 2021). However, many of these applications focus on static or aggregate outputs. In contrast, the simulation model developed in Study C produces dynamic outputs, namely, multiple key performance indicators (KPIs) projected over several future time steps. This introduces a time-dependent structure that must be captured by the surrogate model, despite the absence of historical time series data. As a result, classical forecasting techniques such as autoregressive integrated moving average (ARIMA) or recurrent neural networks are not applicable (Hyndman and Athanasopoulos 2021). Moreover, the combination of time-dependent outputs and multiple KPIs makes the prediction task distinctive and remains insufficiently addressed in the surrogate modeling literature.

Study D addresses these gaps by approximating the simulation model from Study C using machine learning techniques that predict multiple key performance indicators over time. Two modeling strategies are investigated: an all-at-once approach, which predicts the entire output sequence in a single step, and a recursive approach, which iteratively predicts each time step using prior outputs. In doing so, Study D contributes to research on multi-output surrogate modeling for simulation applications and provides empirical insights into the feasibility and accuracy of such approaches when historical data is unavailable. The resulting surrogate model enables fast evaluation of reconditioning outcomes across a wide range of scenarios.

1.3 Structure of the Thesis

The thesis is structured in two parts, as depicted in Figure 1.2. In Part I, Section 2 introduces basic concepts relevant for the entirety of the thesis. This includes background information about the design of EVBs (Section 2.1), such as the structure of EV battery packs and employed cell chemistries, the EoL pathways of EVBs, namely reconditioning (Section 2.2.1), repurposing (Section 2.2.2), and recycling (Section 2.2.3), and the stakeholders involved in the EoL supply chain of EVBs (Section 2.3). Subsequently, the studies A–D included in this thesis are summarized in Section 3. For each study, the motivation and methodology are briefly outlined, followed by a summary of the results and a discussion of the findings and limitations of the approach. Section 4.1 connects the results of the studies with the research objectives set in Section 1.2, before overarching limitations of the thesis are discussed in Section 4.2, along with an outlook on further research. Part I ends with a summary of the thesis in Section 5. In Part II, Studies A–D are included in full length.

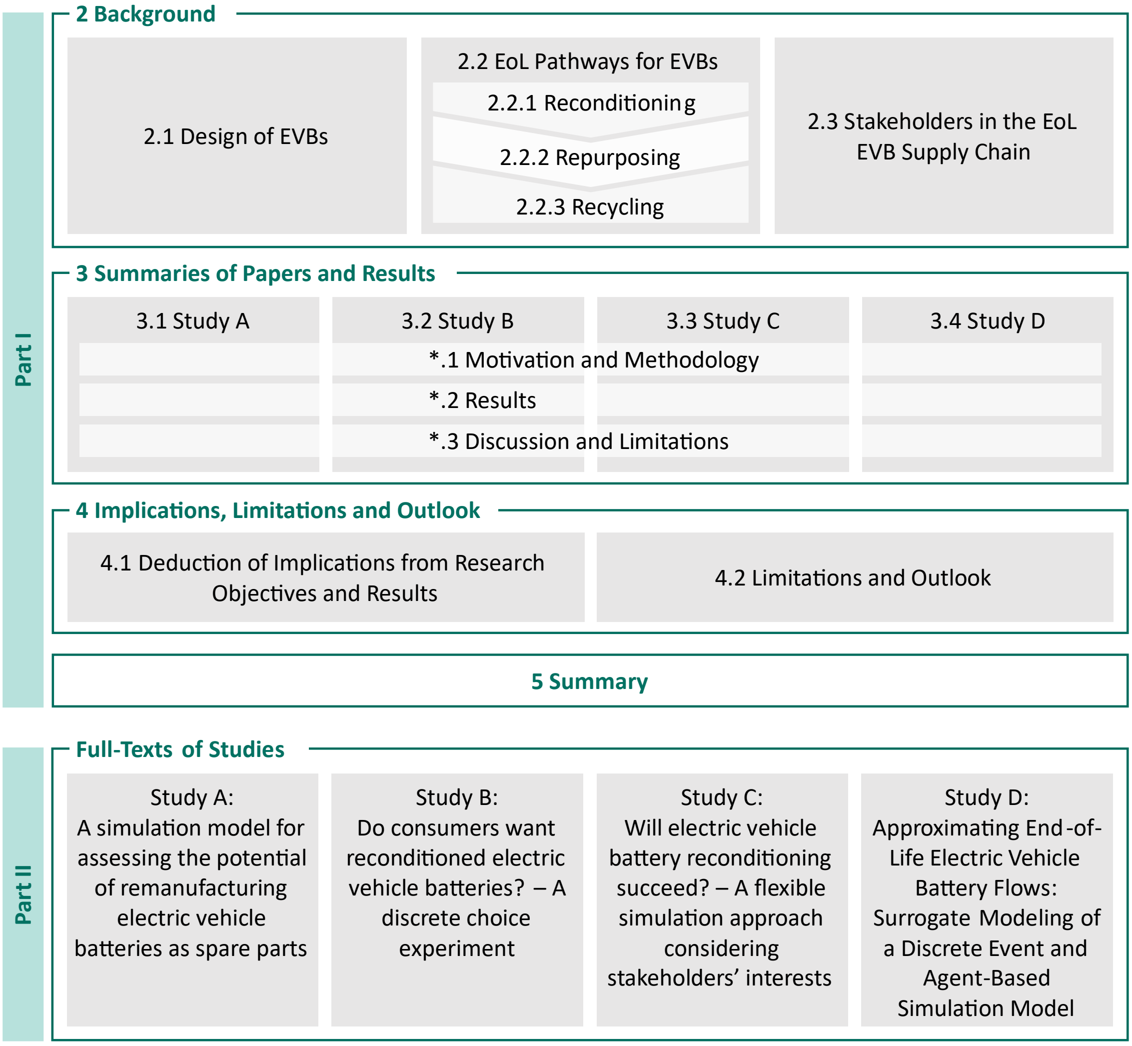


Figure 1.2: Structure of the thesis

2 Background

This section provides background information on EVB design, beginning with the hierarchical structure of battery systems, including cells, modules, and packs, as well as the basic configuration of lithium-ion batteries (LIBs). It then describes the EVB EoL pathways, including reconditioning, repurposing, and recycling. Finally, the roles of relevant stakeholders involved in the EoL value chain are outlined.

2.1 Design of EVBs

EVBs are available in various shapes and sizes. A schematic representation of one possible design is shown in Figure 2.1. Enclosed within a steel or aluminum housing, the battery pack comprises battery modules, a battery management system (BMS), optionally a cooling system, and additional peripheral components such as high-voltage connectors and cabling (Kampker et al. 2018). Each module consists of multiple cells, which form the core functional units of the EVB system. Battery cells are commonly produced in cylindrical, prismatic, or pouch formats (Hettesheimer et al. 2017). No single cell format is inherently superior to the others; therefore, Neef et al. (2022) assume that all formats will continue to coexist in the market. Currently, regional production capacities for cell formats differ: in China, the majority of produced cells are prismatic; in the United States, production predominantly focuses on cylindrical cells; while in Europe, pouch cells constitute the largest share of cell production (Neef et al. 2022). Pouch cells offer advantages in terms of power density and cost-efficiency of production; in contrast, prismatic cells demonstrate superior thermal properties; cylindrical cells, on the other hand, exhibit benefits regarding energy density and standardization potential (Full et al. 2020).

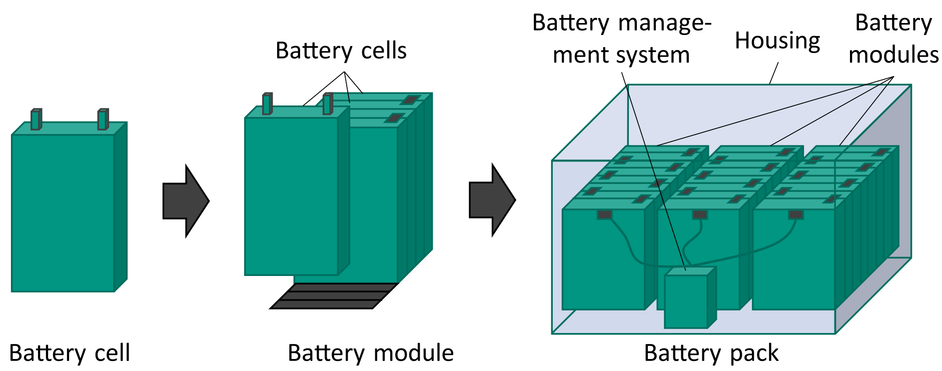


Figure 2.1: Schematic design of an EVB (based on Harper et al., 2019; Kampker et al., 2016)

Currently, the majority of EVBs are LIBs (IEA 2024a). A schematic representation of a LIB is shown in Figure 2.2. As illustrated, LIBs consist of two electrodes, an anode and a cathode, each connected to a current collector, and separated by a separator immersed in an electrolyte (Divakaran et al. 2021). Lithium ions transport energy between the electrodes during charging and discharging (Rathore and Verma 2024). Among the various components, the cathode represents the most valuable part of the battery, accounting for approximately 67% of the total material value (Heimes et al. 2023).

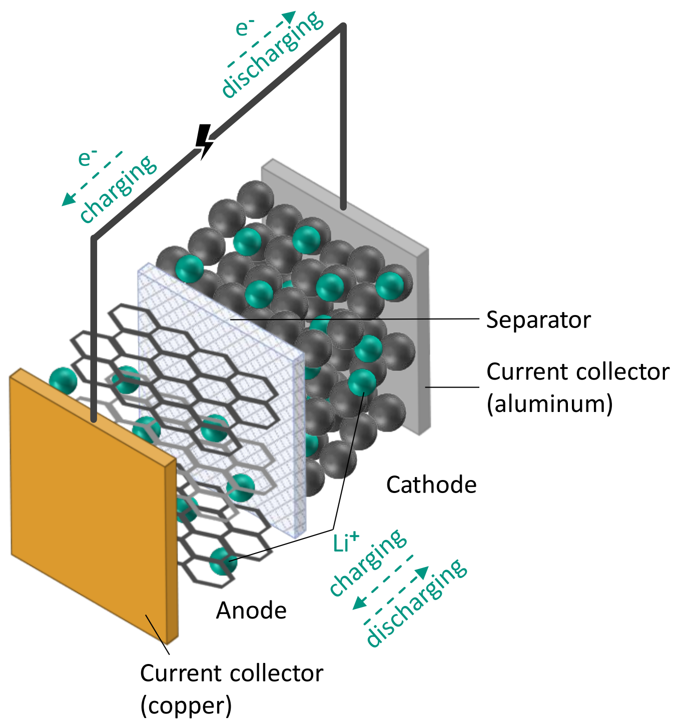


Figure 2.2: Schematic structure of a LIB (based on Divakaran et al., 2021; Neef et al., 2022). Li^+: lithium ion, e^-: electron

LIBs are commonly classified according to the cathode material employed. At present, nickel manganese cobalt (NMC) and lithium iron phosphate (LFP) cathodes are the most widely used types (IEA 2023). In the case of NMC cathodes, the numbers appended to the abbreviation denote the proportional composition of nickel, manganese, and cobalt. For instance, NMC111 indicates approximately equal shares of the three metals, while NMC622 corresponds to a ratio of 6:2:2 for nickel, manganese, and cobalt, respectively. Higher nickel variants, such as NMC811 and in the future NMC955 (90% nickel, 5% manganese, 5% cobalt), reflect a progressive reduction of manganese and cobalt content (Marie and Gifford 2023). In LFP cathodes, nickel, manganese and cobalt, which are all considered critical materials (IEA 2025a), are absent (IEA 2024a). This development mitigates supply risks, particularly with respect to cobalt, which is predominantly sourced from the Democratic Republic of Congo with concerns regarding environmental and health challenges (Nkulu et al. 2018), and simultaneously reduces material costs due to cobalt's relatively high price (Natural Resources Canada 2023). Neef et al. (2022) estimate the cost of NMC111 active material at approximately 32€ per kilogram, NMC811 at 30€ per kilogram, and LFP at approximately 10€ per kilogram. LFP cathodes are therefore generally less expensive than NMC variants and additionally offer advantages in terms of longer cycle life and enhanced safety (Ding et al. 2019). These benefits, however, are offset by lower energy density (Ding et al. 2019). Beyond these dominant chemistries, several alternative cell chemistries exist, though they are currently less common (IEA 2023). Future innovations may emerge from technologies such as all-solid-state batteries, which eliminate the need for liquid electrolytes, or sodium-ion batteries, which utilize sodium ions instead of lithium ions for charge transfer (Iqbal et al. 2023).

Although the rate and degree of degradation vary across battery chemistries, all cells age eventually, which manifests through the loss of lithium inventory and active material (Xiong et al. 2020). Nevertheless, aging does not occur uniformly across the cells within a battery system. Variations introduced during manufacturing, as well as differing operational conditions within the system, such as localized temperature differences, lead to heterogeneous cell degradation (Han et al. 2019). This non-uniform degradation results in performance losses at the system level, as the performance of the battery pack is constrained by its weakest cells (Han et al. 2019). By replacing those degraded cells, a performance close to the original one can be restored (Kampker et al. 2020; Mathew et al. 2017).

Alternative EVB designs, such as cell-to-pack configurations, have been developed to enhance the energy density by omitting the module housing (Hettesheimer et al. 2023). However, these designs pose challenges for disassembly and repair, as the cells are often bonded together using adhesives that are difficult to dissolve without damaging the cells (Rodrigues et al. 2025).

2.2 EoL Pathways for EVBs

The significance of a circular economy (CE) in facilitating the transition toward a sustainable business ecosystem is reflected in several recent regulatory developments and initiatives, such as the Circular Economy Action Plan as an overarching framework, the Ecodesign for Sustainable Products Regulation, and the revised End-of-Life Vehicles Regulation (European Parliament and European Council 2020, 2023, 2024b). The strategic relevance of batteries within this context is underscored by a dedicated legislative framework: Regulation (EU) 2023/1542 on Batteries and Waste Batteries, referred to hereafter as the EU Battery Regulation. Within this regulation, EVBs are classified as a distinct category, allowing for the definition of EVB-specific rules. Promoting battery circularity is a central objective of the EU Battery Regulation, which defines four EoL strategies: recycling, reuse, repurposing, and remanufacturing. It also includes the preparation for reuse and repurposing. Recycling is defined as a circular strategy at the material level, wherein waste materials are reprocessed into new products, substances, or materials (European Parliament and European Council 2008). Repurposing refers to the use of an entire battery or battery components "for a purpose or application other than that for which the battery was originally designed" (European Parliament and European Council 2024a). Reuse is defined as applying a product or component for the same purpose as before, with preparation limited to checking, cleaning, or repairs, without further extensive preprocessing (European Parliament and European Council 2008). Remanufacturing, on the other hand, is described as an "extreme case of re-use entailing the disassembly and evaluation of the cells and modules of the battery and the replacement of a certain amount of these cells and modules" (European Parliament and European Council 2024a). Consequently, remanufactured batteries may only be used in their original application. Moreover, specific technical criteria are required: a minimum of 90% of the original capacity must be retained, and the state-of-health across cells must be homogeneous, with a maximum deviation of 3% (European Parliament and European Council 2024a).

As noted in Section 1, this definition of remanufacturing diverges from that used in the automotive sector, where remanufactured products are expected to meet at least as-new specifications (CLEPA et al. 2016; Deutsches Institut für Normung e. V. 2023). To address the discrepancy between definitions, the term "reconditioning" can be used to describe a functional, though not like-new, condition (Ijomah et al. 2004). In the following, the terms remanufacturing and reconditioning are used interchangeably, reflecting the terminology of the EU Battery Regulation, although "reconditioning" would be more precise The CE pathways of EVBs are schematically depicted in Figure 2.3.

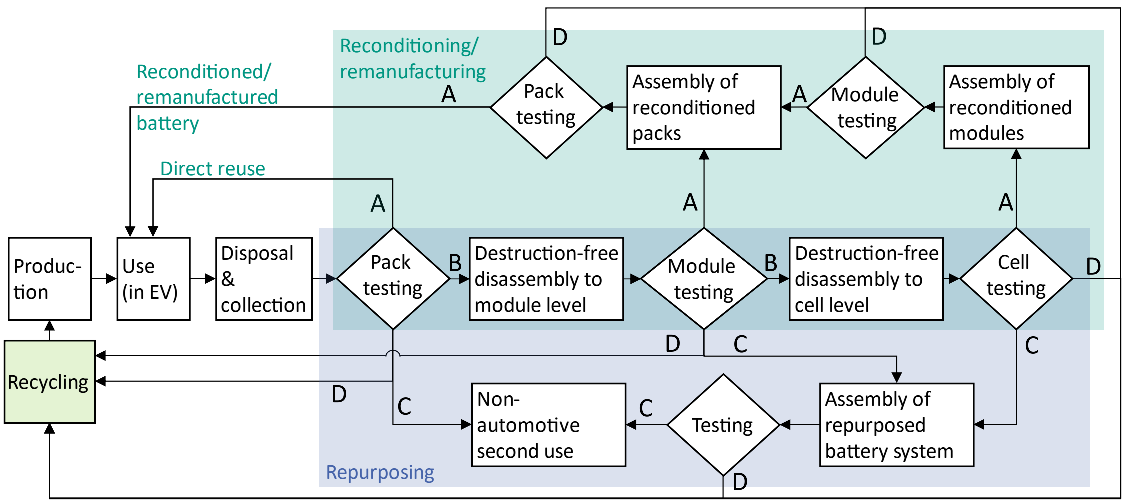


Figure 2.3: EoL pathways for EVBs (based on Börner et al. 2022; Glöser-Chahoud et al. 2021; Huster et al. 2024b; Kampker et al. 2020; Neri et al. 2024). A: Suitable for automotive reuse; B: Partially suitable for automotive or non-automotive reuse; C: suitable for non-automotive reuse; D: Unsuitable for any reuse

While the EU Battery Regulation does not rank the battery EoL options, the EU waste hierarchy states that preparation for reuse should be prioritized over material recovery (European Parliament and European Council 2008). In the context of EVBs, this places direct reuse, reconditioning, and repurposing above recycling. This ranking is also supported by circular economy literature (Muñoz et al. 2024; Potting et al. 2017). It is important to note, however, that reconditioning and repurposing do not replace recycling; rather, they delay it. This delay has benefits, as it allows for more effective use of the material and energy invested in the product, but at the same time, it also presents challenges, since the materials remain unavailable for new battery production during the extended use phase (Chen et al. 2019).

There is currently no consensus on the minimum quality a battery pack, module, or cell must meet to be considered suitable for automotive or non-automotive reuse. The most commonly used metric for such assessments is the state of health (SoH). It describes the aging of a battery and is typically determined by relating the current value of a performance measure, such as capacity or impedance, to its initial value (Yang et al. 2021). Regarding SoH thresholds, the EU Battery Regulation requires a minimum of 90 percent for remanufactured batteries (European Parliament and European Council 2024a). Kampker et al. (2023) consider entire battery packs with an SoH of at least 80 percent suitable for reuse in EVs, while modules below this threshold may still be eligible for repurposing. However, batteries with an SoH below 80 percent, combined with a cell-to-pack design, or those that have undergone deep discharge, are generally excluded from any form of reuse or repurposing (Kampker et al. 2023a). Packianather et al. (2024), on the other hand, classify battery packs with an SoH of 90 percent or more as suitable for direct reuse in electric vehicles, and those with at least 80 percent as candidates for repurposing without requiring disassembly. On the module level, they propose a threshold of 85 percent SoH for repurposing and 50 percent for individual cells. Patel et al. (2024) also identify batteries with more than 80 percent SoH as appropriate for reuse, and define the repurposing range as 30 to 80 percent. Montes et al. (2022) assume that the second-life phase of a battery begins at around 75 to 80 percent SoH and concludes at approximately 50 percent. Fallah & Fitzpatrick (2024) add an age limit of twelve years, from which onwards the share of reusable cells in a battery pack is assumed to be low, leading directly to recycling. Given the variation in reported thresholds, no universally applicable SoH values can be assigned to the quality categories A to D in Figure 2.3. Montes et al. (2022) point out, that besides the SoH, it should be considered that different second-life applications pose different requirements on battery capacity, power, configurability and other characteristics. Those characteristics and application requirements should be carefully matched.

The following sections provide a more detailed overview of reconditioning, repurposing and recycling.

2.2.1 Reconditioning

Reconditioning EVBs for reuse as spare parts in an EV involves complex processes including partial disassembly, testing, and reassembly, as depicted in Figure 2.3Figure 2.3. Because reconditioning requires the destruction-free replacement of faulty modules or cells, it shares certain characteristics with repurposing at the module or cell level. However, reconditioning imposes higher requirements on the battery performance, as it is intended for another use cycle in the EV, with the corresponding requirements in terms of power, safety and durability (Neri et al. 2024). Ensuring such high quality necessitates thorough testing of both individual modules and the entire reconditioned battery system with regard to electrical performance and thermal stability (Neri et al. 2024). While the process depicted in Figure 2.3 assumes the exclusive use of recovered battery components, it is also possible to integrate new cells or modules to meet the high quality needs (Kampker et al. 2020). Naturally, the use of new components increases the environmental impact.

Disassembly remains one of the key challenges in reconditioning. Currently, EVB disassembly is mainly performed manually (Zorn et al. 2022), making the process both time-consuming and costly, but also flexible (Lander et al. 2023). The flexibility is necessary given the wide variety of EVB shapes, joining techniques, and designs (Rettenmeier et al. 2024). Enhancing cost-efficiency in disassembly could be achieved through standardization of battery design, which would not only facilitate automation but also improve the compatibility of components and thus increase the feasibility of recombining them into reconditioned modules (Alamerew and Brissaud 2020). Designing EVBs for disassembly in the first place would likewise contribute to more cost-effective and straighforward disassembly and reassembly (Rosenberg et al. 2022). Further improvements are expected from the EU Battery Regulations's requirement to provide parties with legitimate interests, e.g., reconditioners, with battery dismantling information via a Battery Passport in the future (European Parliament and European Council 2024a).

A further challenge is the diagnostic assessment of the battery prior to disassembly (Eggleston et al. 2024). Reconditioners must be able to evaluate the EVB's condition in detail to make informed decisions about whether to acquire the battery and to what extent it should be disassembled (Slattery et al. 2024). Currently, such information is typically accessible only to OEMs via the BMS (Spancken and Stelter 2024). This situation is expected to change, as the EU Battery Regulation mandates that battery owners and parties with legitimate interest are entitled to information about the EVB's condition stored in the BMS, e.g., the SoH and expected lifetime (European Parliament and European Council 2024a). Until this system is implemented, battery grading remains costly and time-consuming, and it is generally not possible to assess the SoH of individual cells without disassembly (Kampker et al. 2020).

The cost of reconditioning and the resulting price of the reconditioned battery are also critical factors for market viability. Some studies suggest that EVBs are generally too costly to replace (Wang et al. 2020), which highlights consumers' sensitivity to price and the potential trade-off between purchasing a (reconditioned) spare battery and scrapping the vehicle entirely. Others, however, present reconditioning as a means for OEMs to reduce warranty-related costs (Sainz 2023). As a result, demand for reconditioned batteries may originate both from end consumers and OEMs. Kampker et al. (2023) assume that a reused battery pack retains about half of its value compared to a new one and can be aquired for approximately 75 €/kWh. Alamerew & Brissaud (2020), on the other hand, assume a 40 percent value loss, with reconditioning costs of about 100 €/kWh. It should be noted that the relative values are based on assumed prices for new batteries at the time of the studies. As battery prices per kWh are volatile, though generally trending downward (IEA 2025b), the retained value of reconditioned batteries and the processing costs must be evaluated against current market prices, which may influence the economic viability of reconditioning.

In the EU, reused or reconditioned batteries must comply with most of the regulatory requirements applicable to new batteries under the EU Battery Regulation. The economic operator placing the reconditioned battery on the market assumes responsibilities of the original manufacturer concerning regulatory compliance, including safety, durability, labelling, and extended producer responsibility (European Parliament and European Council 2024a).

2.2.2 Repurposing

EVBs can also be given a second life after their use in vehicles by being repurposed for alternative applications such as stationary energy storage for renewable energies, grid stabilization, or emergency backup systems (Dong et al. 2023). These applications typically share a common feature: they place lower demands on battery power due to reduced charging and discharging rates compared to automotive use (Lee et al. 2021). Depending on the intended use case, two general approaches to repurposing can be distinguished, as depicted in Figure 2.3. After collection and inspection, one option is to retain the battery system in its entirety and reuse it without disassembly (Patel et al. 2024). The alternative is to disassemble the system at least to the module level, test individual modules or cells, and reassemble a new battery system using only those modules or cells that meet the required quality standards (S et al. 2025). As laid out in Section 2.2.1, disassembly remains a cost-intensive process, thus, avoiding this step offers potential cost advantages in the first approach. Although more costly, the second approach allows for selective use of the most suitable modules and cells and enables the design of repurposed systems tailored to specific use cases (Montes et al. 2022). For an overview of European companies engaged in repurposing activities, categorized by collection, transportation, testing and diagnosis, disassembly, and integration and installation, see Bockey & Heimes (2024).

Most challenges described for reconditioning also apply to repurposing batteries, like the labor-intensive disassembly of unstandardized EVBs, the determination of the SoH, and the transfer of producer responsibilities from the original manufacturer to the operator placing the repurposed battery on the market (Kampker et al. 2023b). Also the economic and technical viability of repurposing EVBs is challenged by alternative battery chemistries better suited for stationary applications. Technologies commonly used in stationary storage and technologies under development may outperform repurposed EVBs in terms of cyclic lifetime and cost efficiency, particularly due to lower material costs, such as reduced cobalt content (Börner et al. 2022; Kyon Energy 2024). As Börner et al. (2022) highlight, EV batteries are optimized for vehicle-specific requirements like power density and fast charging, making them suboptimal for stationary use cases that demand long cycle life and stable performance over time. However, repurposed batteries have the advantage of availability, and Aguilar Lopez et al. (2024) show that all demand for stationary grid storage of the European Union could be fulfilled with repurposed EVBs by 2047 even in a high storage demand scenario.

2.2.3 Recycling

Battery recycling activities were well established long before EVBs became widespread, as batteries have long been used in applications such as portable electronics, starter batteries for internal combustion engine vehicles, and industrial energy storage systems. While lithium-ion batteries were already in use, their volumes were relatively modest, and the recycling industry was primarily focused on lead-acid chemistries (Eurostat 2024). However, the growing adoption of EVs is expected to significantly raise the volume of EoL LIB batteries, thereby creating a much greater need for recycling infrastructure (Haas et al. 2023). In response, recycling capacity has expanded considerably, and is expected to keep growing from about 340 GWh in 2023 to 1,550 GWh in 2030 worldwide (IEA 2024b). This growth is supported by regulatory frameworks. In the EU, for instance, the Battery Regulation introduces mandatory minimum levels of recycled content in new batteries. From August 2031, batteries containing lithium, cobalt, or nickel must include at least 6 percent recycled lithium, 16 percent recycled cobalt, and 6 percent recycled nickel. These thresholds will increase to 12 percent (lithium), 26 percent (cobalt), and 15 percent (nickel) by August 2036 (European Parliament and European Council 2024a). Given cobalt's predominant use in battery manufacturing (Natural Resources Canada 2023), most of the recycled content will necessarily come from battery recycling. Additionally, the regulation requires recycling processes to achieve minimum recovery rates: from 2028, at least 50 percent of lithium, 90 percent of cobalt, and 90 percent of nickel must be recovered, rising to 80 percent for lithium, 95 percent for cobalt, and 95 percent for nickel in 2032 (European Parliament and European Council 2024a).

To date, two main recycling processes are commercially applied for lithium-ion batteries: pyrometallurgy and hydrometallurgy, including combinations of both (Heimes et al. 2023). Additionally, direct recycling is emerging (Lai et al. 2025). While specific recycling routes vary by company (Sommerville et al. 2021), the overall process can generally be divided into three stages after collection: pre-treatment, material recovery, and refining (Windisch-Kern et al. 2022), as illustrated schematically in Figure 2.4.

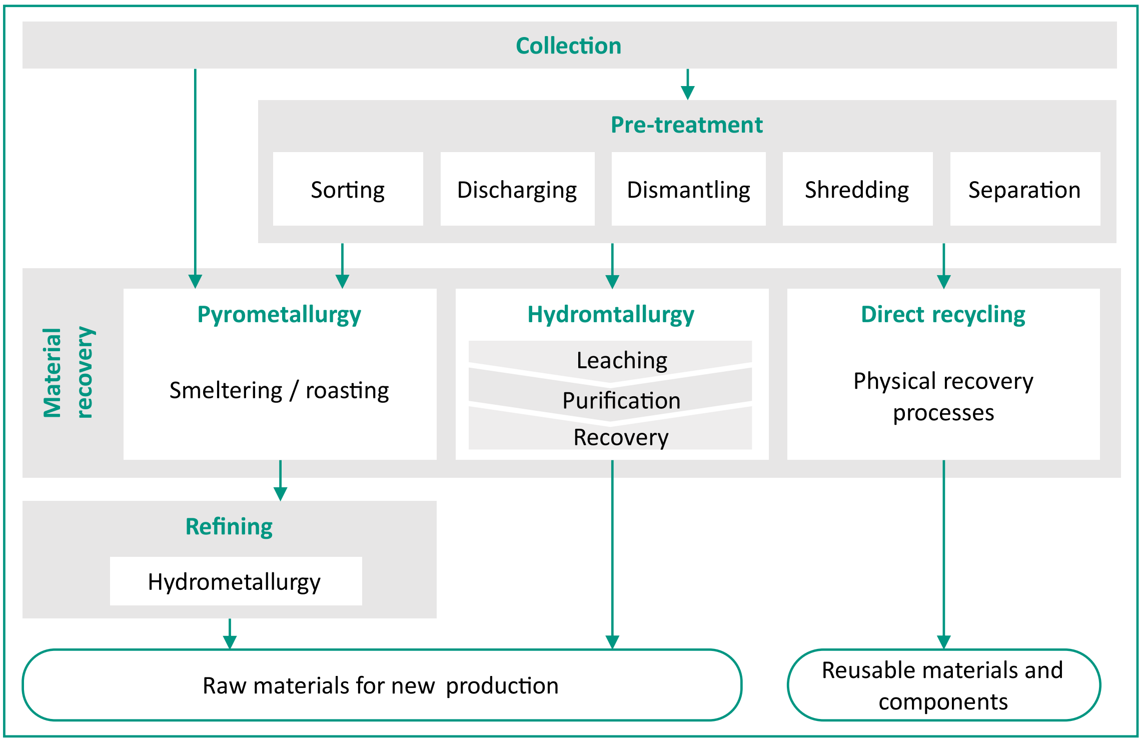


Figure 2.4: Overview of LIB recycling routes (based on Brückner et al., 2020; Chen et al., 2019; Rehman et al., 2025; Windisch-Kern et al., 2022)

The pre-treatment stage typically involves sorting and discharging the batteries, potentially followed by mechanical and thermal treatments (Neumann et al. 2022). Mechanical treatment steps may include the disassembly of battery systems as well as the shredding of battery modules or cells, followed by separation of the resulting material fractions based on density, particle size, or magnetic properties (Heimes et al. 2023). Thermal processes such as pyrolysis or incineration are employed to remove binders and combustible components from the electrolyte, thereby enhancing the safety of subsequent steps (Kim et al. 2021; Neumann et al. 2022). A key output of the pre-treatment phase is the black mass, which contains the active materials from battery cells, primarily the anode and cathode materials (Amalia et al. 2024).

After some or all of those pre-treatment processes the material recovery phase begins, typically via either hydrometallurgical or pyrometallurgical processes (Sommerville et al. 2021). Hydrometallurgy is a chemical method generally comprising three steps: leaching, purification, and metal recovery (Brückner et al. 2020). Leaching dissolves metals from the black mass using acids such as sulfuric acid or hydrogen peroxide (Windisch-Kern et al. 2022). Purification then separates the metals in the solution, and the final step recovers the metals in solid form, as pure metals or metal salts, through processes like crystallization or chemical reduction (Brückner et al. 2020). Pyrometallurgical recycling refers to a set of high-temperature processes used to reduce battery metals into alloys, including smelting, roasting, and microwave heating (Cornelio et al. 2024; Makuza et al. 2021; M. Zhou et al. 2021). Depending on the battery chemistry, the resulting alloy may contain cobalt, nickel, copper, and iron (Baum et al. 2022). These processes also produce a slag, which can contain lithium, manganese, aluminum, iron, and other elements (Makuza et al. 2021). While slag was originally treated as waste and used in construction applications, thereby losing valuable metals like lithium and nickel, emerging technologies are exploring ways to recover these elements, but such methods have not yet reached commercial scale (Chen et al. 2019; Windisch-Kern et al. 2022). The refining phase is particularly relevant for pyrometallurgical processes and often involves a subsequent hydrometallurgical treatment to separate the metals in the alloy (Neumann et al. 2022).

In addition to pyrometallurgical and hydrometallurgical recycling, direct recycling is an emerging method aimed at preserving and reusing active materials. This approach uses physical or magnetic separation techniques to extract functional materials without extensive thermal or chemical processing (Chen et al. 2019). However, direct recycling remains in the developmental stage and is not yet widely applied at scale (Lai et al. 2025).

2.3 Stakeholders in the EoL EVB Supply Chain

Stakeholders can be defined as „groups or individuals who have a stake in the success or failure of a business" (Freeman et al. 2010). Within the context of a CE for EVBs, numerous stakeholder groups are considered to have those stakes, and there is broad consensus in the literature that collaboration among these stakeholders is essential to establishing a successful EVB CE system (Kadner et al. 2021; Wrålsen et al. 2021). Stakeholder groups identified in this context include governmental and regulatory bodies, OEMs, recyclers, repurposers, remanufacturers, workshops, consumers and end users, collection facilities and scrap yards, as well as intermediaries such as resellers (Chirumalla et al. 2022; Kadner et al. 2021; Olsson et al. 2018; Slattery et al. 2024; Wrålsen et al. 2021).

Governments and other legislative bodies are regarded as the most influential stakeholders in shaping EVB EoL activities, primarily through their capacity to define the legal frameworks (Wrålsen et al., 2021). OEMs are ranked second in importance. In addition to manufacturing vehicles, OEMs often operate dealership and service networks and are increasingly involved in downstream EoL activities, including recycling, repurposing, and remanufacturing (Mercedes-Benz Group 2024; Slattery et al. 2024; Wrålsen et al. 2021). Whereas in the internal combustion engine vehicle market OEMs had limited roles in EoL processing due to the positive residual value of vehicles, which supported a strong independent aftermarket, the electrification of vehicles has led to deeper OEM integration into the EoL value chain and new forms of collaboration with independent recyclers and other EoL service providers (Slattery et al. 2024). Recyclers and battery cell manufacturers share the third rank in Wrålsen et al.'s (2021) stakeholder importance ranking due to their technical expertise, which is essential for designing and implementing EoL processes. Battery recyclers often build on experience gained from handling LIBs or other battery chemistries in other sectors, such as mobile devices and consumer electronics (Slattery et al. 2024). However, a potential barrier to further investment in recycling infrastructure is the uncertainty regarding future battery chemistries and designs, which could affect the recycling processes, especially with regard to automation potentials (Olsson et al. 2018). Repurposers represent a stakeholder group that has emerged specifically in the context of EVBs and was not previously relevant in the automotive EoL ecosystem (Slattery et al. 2024). Key challenges faced by repurposers include regulatory uncertainties, particularly regarding extended producer responsibility, insufficient battery collection infrastructure, and limited access to reliable data on battery health and configuration (Olsson et al. 2018). Overlaps between stakeholder roles, such as OEMs or battery manufacturers also engaging in repurposing activities, may introduce internal conflicts of interest. For example, offering repurposed batteries might cannibalize new battery sales (Olsson et al. 2018).

Remanufacturers are only mentioned as stakeholders by Slattery et al. (2024), and include both independent firms and OEMs performing remanufacturing in-house, with the latter being the dominant model at present. The barriers faced by repurposers are likely to apply to remanufacturers as well. The role of workshops, either affiliated with OEM networks or operating independently, in the EoL EVB value chain is mainly described as one of facilitating battery collection, similar to the role of auto dismantlers (Slattery et al. 2024). However, in the non-EV related remanufacturing literature, workshops are seen not only as core suppliers (i.e., providers of parts for remanufacturing) but also as part of the distribution market for remanufactured parts (Kalverkamp and Raabe 2018). They thus serve as intermediaries between remanufacturers and end customers and the decision about new or remanufactured spare parts may lay with them (Kalverkamp and Raabe 2018). The role of end customers for remanufacturing and end users for repurposing has been evaluated differently. Wrålsen et al. (2021) rank vehicle users and buyers as the least influential group in EVB EoL management, and Kalverkamp & Raabe (2018) similarly suggest that consumer influence on remanufacturing marketing systems is limited. In contrast, Olsson et al. (2018) list numerous subgroups of actors within the end-user segment for repurposed batteries. Akano et al. (2021), moreover, include consumers among the three primary stakeholders in remanufacturing, alongside OEMs and independent remanufacturers, emphasizing their critical role in the acceptance and uptake of remanufactured products.

Slattery et al. (2024) emphasize the heterogeneity of information requirements among different stakeholders involved in EVB EoL decision-making: According to their study, dismantlers require information about battery chemistry and overall condition to estimate residual value and identify potential buyers. Additionally, information about the location and dimensions of the battery within the vehicle is needed to ensure safe and efficient disassembly. Repurposers, in contrast, require more detailed data on the battery's condition, particularly detailed SoH metrics at the pack, module, and cell levels, as well as access to the BMS for fault diagnostics (Slattery et al. 2024). For recyclers, Slattery et al. (2024) note that the battery condition is relevant primarily for safety assessment. Beyond that, detailed information on the battery's chemical composition is essential for recyclers for estimating material recovery value and for grouping similar battery types in the recycling process.

3 Summaries of Papers and Results

This section summarizes Studies A to D. For each study, the motivation and methodological approach are outlined, followed by a summary of the key results and a discussion of the findings and limitations. The full texts of all studies are provided in Part II of the thesis.

3.1 Study A: A Simulation Model for Assessing the Potential of Remanufacturing Electric Vehicle Batteries as Spare Parts

This section refers to the study "A simulation model for assessing the potential of remanufacturing electric vehicle batteries as spare parts" by Sandra Huster, Simon Glöser-Chahoud, Sonja Rosenberg and Frank Schultmann. The study was published in the *Journal of Cleaner Production* and will be cited as Huster et al. (2022) or referred to as Study A. The full text is inserted in Section A, and additional supporting information is available online.

3.1.1 Motivation and Methodology

The remanufacturing of EVBs as spare parts presents a promising pathway to extend the operational life of EVs and mitigate the environmental burden associated with battery production. While the ecological benefits of remanufacturing are increasingly recognized, quantitative insights into its systemic potential remain scarce. Study A addresses this gap by introducing a discrete event simulation (DES) model with agent-based elements to estimate the potential supply and demand for reconditioned EVBs. The model is implemented with the simulation software AnyLogic 8.5.2 (University version).

The study addresses the structural mismatch between battery and vehicle lifespans. Batteries may degrade faster than the vehicles they power, leaving the vehicle unusable despite its remaining mechanical integrity. Conversely, EoL batteries may still contain functional modules that could be reused if disassembled and reassembled under suitable conditions. The DES model developed in this study accounts for these asynchronous lifecycles by simulating vehicles and their batteries as separate entities. The study extends prior research by not only estimating the supply of reconditioned batteries based on lifetime distributions, but also modeling demand through defined eligibility criteria for vehicle battery replacement. These criteria incorporate vehicle age and technological compatibility, accounting for the evolution of battery technologies. Also with regard to supply, criteria for battery remanufacturability apply. This dual perspective enables a more realistic assessment of reconditioning potential in future EV fleets.

The model logic is schematically depicted in Figure 3.1. It considers a fleet of battery electric vehicles (BEVs) entering the market and tracks their usage over time. Each EVB is characterized by a stochastically assigned lifespan, independent from that of its host vehicle. Failure of a battery while the vehicle is still functional creates a potential demand event for a spare battery. Supply is generated from batteries that fail early but contain reusable modules suitable for remanufacturing, and from still-functioning batteries from failed vehicles. The simulation includes key parameters such as annual vehicle sales, average vehicle and battery lifespans, and reconditioning yield rates. The model also accounts for the possibility of repurposing batteries for non-automotive applications in scenarios where batteries are unsuitable for remanufacturing for automotive reuse.

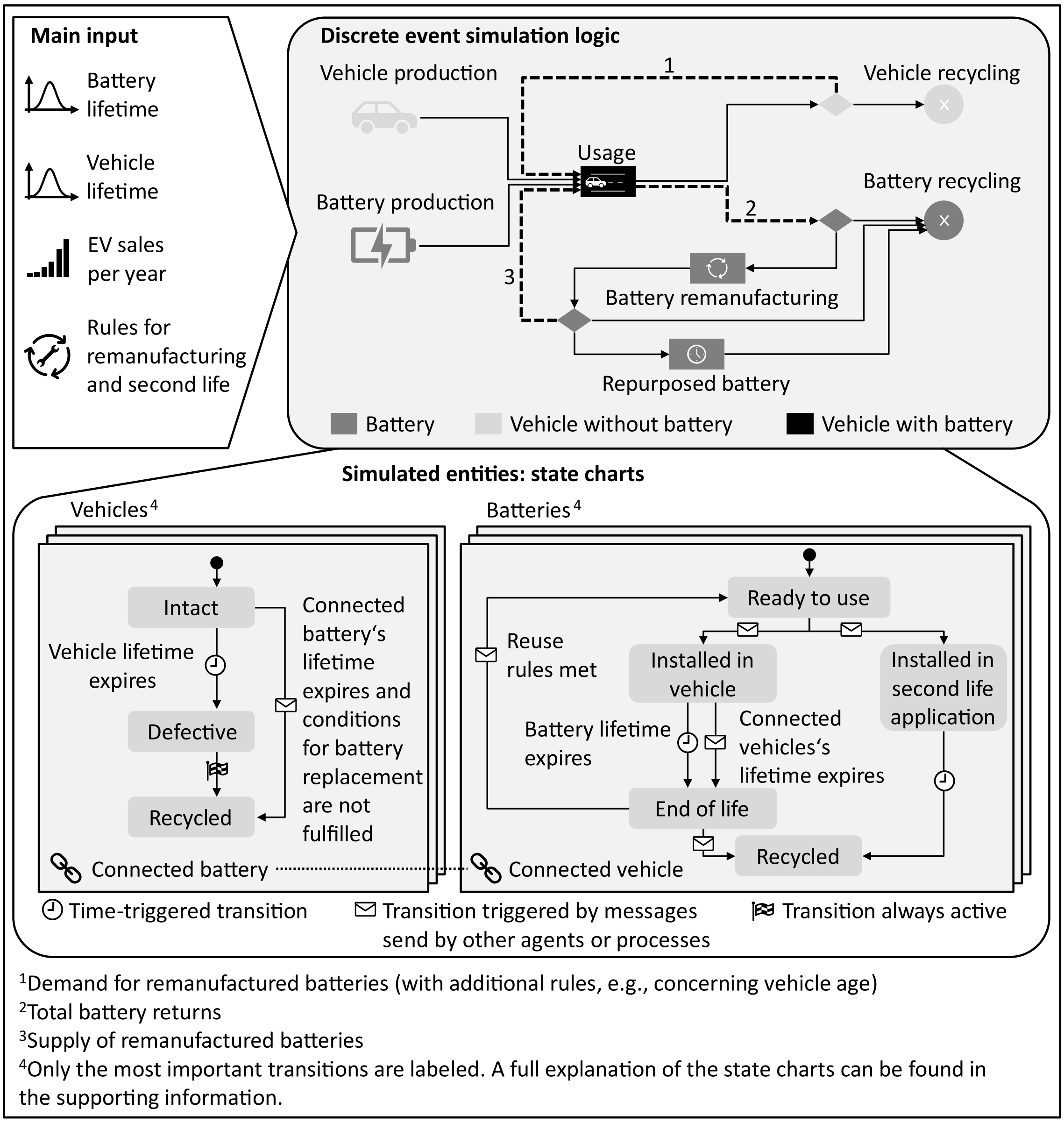


Figure 3.1: Simulation logic, reproduced from Huster et al. (2022), published in Journal of Cleaner Production, © 2022 Elsevier

The model was tested with a case study encompassing 5% of the German EV market, representing one OEM. The parameters were calibrated to national statistics and projections. Scenarios vary according to assumed battery lifetime (expected values of 10, 15, and 20 years) while maintaining a fixed average vehicle lifespan of 15 years. The base case assumes a linear system with no reconditioning. Results from this are compared with scenarios allowing remanufactured batteries.

3.1.2 Results

The simulation results underscore the potential of remanufacturing to reduce the need for newly manufactured batteries, particularly in scenarios where battery lifespans are shorter than vehicle lifespans. Figure 3.2a compares the total number of batteries manufactured under a linear case, in which new batteries are used both for new vehicles and as spares, and a remanufacturing case, where remanufactured batteries are prioritized as spares when available. The model reveals that the use of remanufactured batteries leads to a reduction in new battery production ranging from 2.0% to 6.9%, depending on the assumed battery lifespan.

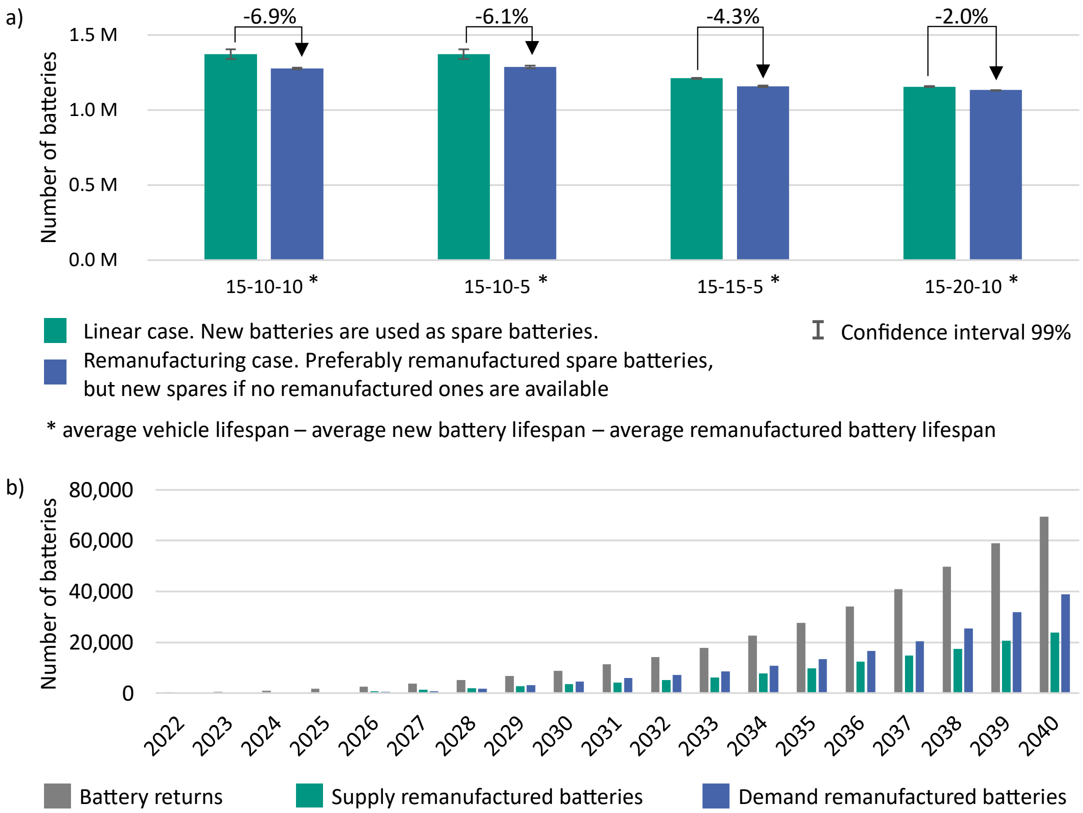


Figure 3.2: Manufactured batteries and battery supply and demand. a) Number of manufactured batteries in the linear scenario and in a remanufacturing scenario. b) Battery returns and supply and demand of remanufactured batteries in the remanufacturing scenario, with average vehicle lifetimes of 15 years and average battery lifespans (new and remanufactured) of 10 years. Adapted from Huster et al. (2022), published in Journal of Cleaner Production, © 2022 Elsevier

The highest reduction (6.9%) is observed in the 15-10-10 scenario, where the average vehicle lifespan is 15 years, and the average battery lifespan for both new and remanufactured batteries is 10 years. Even under the assumption that new batteries outlast vehicles on average, reflected in the 15-20-10 scenario (average lifespans: 15 years vehicles, 20 years new batteries, 10 years remanufactured batteries), remanufacturing still reduces new battery production by 2.0%, illustrating residual potential even in longevity-optimized systems.

Figure 3.2b provides a time series perspective of the remanufacturing case, showing annual battery returns alongside the supply and demand of reconditioned batteries from 2022 to 2040 for the case “average vehicle life: 15 years – average new battery life: 10 years – average remanufactured battery life: 10 years”. Battery returns (grey bars) increase steadily with vehicle uptake, forming the basis for potential remanufacturing. Notably, while supply (green bars) and demand (blue bars) for remanufactured batteries both increase over time, the demand consistently exceeds supply, particularly from the early 2030s onward. This highlights a supply constraint and suggests that without expanded remanufacturing capacity or improvements in yield, new battery production for battery spare parts will still be necessary to cover the shortfall.

3.1.3 Discussion and Limitations

The findings of Study A demonstrate that remanufacturing EVBs can significantly reduce the demand for newly manufactured spare batteries, particularly when average battery lifetimes are shorter than vehicle lifespans. This confirms that a secondary use pathway for EVBs as reconditioned spare parts has measurable potential within circular economy strategies. However, a central insight of the study is that the magnitude of this potential is highly scenario-dependent. In cases where battery lifespans are significantly shorter than vehicle lifespans, remanufacturing can offset much more new battery production than in cases where battery lifespans exceed those of vehicles. The analysis also highlights a persistent supply-demand imbalance. As shown in Figure 4b, demand for remanufactured batteries exceeds supply in nearly all modeled years. Without parallel investments in remanufacturing infrastructure, yield improvements, or design-for-reuse strategies, the practical realization of this potential will remain constrained.

Several limitations must be acknowledged. First, the model relies on idealized assumptions regarding remanufacturing feasibility, including perfect module quality identification and immediate availability for remanufacturing. In reality, challenges regarding battery diagnostics and disassembly, or logistical delays may reduce the effective recovery rate. Second, the study assumes fixed vehicle and battery lifespan distributions and does not model the evolution of battery chemistry or architecture in detail. Although compatibility is partially addressed through age and technological matching, these remain simplified proxies. Future work should incorporate a more granular technology compatibility model, particularly given the pace of battery innovation. Third, the model omits consumer acceptance and OEM decision-making, both of which may critically affect uptake.

3.2 Study B: Do Consumers Want Reconditioned Electric Vehicle Batteries? – A Discrete Choice Experiment

This section refers to the study "Do consumers want reconditioned electric vehicle batteries? – A discrete choice experiment" by Sandra Huster, Sonja Rosenberg, Simon Hufnagel, Andreas Rudi, and Frank Schultmann. The study was published in *Sustainable Production and Consumption* and will be cited as Huster et al. (2024b) or referred to as study B. The full text is inserted in Section B, and additional supporting information is available online.

3.2.1 Motivation and Methodology

Despite growing industrial interest in reconditioned EVBs, empirical evidence on consumer acceptance remains scarce. Since the success of reconditioning as a CE strategy depends not only on technical and economic feasibility but also on consumer demand, a deeper understanding of user decision-making is essential. Study B addresses this gap by investigating consumer acceptance of reconditioned EVBs through a discrete choice experiment. The primary objective is to quantify consumers' willingness to opt for a reconditioned battery instead of purchasing a new battery or replacing the vehicle entirely. The study further examines heterogeneity in preferences across demographic groups and assesses how economic trade-offs, such as cost versus lifetime, affect these decisions. By doing so, it provides data-driven insights for the design of effective reconditioning strategies.

DCEs are a widely used method for analyzing consumer preferences in situations where individuals must choose between different options with varying attributes. In this case, participants were asked to consider a scenario in which the battery of their EV had failed. Each of the 14 choice tasks presented respondents with three alternatives: (a) purchasing a new battery, (b) selecting a reconditioned battery, or (c) scrapping the vehicle and acquiring a new or used one. The alternatives varied across four attributes considered relevant to consumer decision-making:

- Original car price
- Battery price (with reconditioned batteries offered at varying discount levels),
- Battery lifespan, and
- GHG intensity.

An example of a choice set is presented in Figure 3.3.

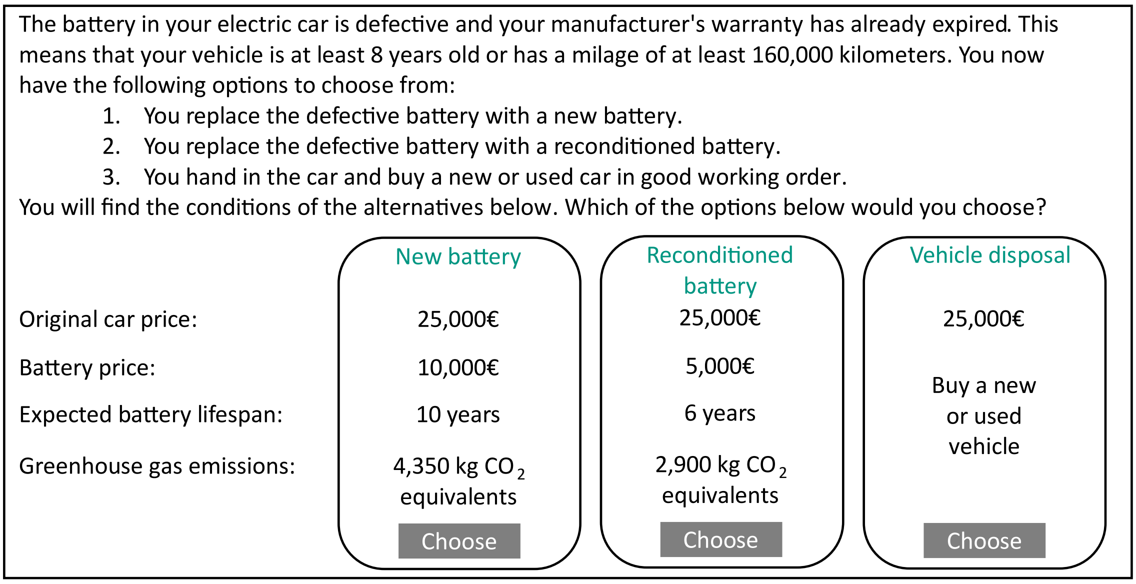


Figure 3.3: Example of a choice set presented to the survey participants reproduced from Huster et al. (2024b), Sustainable Production and Consumption, © The Authors, CC BY-NC-ND 4.0.

The survey was conducted online in Germany and yielded 1,152 responses, of which 837 provided complete data for analysis. Respondents also supplied demographic information, including age, income, and EV ownership status. The data were analyzed using a mixed logit model. This model allows for random taste variations across individuals, capturing the fact that different consumers may rate the importance of each attribute differently. Additionally, the Hierarchical Bayes estimation technique is used to estimate individual-level preferences and then aggregate them at the population level.

To obtain a suitable model for the given data, several utility function specifications were tested. These specifications differed in the inclusion of attributes, specifically the original car price, and consumer-specific characteristics. Model performance was evaluated using the Akaike Information Criterion and the Bayesian Information Criterion. Among the tested formulations, the utility specification outlined in Equation 3.1 performed best on both metrics and was selected as the final model. In this specification, the utility U_{nit} that individual n derives from option i in choice situation t is defined as:

$$U_{nit} = asc_{it} + \sum_{\substack{Battery \\ characteristics\ b}} \beta_n^b \cdot x_{it}^b + \beta_{in}^v \cdot x_{it}^v + \varepsilon_{nit}. \tag{3.1}$$

Here, asc_{it} denotes the alternative-specific constant, and x_{it}^b and x_{it}^v represent the battery b and vehicle v attributes respectively. The vectors β contain the estimated preference weights for these attributes, which may vary across individuals n and the options i in the mixed logit framework. The error term ε_{nit} follows an i.i.d. extreme value type I distribution. This functional form allows the model to reflect not only average preferences across the population but also systematic variation across individual-level covariates.

3.2.2 Results

The results of the discrete choice experiment indicate that reconditioned EVBs are a viable option for a substantial portion of consumers. In total, 837 respondents completed the survey, each evaluating 14 hypothetical scenarios, resulting in 11,718 observed choice situations. In 52% of these, the reconditioned battery option was selected. However, the acceptance of reconditioned EVBs depends on the attribute configurations, as Table 3.1 shows.

Table 3.1: Posteriors of the mixed logit model, adapted from Huster et al. (2024b), Sustainable Production and Consumption, © The Authors, CC BY-NC-ND 4.0.

	Mean	Standard Deviation	Corresponding attribute levels for multiplication
$\boldsymbol{asc}_{\boldsymbol{new\ battery}}$[1]	0.00	0.00	Only considered for the option "new battery"
$\boldsymbol{asc}_{\boldsymbol{reconditioned\ battery}}$	3.34	2.47	Only considered for the option "reconditioned battery"
$\boldsymbol{asc}_{\boldsymbol{none\ option}}$	0.89	4.24	Only considered for the option "Vehicle disposal"
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{new\ battery}}$	1.50	0.52	Only considered for the option "new battery". Multiplication factor depends on new car price (0: low price, 1: medium price, 2: high price)
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{reconditioned\ battery}}$	1.13	0.46	Only considered for the option "reconditioned battery". Multiplication factor depends on new car price (0: low price, 1: medium price, 2: high price)
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{none\ option}}$	-0.14	1.05	Only considered for the option "Vehicle disposal". Multiplication factor depends on new car price (0: low price, 1: medium price, 2: high price)
$\boldsymbol{\beta}^{\boldsymbol{battery\ cost\ savings}}$	1.18	0.86	One unit corresponds to 10% of savings compared to a new battery
$\boldsymbol{\beta}^{\boldsymbol{battery\ life\ losses}}$	-1.53	1.03	One unit corresponds to 1 year of lifetime losses compared to a new battery
$\boldsymbol{\beta}^{\boldsymbol{battery\ GHG\ savings}}$	0.26	0.29	One unit corresponds to 10% of savings compared to a new battery

[1]: $\boldsymbol{asc}_{\boldsymbol{new\ battery}}$ is a non-random coefficient with the fixed value "0" as a baseline for the other alternative-specific constants (asc's).

Among the evaluated attributes, expected battery lifespan had the strongest influence on choice behavior. Each reduction in lifetime of one year relative to a new battery was associated with a significant decrease in utility (mean β=−1.53, standard deviation (SD) = 1.03), indicating that product durability plays a central role in consumer evaluations. In contrast, a price reduction relative to a new battery had a positive effect (mean β=1.18, SD = 0.86, per 10% price reduction relative to a new battery). Each 10% of GHG savings compared with a new battery contributed positively, though their overall influence was smaller compared with the lifetime and cost attributes (mean β =0.26, SD = 0.29). Additionally, the price level of the respondent's car showed a positive correlation with battery replacement preferences, indicating that higher-value vehicles may increase the likelihood of selecting either a new or reconditioned battery over vehicle replacement.

Slight variation in preferences was observed across demographic subgroups. Younger respondents (aged ≤29) were more likely to reject the reconditioned option, particularly when it involved lifetime reductions, whereas older respondents (aged ≥60) exhibited higher levels of acceptance. Respondents who already owned an electric vehicle were more inclined to select the reconditioned option.

3.2.3 Discussion and Limitations

The results of the DCE offer implications for the development and positioning of reconditioned EVBs in the market. While acceptance is conditional, the overall share of reconditioned battery selections indicates that this circular option has the potential to be adopted by a significant portion of consumers, especially if concerns around battery longevity are adequately addressed. This presents opportunities for stakeholders across the battery value chain.

For manufacturers and reconditioners, the findings underscore the need to prioritize technical improvements that extend the expected service life of reconditioned batteries or enhance transparency regarding remaining capacity. Given the sensitivity to price, cost-efficient reconditioning processes are also essential. Pricing strategies that clearly communicate economic benefits relative to new batteries may increase uptake, particularly in market segments with lower willingness to pay. Policy makers and regulatory bodies may support the diffusion of reconditioned batteries by fostering quality standards, warranty frameworks, and labeling schemes that help reduce information asymmetries and enhance consumer confidence. Also, incorporating reconditioning into broader policy instruments, such as public procurement criteria, may serve as a means to stimulate demand. As environmental considerations were not the primary driver of decision-making, relying on ecological benefits alone may not suffice to increase adoption.

Several limitations should be considered when interpreting the results. First, while DCEs are well suited to eliciting preferences in complex decision contexts, they are based on hypothetical scenarios and do not necessarily reflect actual behavior in real-world settings. Second, some potentially relevant aspects such as policy interventions were not directly captured in the choice attributes. Third, the sample was not gender-balanced: the majority of respondents identified as male, which may have influenced the overall pattern of preferences and limits the generalizability of findings across genders. Finally, the study focused on consumers in Germany, and preferences may differ in other countries depending on market maturity, or policy environments.

3.3 Study C: Will Electric Vehicle Battery Reconditioning Succeed? – A Flexible Simulation Approach Considering Stakeholders' Interests

This section refers to the study "Will electric vehicle battery reconditioning succeed? – A flexible simulation approach considering stakeholders' interests" by Sandra Huster, Raphael Heck, Andreas Rudi, Sonja Rosenberg, and Frank Schultmann. The study was published in the *Journal of Environmental Management* and will be cited as Huster et al. (2025) or referred to as study C. The full text is inserted in Section C, and additional supporting information is available online.

3.3.1 Motivation and Methodology

Although consumer preferences provide important insights into potential demand for reconditioned EVBs, broader systemic factors must also be considered to assess the feasibility of reconditioning. The future role of reconditioned batteries depends not only on willingness to adopt among end users, but also on the availability of used batteries, the strategic behavior of OEMs, and evolving policy frameworks. These elements develop over time and interact in ways that are not easily captured through static analyses. Study C addresses this complexity through a simulation-based approach that considers dynamic interactions among key actors and material flows. The model is designed as a decision-support tool, particularly for OEMs, and allows for the systematic evaluation of potential future scenarios in the EVB value chain. Those what-if scenarios are enabled by the parametrizability of the model with 49 input factors, covering both OEM-internal levers and external factors beyond OEM control, such as consumer preferences and regulatory requirements. The results of the model can be used for robust capacity planning of reconditioning facilities.

To this end, a hybrid simulation model combining DES and agent-based modeling (ABM) elements was developed. The DES framework structures the time-dependent processes of battery manufacturing, replacement, and treatment flows, while the ABM component represents decision-making behavior by stakeholder groups. The model includes four main actor groups: the group of business entities, which comprises OEMs and EoL providers, the group of car workshops, the group of consumers, and regulatory bodies. OEMs decide, for example, whether to integrate reconditioned batteries into their warranty strategies, and EoL providers opt for the most profitable option based on demand and battery cell chemistry. Workshops can offer reconditioned batteries or decide against it. Consumers influence demand for replacement options, with preference data stemming from the findings of Study B, and regulatory actors influence the system through policy instruments such as minimum recycling quotas. Information about the business entities and workshops was retrieved via interviews. The interviews indicated that the decisions of business entities are primarily shaped by economic considerations, while workshop behavior appears additionally influenced by subjective perceptions and informal norms.

Figure 3.4 provides an overview of the model structure, including the key stakeholders and the DES guiding the material flow of batteries through the system. The model tracks the movement of EVBs from manufacturing and usage to initial failure and subsequent treatment pathways (reconditioning, repurposing or recycling) depending on stakeholder decisions and system constraints. It is parametrized with 49 input variables, covering aspects such as EV sales projections, battery and vehicle life expectancies, reconditioning yields, cost assumptions, and regulatory conditions. The model generates five key output indicators, monitored as time series from 2025 to 2050 with a five-year resolution: the total EVB returns, the supply and demand of reconditioned EVBs, the quantity of repurposed EVBs, and the quantity of recycled EVBs. This structure enables the exploration of how changes in stakeholder strategies and external conditions may influence the future role of reconditioning within the battery value chain.

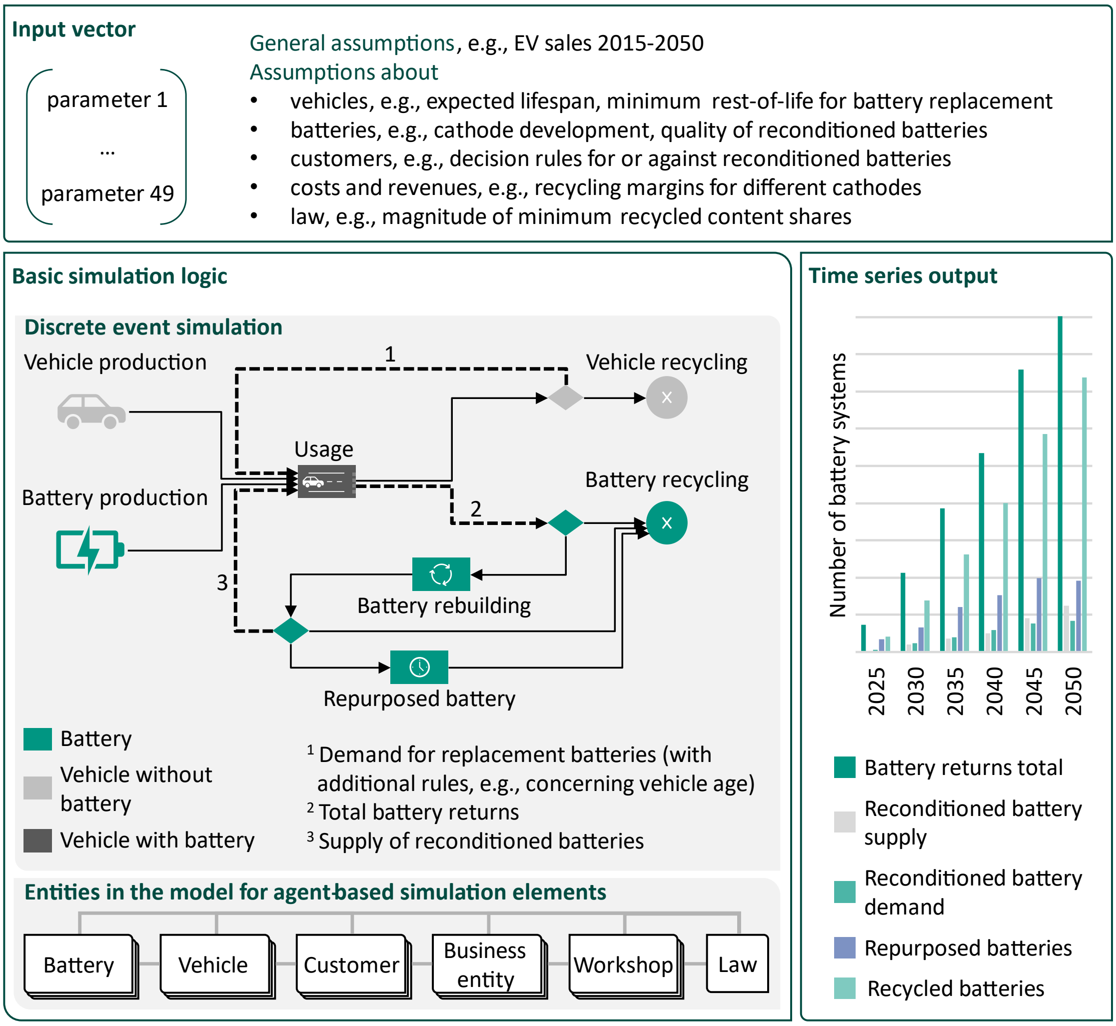
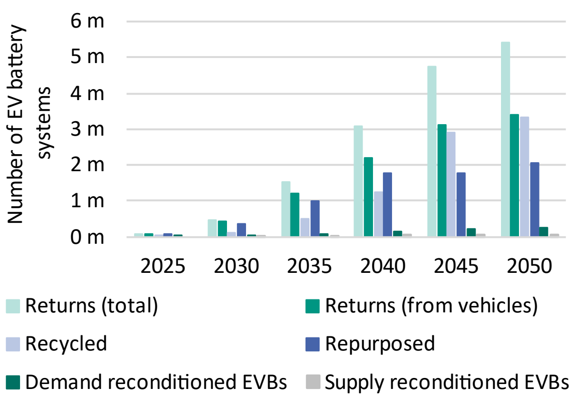


Figure 3.4: General simulation logic of Study C, adapted from Huster et al. (2025), Journal of Environmental Management, © The Authors, CC BY 4.0.

The model is implemented in AnyLogic University 8.9.0 and applied to a case study of the German EV market over a time horizon from 2020 to 2050. In a base case scenario, an average vehicle lifetime of 15 years and a battery lifetime of 10 to 12 years are assumed, depending on the cell chemistry. The scenario reflects an LFP-rich chemistry mix over time, which influences the overall technical characteristics and economic potential of end-of-life batteries. OEMs do not utilize reconditioned batteries for warranty replacements in this setting, and minimum recycling quota as defined in the EU Battery Regulation are assumed. Consumer demand for reconditioned batteries is modeled based on the outcomes of Study B. Subsequently, a sensitivity analysis is used to explore the implications of varying assumptions regarding stakeholder behavior, market developments, and policy interventions. The purpose is not to predict exact market outcomes but to examine the systemic conditions under which reconditioning may play a more or less significant role within the broader circular economy framework for EVBs.

3.3.2 Results

Figure 3.5 presents the simulation outcomes for the base case scenario. As the EV sales rise, the number of EVBs reaching EoL increases substantially from 2025 to 2050. In terms of treatment pathways, repurposing dominates in the early years. Over time, however, recycling becomes the most common use for end-of-life batteries, primarily due to returns of batteries that have been reused before and cannot be reused again. Reconditioning remains comparatively limited throughout the simulation period. By 2050, about 50,000 batteries are reconditioned annually, accounting for only a minor share of total returns, while the demand peaks at about 200,000 units. This outcome reflects limitations in the economic viability of reconditioning given the assumptions of the base case.



Aggregated over all years:

- Returning EV batteries (from vehicles and second-life applications: 65.3. m (4,960 GWh)
- Reconditioned EV battery supply: 0.85 m (65 GWh)
- Reconditioned EV battery demand: 3.2 m (240 GWh)
- Recycled NCA EV batteries: 9.0 m (605)
- Recycled NMC111 EV batteries: 0.7 m (50 GWh)
- Recycled NMC532 EV batteries: 1.0 m (75 GWh)
- Recycled NMC622 EV batteries: 5.2 m (395 GWh)
- Recycled NMC811 EV batteries: 2.8 m (210 GWh)
- Recycled NMC955 EV batteries: 0.35 m (25 GWh)
- Recycled LFP EV batteries: 14.2 m (1,075 GWh)
- Manufactured EV batteries: 75.8 m (5,760 GWh)

Figure 3.5: Results of the base case, reproduced from Huster et al. (2025), Journal of Environmental Management, © The Authors, CC BY 4.0

To examine the impact of individual assumptions on the demand and supply of reconditioned EVBs, sensitivity analyses were conducted. The results are depicted in Figure 3.6. The most substantial effect can be observed if assuming that OEMs use reconditioned batteries in warranty cases, which increases cumulative demand by nearly 900% and supply by almost 300%

compared to the base case. Nonetheless, only two-thirds of this demand can be met, due to timing mismatches and material constraints.

Changes in consumer behavior also have significant influence: assuming universal preference for reconditioned batteries after warranty increases demand by 320% and supply by 230%. Varying battery and vehicle lifetime assumptions of two years more or less yield shifts of ±25–45%, depending on direction of the changes. Extending vehicle eligibility for replacements by two years leads to a 40–45% increase in both demand and supply.

Smaller but still relevant effects are observed for environmental and economic parameters. Enhancing CO_2 savings from 50% to 70% raises demand by 10%, while improving battery quality, defined as reduced lifetime loss by two years, can increase demand by up to 45%. In contrast, changes to sales margins primarily affect supply, with shifts of ±8%. Cathode chemistry availability also has an effect: a chemistry mix favoring nickel-based batteries ("Cathode scenario: NCx") raises demand but reduces supply. In contrast, modifying recycled content requirements has minimal effect on the numbers of reconditioning supply and demand.

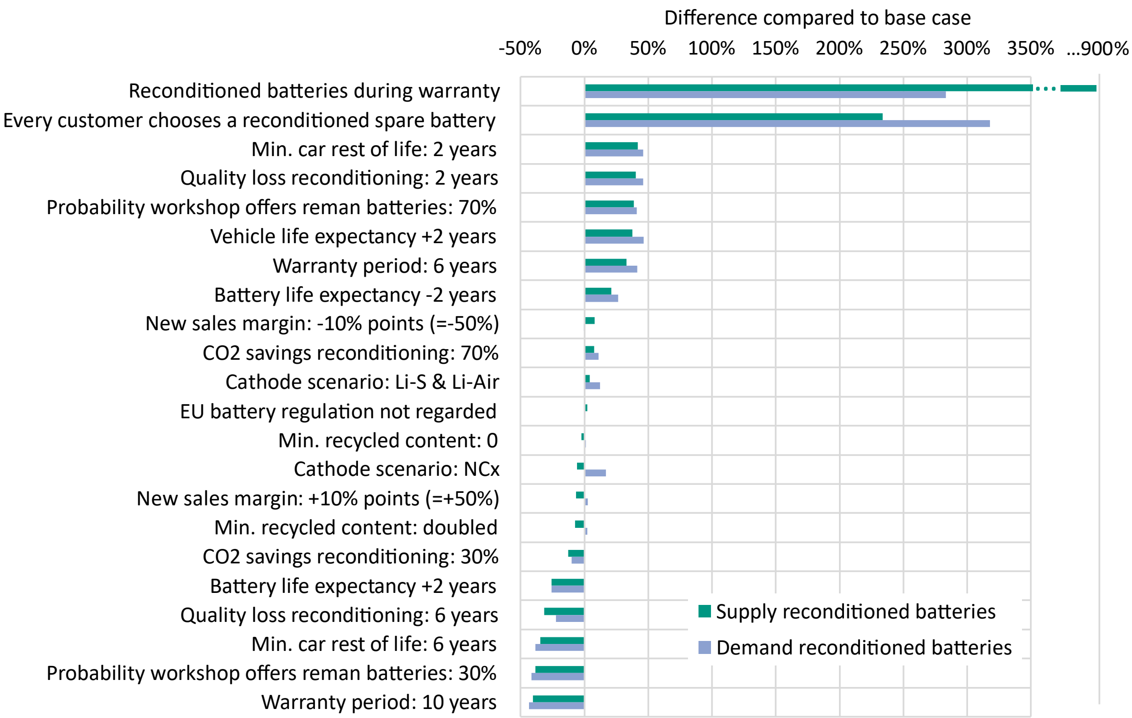


Figure 3.6: Difference of supply and demand for reconditioned batteries compared to the base case for certain parameter variations, reproduced from Huster et al. (2025), Journal of Environmental Management, © The Authors, CC BY 4.0

3.3.3 Discussion and Limitations

The simulation results indicate that the future significance of reconditioned EVBs depends on the interaction of battery characteristics and stakeholder decisions. While reconditioning plays a minor role in the base case, the scenario analyses show that changes in OEM practices, assumed battery technology, or consumer preferences can substantially influence both demand and supply. Among these, OEM adoption of reconditioned batteries for warranty cases emerges as the most influential factor. The findings offer implications for multiple stakeholders. For instance, OEMs can play a central role by integrating reconditioned batteries into after-sales services, supported by investments in the quality of reconditioned EVBs, and policymakers may facilitate broader adoption through regulatory clarity and targeted incentives.

Several limitations should be acknowledged. First, the influence of parameters was examined through scenario-based sensitivity analysis, but this approach does not substitute for a systematic feature importance assessment. Because the model is complex and each evaluation takes about thirty minutes, including three replications to address stochasticity, large-scale analyses are impractical without simplification or approximation. The model also omits demand-side modeling for repurposed batteries, possibly overestimating their integration potential into stationary applications. Moreover, technical feasibility is simplified through predefined age thresholds, and a more granular integration of cell-level aging dynamics would enhance the robustness of reuse pathway decisions. Lastly, while 49 input parameters allow for a broad range of scenarios, structural changes in stakeholder roles or system dynamics may require direct model modifications beyond parameterization.

3.4 Study D: Approximating End-of-Life Electric Vehicle Battery Flows: Surrogate Modeling of a Discrete Event and Agent-Based Simulation Model

This section refers to the study "Approximating End-of-Life Electric Vehicle Battery Flows: Surrogate Modeling of a Discrete Event and Agent-Based Simulation Model" by Sandra Huster, Mona Faraji-Niri, Andreas Rudi, and Frank Schultmann. The study is published in the journal *Annals of Operations Research* as Huster et al. (2026). It will be referred to as study D. The full text is inserted in Section D.

3.4.1 Motivation and Methodology

The simulation model developed in Study C enables detailed exploration of reconditioned EVB flows, with each evaluation taking approximately thirty minutes. While manageable for single evaluations, this runtime becomes a limiting factor when exploring a large number of parameter combinations. In particular, the model's high-dimensional input space, consisting of 49 parameters, poses challenges for scenario analysis and optimization. Study D addresses these constraints by developing a machine learning-based meta-model that approximates the simulation's behavior while significantly reducing computational effort. The goal is to enable rapid prediction of simulation outcomes based on input parameters and thereby facilitate broader scenario analyses. However, the structure of the input and output data is unusual: the input data is static, while the output data is of time-series nature, but without predecessors. For example, there is no data on previous supply and demand of reconditioned batteries, but all supply and demand is determined for future periods based on the inputs of the simulation model. The inputs comprise, for instance, assumptions about new EV registrations or the life expectancy of batteries of different cell chemistries, and those inputs do not change over time. Because of these particularities, it is unclear a priori which type of surrogate modeling approach is best suited to the problem.

To address this, the study compares two modeling strategies. The *recursive approach* (rec) predicts each output sequentially, using earlier predictions as additional inputs for subsequent ones. This allows the model to capture potential interdependencies among output variables and mimic logical relationships observed in the simulation, but it may also propagate errors through the prediction chain. In contrast, the *all-at-once approach* (aao) treats the five output time series as a multivariate target and predicts them simultaneously. While this method avoids error accumulation and reduces complexity in implementation, it may be less flexible in capturing relationships between outputs.

Multiple model types are tested under both strategies, namely artificial neural networks (ANNs), tree-based regressors (random forest (RF), decision trees (DT), and XGBoost (XGB)), and Gaussian process regression (GPR). All models are testes with various settings, e.g., regarding the number of layers and neurons in the ANNs, or the number of trees for the RF models. The training dataset is generated via Latin Hypercube Sampling (LHS) to ensure broad coverage of the input space. The dataset comprised 490 parameter combinations with three replications each, resulting in 1,470 simulation runs. Model performance is evaluated using R^2, root mean squared error (RMSE) and mean squared error (MSE) metrics to assess accuracy. Additionally, the model fitting time is monitored. The exploratory design enables identification of suitable surrogate models and provides a methodological basis for accelerating complex systems analysis in the context of emerging products predictions.

3.4.2 Results

A total of 232 surrogate models were developed, with 116 employing the aao approach and 116 using the rec approach. Both strategies performed equally well on average: in 50% of the cases, the aao model achieved the higher R^2 value, while in the remaining 50%, the rec model performed better. On average, aao models attained an R^2 of 0.34 and required 11.6 seconds to train, whereas rec models achieved a slightly higher average R^2 of 0.41 but with a substantially longer average training time of 54.9 seconds. This indicates that the rec approach entails significantly greater computational effort, with only a modest improvement in accuracy. However, average performance values across all models mask considerable variation: some models performed poorly, with DT models even producing negative R^2 values. Moreover, models that performed well in one approach did not necessarily yield comparable results when applied under the other. For instance, certain neural networks ranked among the top-performing rec models but showed weak performance in the aao configuration. Conversely, the aao XGB model delivered the highest average accuracy across all KPIs and time periods, but performed notably worse in the rec setup. These inconsistencies, together with the low overall R^2 values across all models, highlight that aggregated metrics are not representative of actual performance on the level of individual KPIs or specific years.

Instead, performance varies depending on the specific output variable and prediction year. This variability is illustrated in Figure 3.7, which compares the best-performing models per KPI and time point. For example, XGB performs best for nine out of 30 targets, but ANNs and GPR models with a certain kernel setting perform better for other targets. RFs are never among the top performing models.

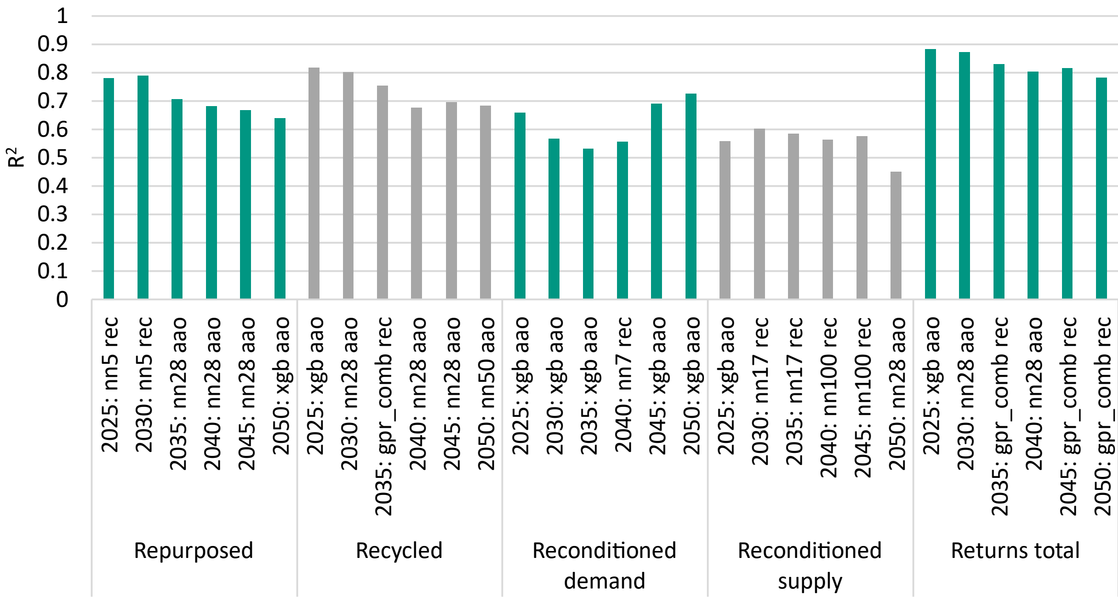


Figure 3.7: R^2 of the best performing surrogate model per KPI and year. aao: all-at-once approach; gpr_comb: Gaussian process regression with a combination of constant, radial basis function and matern kernels; nn5: neural network with four layers (128, 64, 32, 16 neurons), activation: logistic, solver: lbfgs; nn7: neural network with four layers (128, 64, 32, 16 neurons), activation: relu, solver: adam; nn17: neural network with three layers (128, 64, 32 neurons), activation: logistic, solver: lbfgs; nn28: neural network with two layers (128, 64 neurons), activation: logistic, solver: adam; nn50: neural network with three layers (32, 16, 8 neurons), activation: identity, solver: lbfgs; nn100: neural network with two layers (64, 32 neurons), activation: logistic, solver: adam; rec: recursive approach; xgb: XGBoost. Reproduced from Huster et al. (2026), Annals of Operations Research,

To assess whether model complexity could be reduced while maintaining predictive accuracy, a feature selection procedure was applied using the built-in feature importance rankings of XGB. For each KPI and year, the ten most important input features were identified and used to train one reduced model per KPI and year. As shown in Figure 3.8, this simplification had little to no negative effect on most output indicators with regard to R^2. For the total number of returning batteries, for repurposing and recycling volumes, and for reconditioning supply, the reduced models performed similarly or even slightly better than their full-feature counterparts. However, for reconditioning demand, the performance declined considerably when using only ten input variables, indicating that this output relies on a broader and more distributed set of input parameters. These findings suggest that model simplification through targeted feature selection is feasible for some KPIs, but should be applied with caution for outputs that are more sensitive to a wider range of factors.

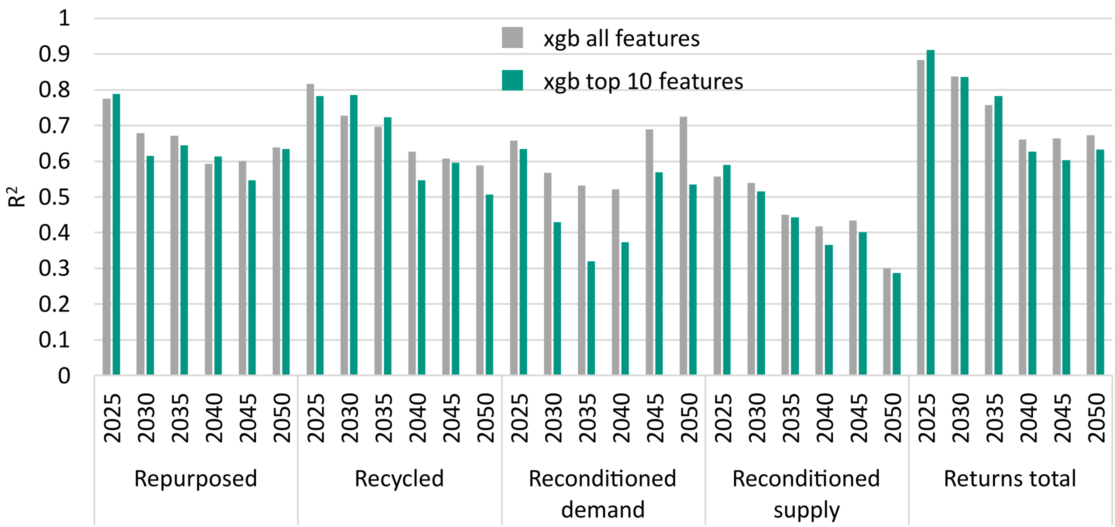


Figure 3.8: R^2 of the xgb surrogate modelestimated with all 49 features and with the 10 most important features of each KPI and year. xgb: XGBoost. Reproduced from Huster et al. (2026), Annals of Operations Research, © The Authors, CC BY 4.0

3.4.3 Discussion and Limitations

The results of Study D highlight both the potential and the constraints of using machine learning to approximate simulation models with static inputs and time-dependent outputs. On average, recursive models achieved slightly higher predictive accuracy than all-at-once models, though they required significantly more time to train. Given that training times for all models remained below three minutes, this difference is unlikely to be practically relevant in the current setting but may become more important for larger datasets or repeated evaluations. Performance varied across output indicators. Outputs such as battery return volumes, which followed relatively stable trends, were predicted with higher accuracy. In contrast, reconditioning demand was more difficult to model due to its structural complexity and a large proportion of zero values, which result from numerous input parameter configurations that yield zero or very low demand, like high reconditioning costs compared to recycling and repurposing. These sparse outputs pose challenges for regression models, as they contain limited information for learning consistent patterns. Feature selection helped reduce model complexity for most KPIs without major losses in accuracy. However, for reconditioning demand, limiting the input to ten features significantly decreased performance, highlighting the need for comprehensive input representation in such cases.

The study is limited by the relatively small training dataset (490 samples), which may restrict the models' ability to learn complex relationships. The unusual data structure of static inputs with time-series outputs is also challenging for standard regression and forecasting approaches. These limitations point to the need for future research on adaptive sampling strategies and hybrid model architectures to evaluate their effect on surrogate model performance. Despite these constraints, the results demonstrate that machine learning can meaningfully reduce computational effort and enable broader scenario exploration, particularly in early-stage planning for circular economy applications.

4 Implications, Limitations and Outlook

In the following, the results outlined in Section 3 are connected to the research objectives introduced in Section 1.2. Subsequently, the limitations of the presented work as a whole, beyond that of the single studies, are discussed, along with an outlook on potential further research directions.

4.1 Deduction of Implications from Research Objectives and Results

Figure 4.1 summarizes the results with regard to the research objectives. The first research objective aimed at evaluating the product flow of reconditioned EVBs. To this end, study A introduced a DES model to capture the effects of lifetime mismatches between EVs and their batteries. A case study demonstrated that early battery failures occur even when the average EVB lifetime equals or exceeds that of EVs, which results in a demand for spare parts, given that vehicles require functional batteries up to a certain age. This need for replacement batteries could partially be covered by reconditioned batteries, thereby reducing material consumption and energy use. The simulation model's ability to visualize product flows over time enables a more practical estimation of future EoL processing capacities. The approach of analyzing product flows based on lifetime mismatches is transferable to other multi-component products facing similar challenges. Lieder et al. (2017) addressed this issue for washing machines, where the failure of key components, such as the motor or control electronics, often necessitates repair or replacement decisions. A comparable situation arises for mobile phones and other consumer electronics, where battery degradation frequently drives product replacement despite the remaining functionality of the device (Borthakur and Singh 2021). Applying such modeling approaches to these product groups could support the development of reconditioning strategies, improve spare part availability, and contribute to longer product lifespans and resource conservation.

The second research objective, which is gathering information about the EVB reconditioning stakeholders regarding their decision-making criteria, is addressed in studies B and C. Based on a discrete choice experiment, study B identified that end customers' acceptance of reconditioned batteries is primarily influenced by two factors: the expected remaining lifetime of the battery and its price. Environmental aspects play a subordinate role in purchase decisions, functioning more as an additional benefit rather than a primary decision driver. Preferences vary across customer groups, with younger individuals and non-EV owners showing greater concern regarding reduced battery lifetime. Regarding OEMs, recyclers, reconditioners, repurposers, and workshops, study C revealed that those base their decisions largely on economic considerations, though workshops are additionally influenced by subjective beliefs. The insights derived from this stakeholder analysis are not only relevant for predicting EoL battery flows, but also offer broader applicability for both industry and policy. For OEMs and other reconditioners, the results provide information to tailor marketing and communication strategies, for example, by targeting specific customer segments with customized information on reconditioned battery lifetimes and cost advantages. Moreover, policymakers aiming to influence the uptake of particular EoL strategies, whether to promote reconditioning, repurposing, or recycling, can use these insights to design supportive or corrective policy instruments, such as warranty regulations, incentives for high-quality reconditioning, or certification schemes that enhance customer trust. Beyond the EV sector, similar stakeholder-driven approaches may be applicable in other markets where component remanufacturing plays a role, such as in medical devices or consumer electronics, where trust in the reliability and safety of reconditioned components remains a critical factor for market acceptance (Aydin and Mansour 2023; Pinheiro et al. 2024).

Evaluation of the product flow of reconditioned EVBs

- Vehicles will experience early battery failures not only when the average battery lifetime is shorter than the average vehicle lifetime, but also when both are equal or even when battery lifetimes are longer.
- About 2% to 7% of the demand for new spare batteries could be offset by reconditioned batteries up to 2040.
- The demand for spare batteries may exceed the supply of reconditioned batteries starting around 2030.

Stakeholder information gathering

- End customer acceptance of reconditioned EVBs depends mainly on battery life expectancy and price, and to a lesser extent on environmental benefits.
- Preferences differ between age groups as well as between EV owners and non-EV owners.
- OEMs, recyclers, reconditioners, and repurposers primarily base their decisions on economic considerations.
- Workshops' decisions regarding the offering of reconditioned products are influenced by economic considerations and subjective beliefs.

Integration of the product and stakeholder view

- A multi-method simulation model predicts the demand and supply of reconditioned EVBs based on 49 parameters, capturing decisions by consumers, OEMs, policymakers, and other stakeholders, as well as battery and vehicle lifetimes and technological developments.
- The OEMs' decisions regarding the use of reconditioned batteries in warranty cases have the greatest influence on demand and supply.
- Additional significant influences include consumer preferences for spare batteries, variations in warranty periods, and the quality of reconditioned batteries.

Acceleration of the estimation process

- The input-output relationships of the 49-parameter simulation model are approximated using machine learning methods, reducing the computation time from approximately 30 minutes per evaluation to a fraction of a second.
- The machine learning models differ in predictive performance across KPIs.
- KPIs related to the total number of EVB returns can be predicted reliably with R^2 values of 0.8 to 0.9, whereas the demand for reconditioned EVBs can only be approximated with R^2 values between 0.53 to 0.73, depending on the period examined.

Figure 4.1: Results with regard to the research objectives

Study C worked towards the third research objective, which was combining the product flow modeling with stakeholder preferences, by integrating technical, economic, and behavioral factors into a multi-method simulation framework. The simulation model incorporates 49 parameters representing decisions by consumers, OEMs, policymakers, reconditioners and other stakeholders, as well as technological and regulatory developments. The simulation results demonstrate that OEMs' decisions on whether to use reconditioned batteries in warranty cases have the greatest influence on the overall market size. In addition, variations in consumer preferences, warranty conditions, and technical specifications of reconditioned batteries significantly affect both supply and demand of reconditioned EVBs over time. The integrated modeling approach offers practical applicability beyond forecasting EoL quantities. It can serve as a decision-support tool, allowing stakeholders to explore the potential effects of alternative strategic or regulatory scenarios before implementation. For OEMs and reconditioners, for instance, it enables the systematic assessment of how changes in warranty policies, product characteristics, or customer preferences could shape future business opportunities in reconditioning. For policymakers, the model provides a basis for evaluating how specific interventions, such as changing minimum recycled content requirements or setting minimum quality standards for reconditioned batteries, may influence stakeholder behavior and the uptake of reconditioning within the broader circular economy context.

Addressing the fourth research objective, Study D explored the use of surrogate modeling to accelerate the simulation of reconditioned battery flows. The discrete event and agent-based simulation model, while flexible and comprehensive, is computationally intensive due to the large number of parameters and time-dependent outputs. Each run takes approximately ten minutes, and three replications are required to account for stochasticity, resulting in about 30 minutes per evaluation. To overcome this computational burden, machine learning methods were applied to approximate the model's input-output behavior. This reduced evaluation time to fractions of a second and enabled large-scale scenario analyses and sensitivity studies that would otherwise be impractical. The results showed that the predictive performance of the surrogate models varied across different key performance indicators: while total battery returns could be predicted with high accuracy, forecasts for reconditioned battery demand were less precise, particularly for earlier time periods with lower reconditioning quantities. The methodological approach demonstrated in this study extends beyond the specific application of reconditioned EVBs. Surrogate modeling can be applied to a wide range of complex simulation models in circular economy research, where high computational requirements may limit the scope of analysis. The ability to approximate simulation models efficiently enables fast exploration of large parameter spaces, supports decision-making under uncertainty, and facilitates fast policy or business scenario testing. Such applications may be relevant in other fields where dynamic simulations are employed, for example, climate modeling, which faces even larger computational challenges (Segura et al. 2025).

4.2 Limitations and Outlook

While this dissertation contributes to a better understanding of the demand and supply of reconditioned EVBs considering stakeholder interests, several limitations remain that offer avenues for further research. A first limitation concerns the technical feasibility and scalability of reconditioning processes. Although several companies, such as Stellantis and Mercedes-Benz, are already engaged in battery reconditioning (Mercedes-Benz n.d.; Stellantis 2023), the processes remain largely manual and labor-intensive, thus limiting their scalability and price competitiveness. Current research projects are investigating key prerequisites for scaling, such as improved disassemblability of battery systems and advanced testing capabilities for battery modules and cells (DemoRec 2023; FASTEST 2023; REVAMP 2023). In this context, the introduction of the Battery Passport, as foreseen in the EU Battery Regulation, may facilitate reconditioning by requiring OEMs to disclose information on battery composition and disassembly procedures to authorized parties (European Parliament and European Council 2024a). However, the timing and extent to which large-scale, economically viable reconditioning will be realized remain highly uncertain. The simulation model applied in this work accounts for some of these uncertainties by incorporating the year of market availability for reconditioning and cost developments as input parameters. Nonetheless, these simplifications only provide a coarse representation of reconditioning business dynamics. The underlying process steps, operational bottlenecks, and possible technological advances in reconditioning are not explicitly modeled.

Secondly, the focus of this research lies on reconditioning as an EoL strategy. While alternative pathways such as recycling and repurposing are included in the model, they are represented in less detail. In particular, for repurposing, only the availability of suitable used batteries was considered, assuming an existing and sufficient demand for stationary applications. A dynamic comparison between supply and demand for repurposing is thus not integrated into the simulation framework but could be incorporated in future model extensions.

A further limitation concerns the applicability of the simulation model beyond the specific geographical and regulatory context it was developed for. The model itself is structurally transferable to other markets; however, its input data primarily originates from the German and European context. The customer preferences integrated into the simulation are based on survey data collected from German consumers, while information on stakeholder behavior was derived from interviews with European companies, often involving German subsidiaries. Furthermore, the regulatory assumptions, such as minimum recycled content quotas, are based on the EU Battery Regulation, although the model allows for different values to be inserted for alternative regulatory environments. As a result, it remains uncertain whether the model's results are directly transferable to markets with different consumer behavior, stakeholder structures, or regulatory frameworks.

In addition, cross-border product flows, particularly exports of vehicles and batteries beyond the EU, have not been explicitly modeled. Incorporating system outflows as a fixed export share would be technically straightforward; it would lead to a proportional reduction in the domestic availability of end-of-life batteries for reconditioning, but also to a correspondingly lower spare part demand, as exported vehicles no longer require replacement batteries within the examined market. However, such a simplified approach would not provide insights into potential measures for influencing these outflows or their long-term implications for domestic battery availability. Exploring mechanisms to retain vehicles and their batteries within the EU through economic incentives or international agreements remains an underexamined area. A better understanding of these dynamics may contribute to more comprehensive demand and supply forecasts for reconditioned EVBs.

Technological developments in battery design and chemistry represent another source of uncertainty. The simulation model allows for differentiation between several cathode chemistries, such as LFP, NMC, and sulfur-based batteries. In the simulation model, these chemistries differ in terms of costs and revenues for recycling and reconditioning, material compositions relevant for recycled content quotas, and durability. However, future developments that are not yet foreseeable, such as the introduction of new cell chemistries, are not represented in the model. In addition to the chemistry itself, battery pack design developments may also influence reconditioning potential. For instance, cell-to-pack designs offer advantages for battery assembly and energy density (Hettesheimer et al. 2023), but may complicate disassembly if cells are bonded directly (Spancken and Stelter 2024), potentially making reconditioning more difficult. The effects of such developments on the availability and economic viability of reconditioning remain uncertain.

Although the simulation model incorporates a set of 49 parameters reflecting technical, economic, and behavioral factors, it cannot be ruled out that additional influential factors or stakeholder groups may have been overlooked. This risk was mitigated through expert interviews, but uncertainties about comprehensiveness remain.

In addition to the technological and market aspects, ecological assessments have not been integrated into this work. While life cycle assessments (LCAs) are available for battery manufacturing, recycling, and repurposing processes (Liu et al. 2023; Popien et al. 2023; Y. Zhou et al. 2025), only limited LCA studies exist for reconditioning. Future research could build on the simulation results presented here to conduct temporal LCAs of reconditioning pathways, as demonstrated for recycling scenarios by Rosenberg et al. (2023).

Finally, while decisive factors influencing reconditioning quantities have been identified, the means of actively steering these factors remain insufficiently explored. For instance, improving the technical quality of reconditioned batteries is crucial for increasing customer acceptance but requires further technological advancements. Thus, future research should complement system-level modeling with investigations into the technical feasibility of process improvements, supported by both experimental studies and field data from ongoing reconditioning activities.

5 Summary

The growing uptake of electric mobility offers opportunities for greenhouse gas reduction but poses significant challenges regarding the end-of-life management of electric vehicle batteries. While battery recycling technologies continue to mature and regulatory frameworks such as the EU Battery Regulation increasingly mandate material recovery, options higher in the waste hierarchy, such as repurposing and reconditioning, remain at an early stage of development. This dissertation investigates the supply and demand dynamics of reconditioned electric vehicle batteries, combining product-oriented and stakeholder-oriented perspectives into an integrated assessment framework.

The first part of the research focused on quantifying the product flow of reconditioned batteries. A discrete event simulation model was developed that captures the asynchronous ageing of vehicles and their batteries and estimates spare part needs. The results show that battery failures occur even when average battery lifespans equal or exceed those of vehicles, leading to a continuous demand for replacement batteries throughout the vehicles' service life. Reconditioning can reduce the production of new batteries by approximately 2% to 7% depending on the underlying lifetime assumptions. However, demand for reconditioned batteries generally exceeds the available supply, indicating that reconditioning can only partially substitute new battery production.

To complement the technical modeling, the preferences and decision-making processes of relevant stakeholders were examined. A discrete choice experiment revealed that consumer acceptance of reconditioned batteries primarily depends on price and expected battery lifetime, while environmental benefits play a subordinate role. Differences in acceptance were observed between consumer segments, with younger respondents and those without previous electric vehicle ownership showing lower acceptance of reconditioned batteries with shorter life expectancies. Interviews with manufacturers, workshops, recyclers and repurposers demonstrated that economic considerations are the dominant factor guiding corporate decision-making. For workshops, subjective perceptions also influence their willingness to offer reconditioned products.

Building on these empirical insights, a simulation model was developed that integrates product flows, stakeholder decisions, regulatory influences and technological developments. The flexible structure of the model incorporates 49 parameters and allows for scenario-based exploration of future developments. The results indicate that stakeholder behavior, particularly the manufacturers' decisions regarding warranty applications of reconditioned batteries, has a strong influence on demand and supply dynamics. Changes in consumer preferences, product quality, warranty conditions and regulatory parameters further affect the potential role of reconditioning. The model can serve as a decision-support tool for businesses and policymakers to evaluate the consequences of alternative strategies under uncertain conditions.

Given the model's complexity and computational intensity, surrogate modeling approaches were explored to accelerate the evaluation process. Machine learning techniques were applied to approximate the simulation's input-output relationships and enable fast scenario analysis. The surrogate models achieved high accuracy for some key performance indicators, such as the total number of battery returns, while forecasts for reconditioned battery demand were more difficult to approximate reliably. Nonetheless, the approach allows for substantial acceleration of scenario evaluation and supports the broader analysis of complex systems.

This dissertation contributes to a more comprehensive understanding of reconditioning as part of a circular economy approach for electric vehicle batteries. The results demonstrate that reconditioning can play a role in future battery end-of-life management but is limited by technical challenges, economic constraints and stakeholder-related factors. The methodological framework developed in this work combines empirical data collection with simulation modeling and allows for flexible scenario analysis under uncertainty. This approach is not only applicable to electric vehicle batteries but may also be transferred to other multi-component products where the lifetime of individual components differs and replacement decisions depend on technical feasibility, economic incentives and user acceptance. Future research should further investigate technological developments that facilitate reconditioning, expand environmental assessments, and explore policy measures that steer the end-of-life pathways of electric vehicle batteries.

6 Use of Generative Artificial Intelligence

During the preparation of this work the author used ChatGPT in order to improve readability and language. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Part II:
Research Papers

List of Included Articles

Study A

Huster, S., Glöser-Chahoud, S., Rosenberg, S., & Schultmann, F. (2022). A simulation model for assessing the potential of remanufacturing electric vehicle batteries as spare parts. Journal of Cleaner Production, 363, 132225. https://doi.org/10.1016/j.jclepro.2022.132225. © 2022 Elsevier. Reproduced with permission.

Study B

Huster, S., Rosenberg, S., Hufnagel, S., Rudi, A., & Schultmann, F. (2024). Do consumers want reconditioned electric vehicle batteries? – A discrete choice experiment. Sustainable Production and Consumption. https://doi.org/10.1016/j.spc.2024.05.027. © 2024 The Authors. Published by Elsevier under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License (CC BY-NC-ND 4.0). https://creativecommons.org/licenses/by-nc-nd/4.0/.

Study C

Huster, S., Heck, R., Rudi, A., Rosenberg, S., & Schultmann, F. (2025). Will electric vehicle battery reconditioning succeed? – A flexible simulation approach considering stakeholders' interests. Journal of Environmental Management, 389, 125783. https://doi.org/10.1016/j.jenvman.2025.125783. © 2025 The Authors. Published by Elsevier under a Creative Commons Attribution 4.0 International License (CC BY 4.0). http://creativecommons.org/licenses/by/4.0/.

Study D

Huster, S., Faraji-Niri, M., Rudi, A., Schultmann, F. (2026). Approximating End-of-Life Electric Vehicle Battery Flows: Surrogate Modeling of a Discrete Event and Agent-Based Simulation Model. Annals of Operations Research. https://doi.org/10.1007/s10479-026-07342-3. © 2026 The Authors. Published by Springer Nature under a Creative Commons Attribution 4.0 International License (CC BY 4.0). http://creativecommons.org/licenses/by/4.0/.

A A Simulation Model for Assessing the Potential of Remanufacturing Electric Vehicle Batteries as Spare Parts

Authors: Sandra Huster, Simon Glöser-Chahoud, Sonja Rosenberg, Frank Schultmann

Abstract

Remanufacturing is a key element of circular economy solutions as it aims at increasing the service lifetime of entire products or specific components, which may reduce the demand for new, resource-consuming devices. To assess the potential of disassembling and subsequent remanufacturing of EV batteries, we present a discrete event simulation approach. This approach depicts the life cycle of batteries and EVs separately, which allows capturing the demand for spare batteries and the potential contribution of remanufacturing batteries to cover this demand. By running various scenarios taking the German EV market as an example, the importance of providing cost-effective spare batteries through remanufacturing is underlined. As a baseline, a linear case is examined, where remanufacturing is not an option. Additionally, we built scenarios where remanufactured batteries are used as spare parts for older vehicles. Another major variation is introduced by different average battery lifetimes (10, 15, and 20 years), while the average vehicle lifetime is 15 years in all cases. The results show that remanufactured spare batteries could decrease the demand for new batteries compared to the linear base case. When battery lifetimes are lower than those of vehicles, new battery demand could be reduced by 6-7%, given our assumptions. In future scenarios where expected battery lifetimes might exceed vehicle lifetimes, up to 2% savings in new batteries could still be possible. Therefore, remanufacturing could be a viable option for improving the sustainability of electric mobility, and (re)manufacturers should consider intensifying their engagement in designing remanufacturable batteries, in research on remanufacturing technologies, and in investing in remanufacturing infrastructure.

Keywords

Remanufacturing; Closed-loop supply chains; Circular economy; Product lifetimes; Simulation

Abbreviations

BEV	battery electric vehicle	*KPI*	key performance indicator
BMS	battery management system	*LCA*	Life cycle assessment
DES	discrete event simulation	*MFA*	material flow analysis
DLM	distributed lag model	*NMC*	Lithium-Nickel-Manganese-Cobalt-Oxide
EoL	End-of-Life	*OEM*	original equipment manufacturer
EV	electric vehicle	*PHEV*	plug-in hybrid electric vehicle
EVB	electric vehicle battery	*PFA*	product flow analysis
GHG	greenhouse gas	*SOH*	state of health
ICEV	internal combustion engine vehicle		

Scenario abbreviations:

la	Linear case, no battery replacement after warranty
lb	Linear case, new spare battery after warranty
raa	Remanufacturing case, only remanufactured batteries as spare parts, same sales data
rab	Remanufacturing case, only remanufactured batteries as spare parts, same stock
rba	Remanufacturing case, remanufactured or new batteries as spare parts, same sales data
rbb	Remanufacturing case, remanufactured or new batteries as spare parts, same stock

A.1 Introduction

Against the background of global warming, sustainability considerations have noticeably increased. One of the most greenhouse gas (GHG) intensive sectors is the transportation sector with about 27% of the total GHG-emissions in the European Union, 71.7% of which come from road transport (European Environment Agency (EEA), 2019). One possibility to reduce the environmental impact of transportation is to replace internal combustion engine vehicles (ICEVs) with electric vehicles (EVs). In 2019, about 7.2 million EVs (battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV)) were registered worldwide, and, given the existing government policy and fossil fuel prices, the number is expected to rise by the factor of 30 by 2030 (IEA, 2020). EVs offer multiple advantages compared to ICEVs. First, they limit the emission of greenhouse gases to the facilities of production of vehicles, batteries and energy, and reduce the overall amount significantly (Girardi et al., 2015). Second, they are more energy-efficient than ICEVs. While an ICEV converts 12% to 30% of the input energy into motion, EVs utilize about 77% of the induced electric energy (U.S. Department of Energy, n.d.). Additionally, electricity needed for powering EVs is mainly generated locally, which reduces the dependence on oil-producing countries (Li et al., 2018).

However, the overall environmental benefits of electric mobility are greatly influenced and limited by the production of EV batteries (EVBs). For instance, EVB manufacturing approximately doubles the CO_2 manufacturing emissions (Hall and Lutsey, 2018) compared to ICEVs (embodied emissions), and accounts for about a quarter of the eutrophication caused within an EV's life cycle and for about half of human toxicity (Girardi et al., 2015). State-of-the-art EV batteries are highly resource-consuming. While key components like manganese, nickel and natural graphite are expected to meet the future demand, supply risks for lithium and cobalt exist due to production capacities and geopolitical concentration of mining and refining to a limited number of countries (Olivetti et al., 2017).

One way to reduce the environmental impact of EVBs, that has recently attracted industry interest (Lienemann 2016, as cited in Kampker et al., 2020), is to remanufacture batteries, i.e., to bring them back to a good-as-new condition (Ijomah et al., 2004), and use them as spare parts for older EVs. For remanufactured batteries, 224 MJ/kWh less energy and 15.6 kg CO_2 equivalent/kWh less would be needed compared to manufacturing new batteries (Kampker et al., 2016), which is a reduction of about 20% in both energy consumption and greenhouse gas intensity when assuming the consumption and emission values of Dai et al. (2019) (1126 MJ/kWh, 72.9 kg CO_2 equivalent/kWh). But not only from an environmental, also from an economic point of view, remanufacturing might be viable and could provide cost-efficient spare parts. Kampker et al. (2016) take the remanufacturers' point of view and estimate, after considering costs and a potential reselling price, a total benefit of about 60 €/kWh. Foster et al. (2014) argue that remanufactured batteries could be provided at a price 40% below that of a new battery.

Nevertheless, these reflections are only relevant if there are older EVs that need batteries as spare parts. This need has two dimensions: The first question is whether there is a significant number of vehicles whose batteries fail prematurely, and the second question is whether consumers want to replace these failed batteries. To elaborate on the second question, it is conceivable that, when faced with the decision to replace a failed EVB or to scrap the EV early, consumers may tend to the latter due to environmental and economic concerns. Environmental concerns would be those mentioned earlier, and a new spare battery would double the harmful effect. Economic concerns may arise since battery replacements are, to date, expensive (Wood et al., 2011), and must be put in relation with the alternative of buying a new or used vehicle. Possibly due to these reasons, vehicle owners rarely replace batteries, as Wang et al. (2020) observed. It is conceivable that the aforementioned concerns about the environment and replacement cost are reduced when the options for vehicle owners are not limited to buying a brand-new battery or scrapping the vehicle but are extended to buying a remanufactured battery. In this way, the lifetimes of both batteries and vehicles could be better seized.

An important role in answering the first question, whether or not there is a significant number of vehicles whose batteries fail prematurely, is ascribed to the battery lifetime in relation to the rest-of-the-vehicle lifetime. For mean vehicle lifespans, information varies from 10 to 23 years (Hao et al., 2016; Masias, 2018; Oguchi and Fuse, 2015; Thielmann et al., 2015). Mueller et al. (2007), for instance, state a mean of more than 15 years and a wide standard deviation that leads to a span of zero to more than 30 years lifespan for ICEVs. It has been stated that EVs last even longer than ICEVs (Hoekstra and Steinbuch, 2020), so the aforementioned life expectancies for conventional vehicles can be seen as lower bounds for EV lifespans. For batteries, there is also a wide span for the assumed useful life. Ding et al. (2019) state that battery lifetimes have to increase to at least 10 years for higher market penetration, indicating a lifespan of less than 10 years in the present. Guenther et al. (2013) estimate the lifetime to range between 8.5 to 13 years, while Drabik and Rizos (2018) assume only 8 years. While the aforementioned battery life expectancies indicate that on average batteries last shorter than vehicles, sources stating the opposite can also be found. According to Schoch (2018), batteries can reach a mean lifetime of up to 25 years when operated with optimal charging strategies and at certain temperatures. Harlow et al. (2019) conclude from their experiments that Lithium-Nickel-Manganese-Cobalt-Oxide (NMC) cells could power EVs for over 1.6 million kilometers, which is much more than the average vehicle covers in its life. Hoekstra and Steinbuch (2020) agree that modern batteries will probably last longer than the rest of the EV. Depending on which lifetime prediction for vehicles and batteries is selected, different assumptions about whether or not a significant number of batteries needs to be replaced during a vehicle lifetime have to be made.

When we consider remanufactured spare batteries as an option, we assume that remanufacturing is physically and technically feasible. An often-read concern about End-of-Life (EoL) batteries, especially in non-scientific publications, is that they are only suitable for non-automotive applications (Engel et al., 2019; Nhede, 2020; Niese et al., 2020). While this is probably true for the whole battery system as is, it does not have to be for its components. A battery system should not be seen as one unit with a binary condition (intact or failed). Instead, battery systems consist of multiple modules connected in series and parallel, and each module consists of multiple cells connected in series (Rothermel et al., 2018). When the battery system's State-of-Health (SOH), i.e., the energy storage capacity compared to the original storage capacity, reaches 70% to 80%, it is assumed to be unsuitable for automotive applications (Podias et al., 2018). Two facts should be highlighted at this point: First, there is much storage capacity left that should not remain unused. Second, and more importantly, cells do not age evenly, e.g., due to non-uniform temperature distribution within the battery pack (Paul et al., 2013) and cell production-based variance (Baumhöfer et al., 2014). The battery system's capacity is defined as "the electric quantity released from a fully charged cell to a fully discharged cell in the pack" (Zheng et al., 2015). In other words, the system's capacity in serial circuits is the sum of the minimum dischargeable electric quantity and the minimum chargeable electric quantity. This context is illustrated in the supporting information (S1). Although this connection only exists for serial circuits, it becomes evident that by replacing weak cells or entire modules, the overall capacity of a battery system can be increased. Therefore, from a physical point of view, remanufacturing seems to be possible.

From an economic perspective, however, some obstacles have to be addressed if remanufacturing batteries and using these batteries as spare parts for EVs should be introduced as standardized industrial processes. Some efforts were already made on a small and pilot-project scale, e.g., by Daimler (2021) or Autocraft Drivetrain Solutions (n.d.). To encourage battery (re)manufacturers to further engage in designing remanufacturable batteries, in research on remanufacturing technologies and in investing in remanufacturing infrastructure, models for quantifying the number of used EV batteries, that are available for remanufacturing, and of vehicles, that are expected to require spare batteries, are needed. To quantify these numbers while capturing the lifespan mismatch, the life expectancies of batteries and vehicles have to be modeled separately. The aim of this study is to develop a model that fulfills these requirements, and, therefore, can be used for evaluating possible future scenarios regarding the market penetration of EVs and regarding battery and vehicle lifetimes.

The approach of simulating lifetimes of products and key components separately is not only relevant for the case of electric vehicles considered here, but forms an important contribution to cleaner production literature in general as it is transferable to various further product systems in the context of repair and remanufacturing. The goal of this contribution is to enable the evaluation of different future scenarios on a broader level, so that remanufacturing stakeholders get a better view and understanding of the future supply of and demand for remanufactured batteries and can broaden their engagement in facilitating remanufacturing research and infrastructure if it seems reasonable for them. The evaluation must be performed scenario-based. For instance, it is unclear what the actual lifetimes of batteries and vehicles are and what distribution they follow. With the proposed model, the number of spare batteries needed can be determined when certain lifetime distributions are assumed and how the number changes with lifetime modification. The effects of other uncertainties, such as the share of reusable cells or the demand for EVs, can also be assessed. Therefore, the model allows a broader view on vehicles' and batteries' closed-loop supply chains instead of focusing on the small-scale implementation of remanufacturing solutions.

Below, we provide an overview of existing methods for forecasting the quantities of returning used products. Afterward, the model itself is described. Then, we develop scenarios for a case study, which we carry out subsequently. For the case study, we chose the German market for EVs. Lastly, we discuss the results and draw major conclusions.

A.2 State-of-the-Art Forecasting of Used Product Returns

When considering previously published models for determining return quantities of used products, two major groups can be distinguished: First, models that deal with product returns for remanufacturing in general, and those that deal with EV batteries in particular.

General approaches or approaches for other products are often Distributed Lag Models (DLMs) (e.g., Chou et al., 2020; Clottey, 2016; Clottey and Benton, 2014; Krapp et al., 2013; Toktay et al., 2003), but other approaches can also be found, e.g., Artificial Neural Networks (Fang et al., 2018; Kumar et al., 2014), statistical time-series analysis (Ma and Kim, 2016), or network analysis (Zhou et al., 2016). EV-specific publications, on the other hand, mostly use Material Flow Analysis (MFA) and its sub-methods like Product Flow Analysis (PFA), and simulation. One reason why EVB returns forecasts are often limited in terms of method variety could be that EVs and EVBs are new products in a growing market, and long-living products with very long return lags (10 years and more). That induces high uncertainty levels that can be partially captured by depicting different scenarios in MFAs or other simulation models, while general methods are often intended for established products in established markets. Additionally, EVBs are not heterogeneous products that stay the same over the course of time and are compatible with all vehicles, and established forecasting methods are often designed for one non-changing product. Another particularity about EVs is that the component "battery" contributes majorly to the overall value and possibly limits the overall lifetime. However, it does not have to affect the lifetime, as it could be replaced. This special relationship between the super-component "EV" and the sub-component "EVB" suggests considering the components separately, which can rarely be found in general product return forecasting models. We, therefore, focus on EV-specific models for forecasting product returns.

Table A.1 presents a selection of EV-specific publications. Their methodical approaches reach from system dynamics or discrete event simulation over material flow analysis to stochastic distribution delay models, with MFA models and their derivates being the majority. Ai et al. (2019), Natkunarajah et al. (2015), Sanclemente Crespo et al. (2022), Wang et al. (2020) and Wu et al. (2020) are representatives of this majority. They all use MFA (derivates) to determine EVB return quantities in different world regions. In all cases, returns occur at the failure of the EV, without differentiation between vehicle and battery failures. In other words, the EV always fails as a whole. Almost all of the above-mentioned employ lifetime distributions. Only Natkunarajah et al. (2015) assume a fixed lifetime. The return quantities are determined mainly for the EoL option recycling, but Ai et al. (2019), Natkunarajah et al. (2015) and Sanclemente Crespo et al. (2022) also consider a share of batteries for repurposing after their first life in an EV. Whether or not there is demand for the repurposed batteries is not included in the models, i.e., the model gives a total number of batteries for repurposing without matching it to demand. However, Ai et al. (2019) compare the supply of and demand for repurposed batteries subsequent to model execution. Remanufacturing is not an option. Technological evolution in terms of new battery technologies that is likely to occur in the near future is hardly considered. Only Sanclemente Crespo et al. (2022) consider a change in battery weight and cathode material for the recycling material yields.

Elwert et al. (2018), Hoyer et al. (2011) and Richa et al. (2014) form another group of MFA models. They consider battery and vehicle lifetimes separately. Battery lifetimes are distributed, while vehicle lifetimes are fixed or unclear. Hoyer et al. (2011) and Richa et al. (2014) use these independent battery and vehicle lifetimes to determine not only the flow of EoL batteries, but also by replacing failed batteries with new ones, therefore creating an additional waste stream of EoL spare batteries. Since they both consider neither changes in battery technology nor remanufacturing, any new battery can be used as a spare part. Additionally, the condition of the vehicle at battery replacement is not taken into account, so that very old vehicles also get a new spare battery.

Busch et al. (2014) present a dynamic stocks and flows modeling approach with distributed, separate lifetimes for vehicles and batteries. Remanufactured or new batteries replace failed batteries in the model, making them the first to regard remanufacturing of EVBs in a model that estimates return flows. However, they also do not consider changes in battery technology so that every battery can be used in any vehicle at any point in time, and they do not regard the vehicle condition (e.g., age or remaining useful life) when assigning a spare battery. Equivalently, the battery condition is not relevant for the remanufacturing decision, only a certain rate is. Demand for remanufactured batteries is not monitored since remanufactured parts replace the demand for new parts.

Abdelbaky et al. (2020) also include remanufacturing in their distribution delay model. In their model, remanufactured batteries are only re-installed in the same vehicle so that demand and technological changes are not relevant here. Additionally, like in Busch et al. (2014), the battery condition does not influence the remanufacturing decision, only a fixed rate does.

At least, discrete event simulation for battery return flows was introduced in the literature. Kurdve et al. (2019) provide a schematic discrete event model with remanufacturing and point out the detailed conception as a research gap, but they do not set up and solve the model. Liang et al. (2014) apply their general discrete event model to EVB return quantities forecasting including a remanufacturing option. They do not include technological development or matching of supply of and demand for remanufactured batteries, but they address the factor "suitability for remanufacturing" by introducing a quality distribution based on the remaining useful life, i.e., basically based on the age of the product.

Table A.1: Publications about EVB return quantities (distr. = distribution; reman = remanufacturing, repurp,= repurposing, MFA = Material Flow Analysis, PFA = Product Flow Analysis)

Publication	Region	Method	Compound product	Product lifetime	EoL options	Technological evolution	Demand for reman and repurposing
Abdelbaky et al., 2020	EU	Distr. delay	No	Normal distr.	Reman, repurp., recycling	-	-
Ai et al., 2019	USA	PFA	No	Uniform, normal, Weibull distr.	Repurp., recycling	-	Not considered in the model, but subsequent comparison
Busch et al., 2014	UK	Dynamic stocks and flows model	Yes	Vehicles: normal distr. EVBs: normal distr.	Reman, recycling, waste	-	Replaces demand for new batteries
Elwert et al., 2018	EU, CHN, USA	PFA	Yes	Vehicles: fixed. EVBs: discrete distr.	Recycling	-	-
Hoyer et al., 2011	GER	System dynamics	Yes	Vehicles: Unknown. EVBs: Uniform distr.	Repurp., recycling	-	-
Kurdve et al., 2019	None	Discrete event simulation (draft)	No	Unknown	Reuse, repurp., recycling	-	-
Liang et al., 2014	None	Discrete event simulation	No	Weibull distr.	Reman, recycling	-	-
Natkunarajah et al., 2015	GER	MFA	No	Fixed lifetimes	Recycling, repurp.	-	-
Richa et al., 2014	USA	MFA	Yes	Vehicles: fixed. EVBs: discrete distr.	Recycling	-	-
Sanclemente Crespo et al., 2022	Catalonia	PFA	No	Weibull distr.	Repurp., recycling	Considered for material yield	-
Wang et al., 2020	CHN	MFA	No	Weibull distr.	Recycling	No	-
Wu et al., 2020	CHN	PFA	No	Weibull distr.	Recycling	No	-

That means, among the EV-specific battery return forecast models, no model, to our knowledge, predicts battery returns suitable for remanufacturing and, as a consequence, the supply of remanufactured batteries, while also considering demand for spare batteries. Under-examined factors are on the one hand the effect of limited demand due to the condition of vehicles at battery failure, and on the other hand the effect of developments in battery technology perhaps leading to unusable, incompatible battery supply. Examining these factors is only possible when considering batteries' and vehicles' lifetimes independently of each other and therefore capture the lifetime mismatch between the two components.

Concerning suitability of remanufacturing and demand, information about state-of-the-art can be retrieved from non-EV-specific prediction models and publications that focus on aspects other than prediction. As a way to include the state of the battery in the remanufacturing decision, looking at the remaining useful life (Liang et al., 2014) has already been mentioned. Other publications handle the quality factor of returning products by assigning fixed shares for different qualities, e.g., percentages of batteries good-enough for second-use and for recycling (Gu et al., 2018; Scheller et al., 2021), or by determining the different quality shares with probability distributions (Li et al., 2018).

Demand is rather considered in general prediction models or models designed for non-EV purposes. Lieder et al. (2017) designed a multi-method model, combining discrete event and agent-based simulation where a product is composed of different components. When the product fails as a whole, the components for reuse and remanufacturing are stored and only reassembled when there is customer demand. Whether a component is reused, remanufactured, recycled or leaked is determined by fixed shares depending on the design choices. Clottey et al. (2012) also consider demand for remanufactured parts but do not determine it; instead it is a given parameter. Goltsos et al. (2019) find that in existing literature, demand is assumed to be known in advance in most cases, which ignores that demand is uncertain, too. They state that "although remanufacturing companies should never disregard the estimation of returns, the importance of demand forecasting is such that it deserves equal consideration." (Goltsos et al., 2019: 452).

A.3 Methods of the Simulation Modeling

To assess the potential of EV battery remanufacturing, a discrete event modeling approach with agent-based elements is applied. In contrast to system dynamics models or simple stochastic calculations, with discrete event simulation (DES) every battery and every vehicle undergoes the steps of the use, and possibly reuse, phase as a single unit and can therefore be traced in every process step. Decisions on further use of entities can be made solely on their history. In this way, also stochastic outliers, that are likely to occur in reality, must be dealt with. The model is implemented in AnyLogic 8.5.2 (University version), a Java-based multi-method simulation tool, that allows to combine discrete event, agent-based and system dynamics approaches. AnyLogic has pre-defined libraries and modeling blocks, like the "Process Modeling Library" with entity sources, queues and delay blocks for DES, or state chart elements for agent-based modeling, but simulation logic can also be implemented by Java coding. We make use of these pre-defined modeling blocks and adjust their properties by programming.

Before presenting the model, the main assumptions are first disclosed.

A.3.1 Assumptions

The following assumptions are used to address uncertainties in the simulation model:

- It is possible to remanufacture a battery to a state that is suitable for automotive applications (Autocraft Drivetrain Solutions, n.d; Kampker et al., 2020). In practice, this is not performed on a large scale yet, which is why it can be selected in each simulation run from which point of time in the future remanufacturing should be considered an option.
- Battery and vehicle lifetimes are independent of each other. They are implemented as two-parameter Weibull distributions (Wang et al., 2020). Two-parameter Weibull distributions are defined by the shape parameter k and the scale parameter $1/_{\lambda}$ (Härtler, 2016). k is set to 3.6 for vehicles (Oguchi and Fuse, 2015) and 3.5 for batteries (Ai et al., 2019). $1/_{\lambda}$ is determined by the target expected lifetime value E(x) (Härtler, 2016):

  $$E(x) = 1/_{\lambda} * \Gamma(1 + 1/\mathrm{k}) \Leftrightarrow 1/_{\lambda} = \frac{E(x)}{\Gamma(1 + 1/k)} \quad (1)$$

  Therefore, the expected lifetime is the only free parameter that is needed to determine the vehicle and battery lifetime distributions. For vehicles, the expected lifetime is e_v, for new batteries, it is e_{nb}, and for remanufactured batteries, it is e_{rb}.
- Non-automotive second-life applications are also a possibility (repurposing). Lifetimes of repurposed batteries are assumed to follow a uniform distribution (Kurdve et al., 2019) with a minimum of min_{sl} and a maximum of max_{sl}. The change in the assumed lifetime distribution is justified by the fact that the applications of repurposed batteries are very broad and vary in load.
- Some batteries cannot be remanufactured, e.g., when the battery is damaged beyond repair. This manifests in s_r, the share of remanufacturable batteries.
- Every battery can only undergo a limited number of remanufacturing operations n_{max}.
- Not all battery cells that enter the remanufacturing process can actually be brought back to a quality good enough for automotive application. Instead, only a share s_v of cells is suitable for reuse in a vehicle. s_{sl} denotes the share of cells that are suitable for non-automotive applications (repurposing, second-life), and s_w is the share of waste cells that could not be used for remanufacturing. It is assumed that cells of the same quality are grouped to a new battery system, so that s_v and s_{sl} also represent the share of whole battery systems suitable for reuse in vehicles or suitable for repurposing.
- Batteries from failed vehicles are not reused immediately but tested and remanufactured instead. From a model perspective, that means they undergo the same remanufacturing process as every failed battery. This assumption is taken because trust in EVs, specifically their reliability and safety, is critical (She et al., 2017), and because the "Proposal for a Regulation of the European Parliament and of the Council concerning batteries and waste batteries" requires actors, who re-introduce batteries to the market, to ensure the battery's quality and safety (European Parliament and European Council, 2020, Article 59). Both seem to be best achieved by a testing and remanufacturing instance.

- New vehicles and vehicles up to a certain age a_o, e.g., the warranty period, always receive a new battery. Medium old vehicles up to the age a_o receive a remanufactured battery if a suitable one is available. It can be decided before the simulation experiment execution if medium old vehicles can also receive new spare batteries if no remanufactured ones are available. Old vehicles (> a_o) are disposed of when their previous battery fails.
- Battery technologies change over time. A technology life cycle of (t_{tech}) is assumed. That means that one technology is used for t_{tech} years and then a new technology dominates. An overlap of one year is assumed, where the new and the old technology are equally common. The interrelation is depicted in Figure A.1 (shape of model life cycles: Geyer et al., 2007).

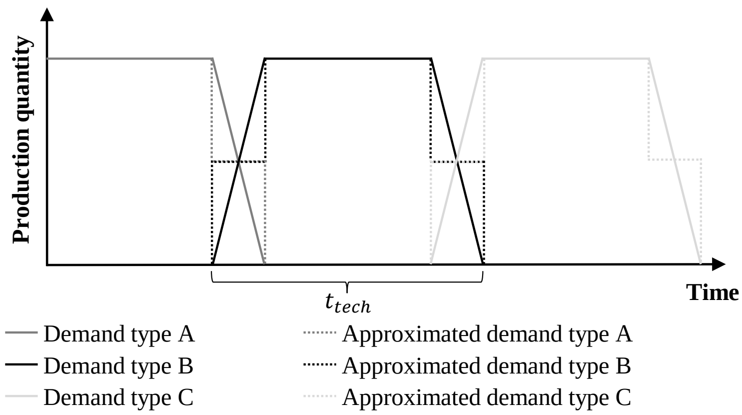


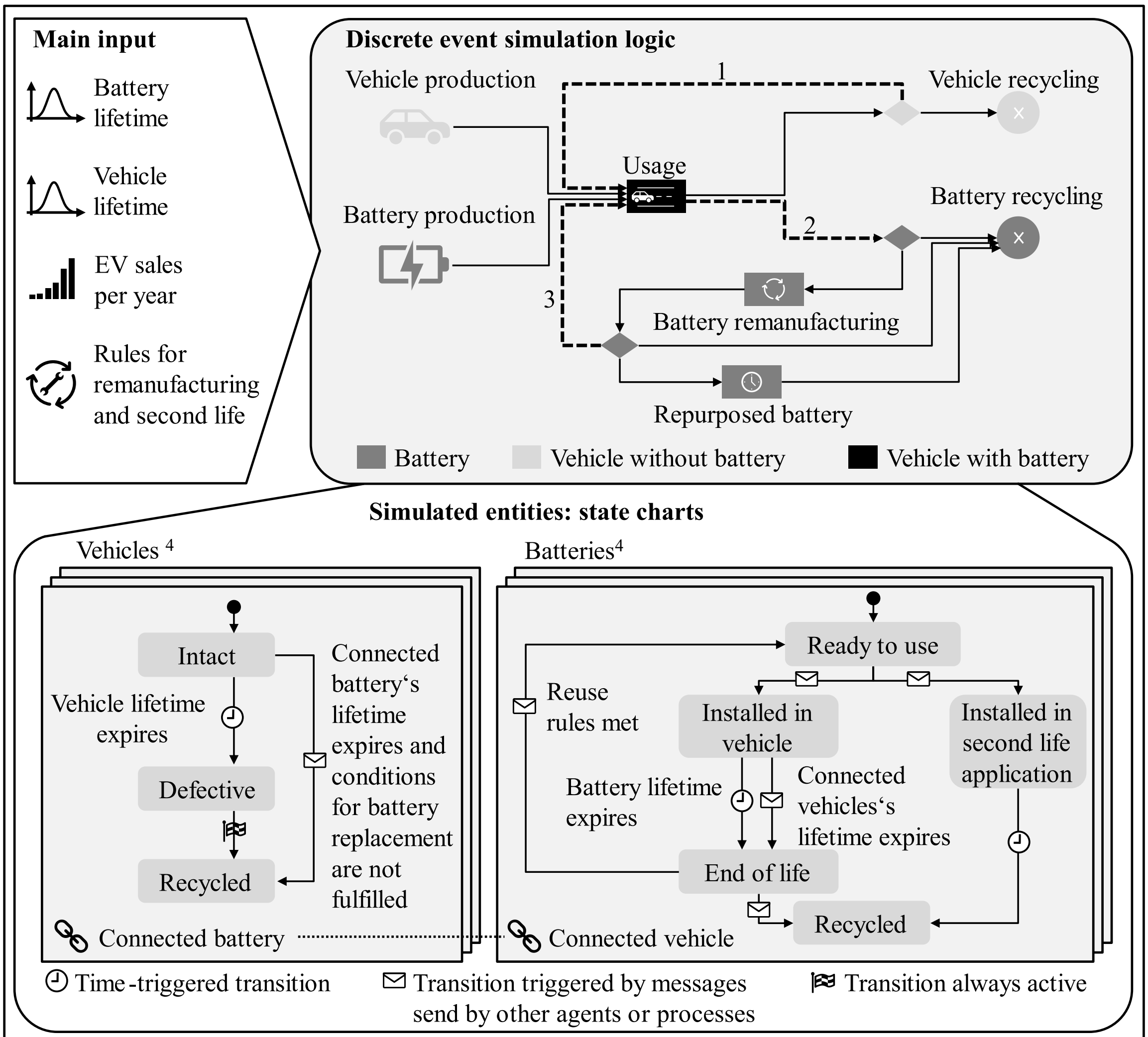
Figure A.1: Technology life cycle for different battery technologies. To address the fact that only components of the same battery type are valid for remanufacturing and battery technology changes over time, we distinguish between different technology cycles (type A, type B, type C, ...).

A.3.2 General Simulation Logic

The model is primarily a DES model. That means it contains a set of processes that entities pass at discrete points of time and that consume a discrete amount of time (Mykoniatis, 2015). The general simulation logic of our model is depicted in Figure A.2.

Our DES model starts with producing the entities, namely EV batteries and vehicles. DES-wise, that means a source releases entities according to a predefined rate or schedule. Afterward, a battery and a vehicle are matched and operate as a whole intact vehicle. The use time ends after the failure of either the battery or the vehicle. Both entities are then treated as two independent objects again and are processed solely depending on their own condition. For the vehicle, that either means the use phase is prolonged by replacing the battery, or it is disposed of. For the battery, recycling, remanufacturing for an automotive application, or repurposing for a non-automotive application are possible further use paths. It is assumed that in a sustainable supply chain, all batteries and vehicles are recycled after disposal.

Matching a vehicle and a battery means that the types and ages of the arriving entities are checked. As mentioned in section A.3.1, there are assumptions concerning up to which age vehicles only receive new batteries and from which age onwards also remanufactured batteries might be considered. Additionally, battery and vehicle types must correspond. From a simulation point of view, a “hard match” between the entities “vehicle” and “battery” could be performed, which would create a new joint entity with new properties and no traceable history.



[1]Demand for remanufactured batteries (with additional rules, e.g., concerning vehicle age)
[2]Total battery returns
[3]Supply of remanufactured batteries
[4]Only the most important transitions are labeled. A full explanation of the state charts can be found in the supporting information.

Figure A.2: General simulation logic. The discrete event simulation depicts the lifecycle of batteries and vehicles. It uses battery and vehicle lifetime distributions, EV sales forecasts, and decision rules about battery remanufacturing as input data. Decisions are made based on the state of the vehicle and battery entities.

This has certain disadvantages in our case since we want to track the history, and, above all, the life and service times of vehicles and batteries. If a new entity was created every time a vehicle and a battery are matched, the DES would have to pass the history of all entities. To avoid this inconvenience, vehicles and batteries are kept as separate entities with their own states but are connected to the other component with which they form an EV. These connections enable communication and interaction between the entities, which is why one could argue that simple agent-based elements are included. Communication comes to action when either the battery or the vehicle fails. This failure happens independently of the other component and independently of the process steps of the DES. Instead, every entity instance changes its state to “defective”/”End of life” according to a predefined lifetime distribution. Afterward, both entities are notified to proceed in the DES, where both are treated depending on their own state. For the vehicle that means direct recycling if it was the failing component. If it is still intact, but the battery failed, the conditions concerning vehicle age and remanufactured battery availability laid out in section A.3.1 are checked. If they are met, the vehicle receives a spare battery. We would like to mention again that the lifetime of the vehicle itself is not affected by this measure. For the batteries, different pre-conditions disqualify them for any kind of reuse, e.g., previous reuse or a certain age (cf. section A.3.1). All other batteries enter the remanufacturing step, which is modeled as a time delay. A certain percentage is afterward classified as suitable for reuse in a vehicle. These batteries are potentially re-installed in a vehicle of the same type, where the batteries start a new lifecycle with a new lifetime, possibly shorter or with a different distribution than in their first life. Another percentage is deemed good enough for non-automotive second-life applications, where they will serve for a certain amount of time. On the last share of batteries, remanufacturing could not be performed satisfactorily so that this share continues to recycling.

For the simulation to work as desired, inputs concerning battery and vehicle lifetime, on EV diffusion and on rules concerning reuse must be made. As mentioned before (cf. section A.3.1), battery and vehicle lifetimes can be set as desired with probability distributions. The battery agent can differentiate between new and remanufactured batteries so that the user can enter separate distributions. EV diffusion manifests in the vehicles produced in the first step of the DES. Any kind of forecast can be fed to the simulation, enabling to regard different future scenarios. Additionally, age limits for equipping vehicles with spare batteries and for reusing batteries must be specified as well as assumptions about the share of reusable batteries.

Three main key performance indicators (KPIs) can be taken from the simulation immediately. The first is the number of vehicles eligible for spare batteries, or only those eligible for remanufactured spare batteries. This is worth noting since that means the model incorporates estimating future demand for remanufactured parts. The second is the total number of returning batteries that must be dealt with. In our model, we have three ways of dealing with returned batteries (recycling, reuse in a vehicle, and repurposing), but even if one would only consider one or two of the options, the model would still give a glimpse at the future EoL battery treatment challenge. Third, the DES gives the number of batteries available for reuse in vehicles and, therefore, the supply side. Since we chose to model vehicles and batteries with their own properties (e.g., types), we can additionally compare supply and demand with matching restrictions, which probably exist due to different technologies (cf. section A.1). For that, it is important to capture statistical outliers, which is possible thanks to the entity-based DES approach. Another advantage of this approach is that the mentioned KPIs could be further decomposed by analyzing, for instance, the age of the batteries in each of the mentioned KPI groups. The time-based approach additionally enables to examine all KPIs over time.

More details on the DES model and the entities can be found in the supporting information (S 2.1 and S 2.2).

A.4 Case Study

A.4.1 Scenarios and Input Data

To demonstrate how the potential of remanufacturing can be evaluated using the proposed model, different model setups as briefly described below are considered in a case study.

1) *Case "linear":* At first, a base case is created that depicts the linear process of making a product, using it and disposing of it afterward. This means batteries are only used once and are not remanufactured. Nevertheless, even in the linear case, battery replacements with new batteries within the warranty period are performed. Battery replacements after the warranty period are considered in two sub-cases of the linear case:
   a) After the warranty period, no battery replacements are performed, because a new battery might not be environmentally and economically beneficial.
   Case name: *"Linear case, no battery replacement after warranty",* or case *la*
   b) After the warranty period, medium old vehicles receive new spare batteries when the old one failed. Only after a certain age limit, vehicles do not receive spare batteries.
   Case name: *"Linear case, new spare battery after warranty",* or case *lb*
2) *Case "remanufacturing":* Another configuration depicts the case that batteries can be remanufactured and used as spare parts for medium old vehicles. As described before, on battery failure, young vehicles within battery warranty receive a new battery, medium old vehicles receive a remanufactured battery on availability. If no remanufactured battery is available, two sub-cases conclude differently:
   a) If no corresponding remanufactured battery is available as a spare part for a medium old vehicle, the vehicle receives no spare battery at all and is directly scrapped and recycled instead. This means the battery life limits the use phase of the vehicle.
   Case name: *"Remanufacturing case, only remanufactured batteries as spare parts"*, or case *ra*
   b) If no remanufactured battery is available as a spare part for a medium old vehicle, a new battery is used as a spare part instead.
   Case name: *"Remanufacturing case, remanufactured or new batteries as spare parts",* or case *rb*

Old vehicles do not receive a spare battery at all (cf. section A.3.1).

Figures illustrating the cases "*linear"* and "*remanufacturing"* can be found in the supporting information (S3).

For the *linear* cases (*la*, *lb*), a sales-based diffusion model is chosen to reflect EV sales. That means vehicles are produced according to annual rates defined by a chosen diffusion forecast. Batteries are pulled into the system according to demand. In the *remanufacturing* cases (*ra*, *rb*), it can be expected that, on average, vehicles have a longer useful life than in case *la* since batteries are replaced even for older vehicles. If the same sales-based diffusion model is applied then, the vehicle stock will be higher than in case *la*. That would mean that more people have an EV in the *remanufacturing* cases (*ra*, *rb*) than in the *linear* case *la*. This seems improbable because the incorporated sales forecasts are not tailored to this paper's assumptions but existing forecasts are used instead. However, in case the vehicle stock increases with the availability of cheap spare parts, cases that combine remanufacturing and the same sales data as in the *linear* cases are considered as one possibility ("*remanufacturing case, [...], same sales data*", or case *raa* and *rba*) to evaluate the effect of remanufacturing on vehicles' useful lives. Additionally, remanufacturing is considered, but instead of the sales data from the cases *la* and *lb*, the vehicle *stocks* from these cases are the target values ("*remanufacturing case, [...], same stock*", or case *rab* and *rbb*). The case *la* sets the stock basis for the *rab* case, and the stock of the *lb* case is used as a base for the *rbb* case. The scenarios are illustrated in Figure A.3.

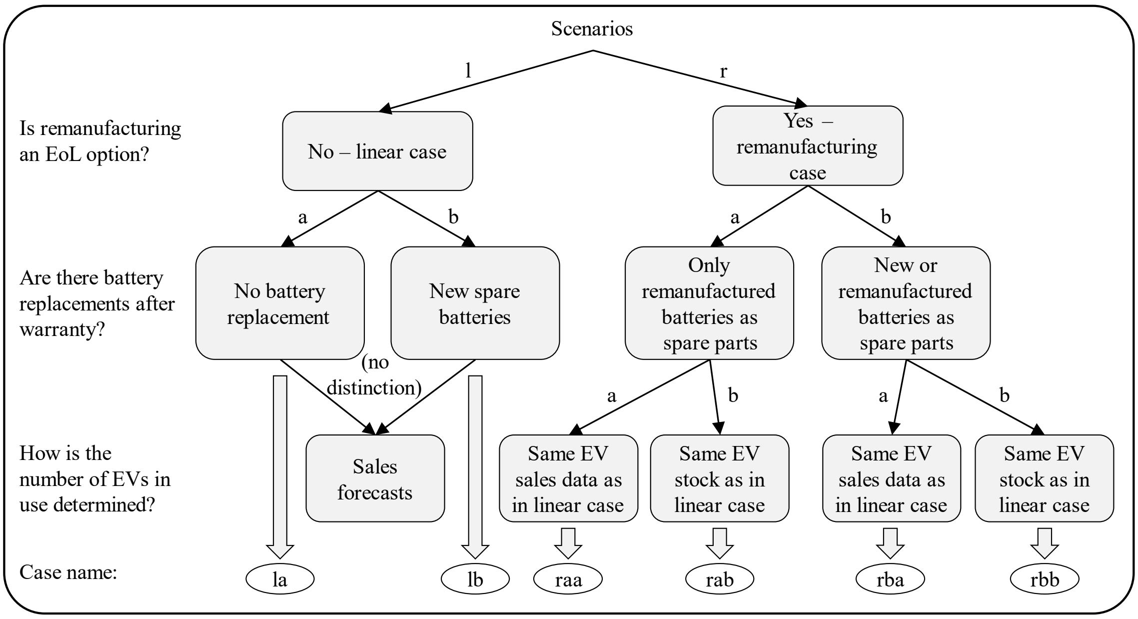


Figure A.3: Case study scenarios. The scenarios can be differentiated by the existence of remanufacturing as an EoL option, by the rules that apply for battery replacements after the warranty has expired, and for the remanufacturing cases, by the way in which the number of EVs in use is determined.

For the cases *la*, *lb*, *raa* and *rba*, sales data has to be determined. As mentioned in the introduction, the case study covers Germany. In order to limit the number of agents and because batteries are not compatible between different car manufacturers and between different EVs (BEVs and PHEVs), only BEVs and only one manufacturer is regarded. Different battery pack design choices, that lead to incompatibilities, can for example be found in Arora et al. (2016) or McKinsey & Company (2021). The manufacturer's market share is assumed to be 5% of Germany's EV sales. Due to the long life expectancies of vehicles and the currently strongly increasing sales numbers of BEVs, it seems reasonable to run the simulations until 2040. To include batteries of present EVs in remanufacturing and to start from a reliable data basis, the simulation begins in the past, in 2015. So, the period from 2015 to 2040 is considered for the simulation runs. However, remanufacturing is only considered from 2025 onwards in anticipation of technological developments in the next few years. From 2015 to 2020, the actual sales data according to the Federal Motor Transport Authority of Germany were used (Kraftfahrt-Bundesamt, 2021). For 2021 to 2040, we use a forecast for BEV sales in Germany provided by Deloitte (Deloitte, 2020). This forecast seems realistic since it already incorporates the Covid-19 crisis and subventions for which, according to Deloitte (2020), the maximum number of eligible vehicles will be reached by

2023, resulting in a temporarily decreasing demand in 2023. The resulting sales data for the simulation are illustrated in Figure A.4.

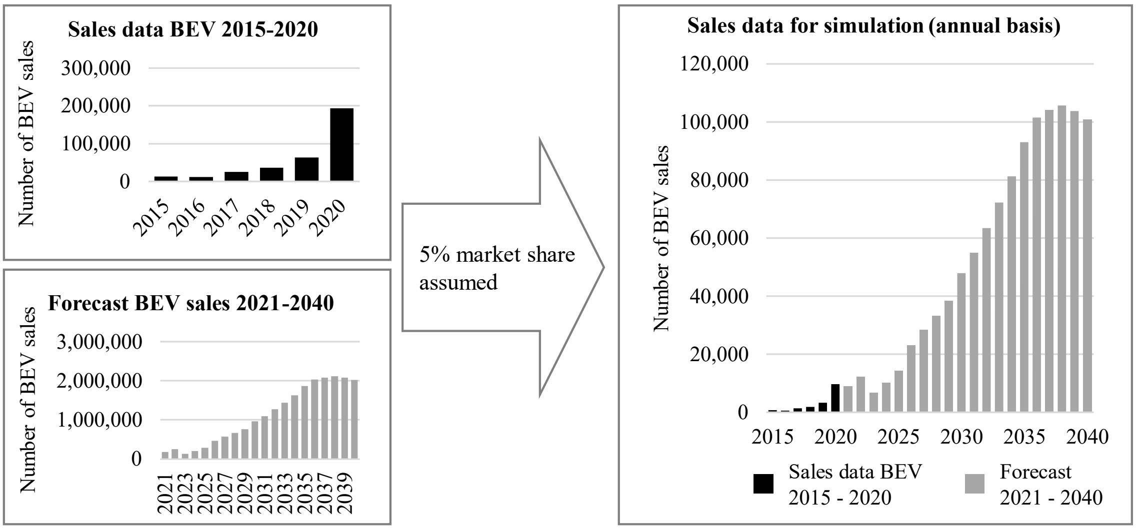


Figure A.4: Sales data for the simulation (Deloitte, 2020; Kraftfahrt-Bundesamt, 2021). From 2015 to 2020, actual sales data was used to generate EV demand in the simulation. From 2021 to 2040, forecast data was used.

Further parameter assumptions, that are equal for all cases, can be found in Table A.2.

Subject to variation and, therefore, the base for scenarios, are the expected lifetimes for new batteries (e_{nb}) and remanufactured batteries (e_{rb}). The following scenarios are studied (in brackets: $e_v - e_{nb} - e_{rb}$ in years):

- Vehicle lifetime > new battery lifetime = remanufactured battery lifetime (15-10-10)
- Vehicle lifetime > new battery lifetime > remanufactured battery lifetime (15-10-5)
- Vehicle lifetime = new battery lifetime > remanufactured battery lifetime (15-15-5)
- Vehicle lifetime < new battery lifetime > remanufactured battery lifetime (15-20-10)

In the following, the scenarios are designated with the expected vehicle lifetime, expected new battery lifetime and expected remanufactured battery lifetime $e_v - e_{nb} - e_{rb}$.

A.4.2 Results

At first, simulations for the *linear* cases *Ia* and *Ib* were conducted for determining the base stocks for the remanufacturing cases that have the same target stock as the linear cases (*rab*, *rbb*) (cf. section A.4.1). The results are shown in Figure A.5. As it is evident, the base stocks for the examined vehicle and battery lifetimes follow an almost similar pattern. In the *linear* case *Ia*, where no battery replacements are performed if the battery fails after the warranty period (Figure A.5 i), stocks of the 15-20-x and the 15-15-x-scenario are slightly higher than those of the 15-10-x-scenario. Lifetimes of remanufactured batteries (“x”) are not considered since there is no remanufacturing for automotive purposes in cases *Ia* and *Ib*. In Figure A.5 ii), case *Ib*, there is no noticeable difference between the different battery lifetime scenarios.

Table A.2: Parameter settings for all scenarios

Parameter	Description	Value
t	Simulation time	26 years
e_v	Expected vehicle lifetime	15 years (Oguchi and Fuse, 2015)
e_{nb}	Expected lifetime of new batteries	Subject to variation
e_{rb}	Expected lifetime of remanufactured batteries	Subject to variation
a_y	Age limit up to which a vehicle is considered young (warranty)	8 years (Energy sage, 2019)
a_o	Age limit from which on a vehicle is considered old	a_y (case la) e_v (all other cases)
ab_o	Age limit from which on a battery is considered too old for remanufacturing	e_{nb}
n_{max}	Maximum number of remanufacturing operations per battery	0 (cases la and lb) 1 (cases raa, rab, rba, rbb) (conservative assumption, Mathew et al. (2017) replace cells several times)
s_r	Share of remanufacturable batteries	0.85 (Standridge and Corneal, 2014)
s_v	Share of cells that are suitable for reuse in a vehicle after remanufacturing	0.68 (Kampker et al., 2020)
s_{sl}	Share of cells that are suitable for non-automotive second-life applications after remanufacturing	0.16 (Kampker et al., 2020)
s_w	Share of waste cells	0.16 (Kampker et al., 2020)
min_{sl}	Minimum battery lifetime in non-automotive second-life applications (repurposing)	1 year (Kurdve et al., 2019)
max_{sl}	Maximum battery lifetime in non-automotive second-life applications (repurposing)	20 years (Kurdve et al., 2019)
t_{tech}	Technology lifetime of battery technologies	5 years (Volpato and Stocchetti, 2006)

A.4.2.1 Number of Manufactured Batteries

An important indicator to determine if the amount of newly produced batteries and corresponding resource consumption can be reduced by using remanufactured batteries is the number of manufactured batteries in the different scenarios (Figure A.6). The simulation results are ambiguous about this KPI and show different results for different assumptions. The confidence intervals, however, are small in all cases, so that the data, within the model assumptions, are reliable. Further confidence intervals can be found in the spreadsheet of the supporting information accompanying this article.

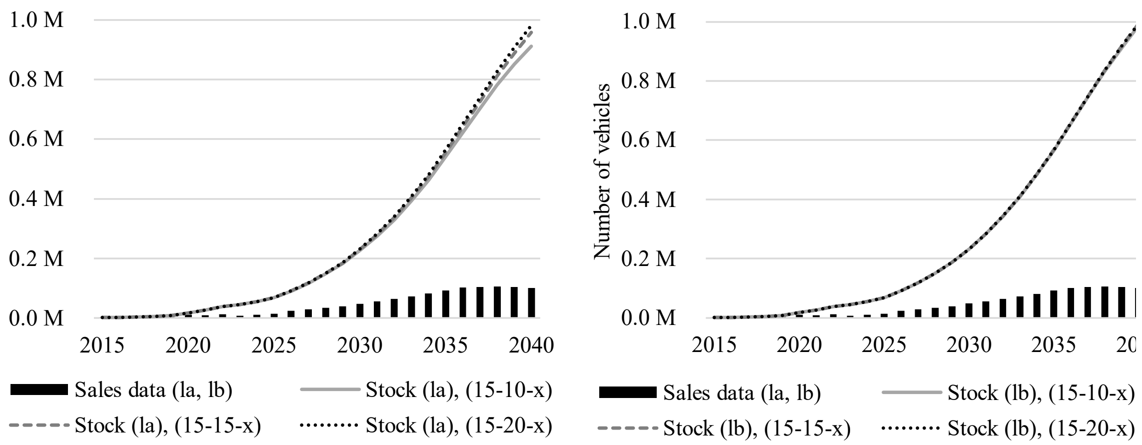


Figure A.5: Vehicle sales and stocks in the “linear” cases la and lb. i) case la,, no battery replacement after warranty. ii) case lb, new spare battery after warranty. In a), the EV stock is the highest in the 15-20-x scenario and the lowest in the 15-10-x scenario. In b), there is no noticeable difference in EV stocks between the scenarios.

In cases where battery replacements after the warranty period are not performed (case *la*) or only with remanufactured batteries (same sales data, case *raa*), the amount of manufactured batteries does not decrease in any lifetime scenario. This is in line with expectations since, in these cases, the same amount of new batteries is installed in the same number of new vehicles, and battery warranty claims, which require new spare batteries, occur with equal frequency. In the same stock case *rab*, however, there is a decrease in new battery demand (e.g., minus 5.9% in the 15-10-10 scenario in Figure A.6). This is also in line with expectations because, with a fixed stock level, an increased use phase leads to fewer new vehicles, and, as a consequence, fewer batteries are needed. However, this effect is not noticeable anymore when batteries on average outlast vehicles (15-20-10 scenario), mainly because vehicle lifetime extensions due to remanufactured batteries are less likely.

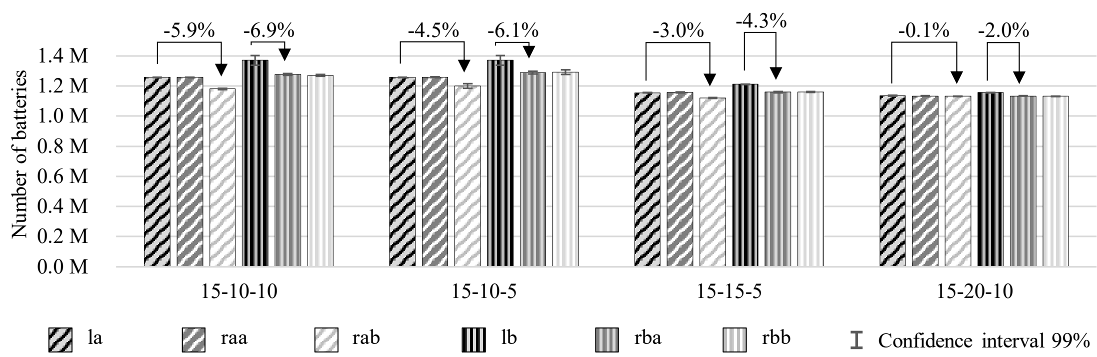


Figure A.6: Number of manufactured batteries in all scenarios. Battery production is lower than in the linear cases when the same stock as in the linear cases is aimed at or when remanufactured batteries are used as spare parts instead of new spare batteries. The effect decreases the longer the average battery life compared to the vehicle lifetime is.

In cases where battery replacements with new spare batteries are also performed after the warranty period (cases *lb*, *rba* and *rbb*), the picture is different. Here, most new batteries are needed in the *linear* case (*lb*) since all battery replacements are performed with new batteries. In contrast, fewer new batteries are produced in the *remanufacturing* cases. That is because every remanufactured battery that is re-installed in a vehicle directly saves a new spare battery. The savings range from 6.9% in the 15-10-10 scenario to 2% in the 15-20-10 scenario. That means, unlike in the cases where battery replacements are only performed with new batteries, there is also a saving in new batteries when batteries on average outlast vehicles. The differences between the two *remanufacturing* cases (*"[...] same sales data" and "[...] same stock"*, cases *rba* and *rbb*), however, are marginal.

A.4.2.2 Repurposed and Remanufactured Batteries

The number of repurposed and remanufactured batteries are further KPIs that are analyzed for the different cases. According to the assumptions and the flow chart in Figure A.2, batteries, after being processed at a remanufacturing facility, can be reconditioned to a quality good enough for automotive applications ("remanufactured battery") or only for other applications like stationary storage, which is also referred to as "repurposing". In Figure A.7, the number of repurposed batteries is given (ii), as well as the number of remanufactured batteries that have been re-installed in vehicles (iii). That means, Figure A.7 iii does not depict all remanufactured batteries, but only those actually used. It is evident in all scenarios that more repurposed batteries are available in the *linear* cases than in the *remanufacturing* cases. This was expected since all batteries that would be considered for automotive remanufacturing are considered for repurposing instead in the *linear* cases. In the *remanufacturing* cases, on the other hand, the share of batteries that is prepared for repurposing is much smaller than that for remanufacturing, which is why there are fewer repurposed batteries.

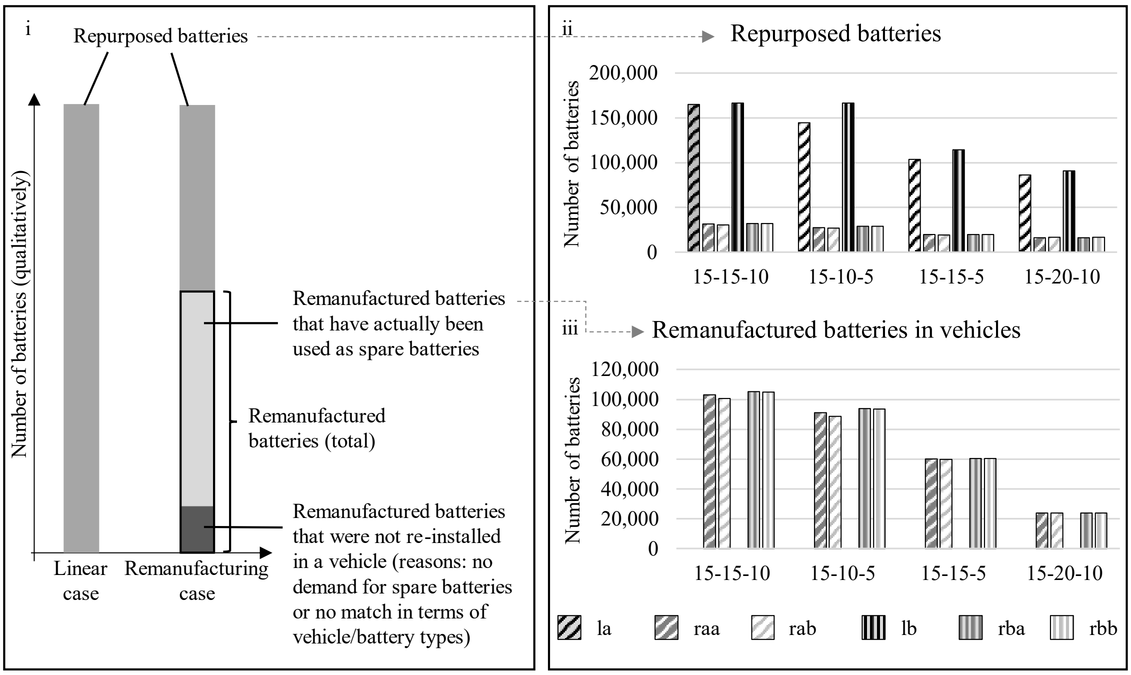


Figure A.7: Repurposed and remanufactured batteries in all scenarios. There are no remanufactured batteries re-installed in vehicles in linear cases (la, lb), but there is a considerable amount of repurposed batteries. In remanufacturing cases (raa, rab, rba, rbb), the number of batteries for repurposing is considerably lower.

The number of remanufactured batteries in vehicles (Figure A.7 ii) is the number of those batteries that would have been repurposed in the linear cases minus those that have been remanufactured but could not be re-installed into a vehicle, as illustrated in Figure A.7 i. The latter can be caused by a lack of demand for remanufactured batteries, either due to a time mismatch or a type mismatch, i.e., vehicles with failed batteries are of a type not corresponding to those of the remanufactured batteries. Also, no demand for remanufactured batteries at all could be a reason, but this is not the case here, as Figure A.8 shows. Figure A.8 depicts the supply and demand for remanufactured batteries for the 15-10-10, the 15-15-5 and the 15-20-10 scenario for the *rbb* case. Additionally, the total returns of batteries are depicted, which include damaged, old and already remanufactured batteries. It is evident that the demand for spare batteries is greater than the supply of remanufactured batteries, at least from around 2030 onwards when the number of EoL batteries to be handled rises. That holds for all scenarios, even those where batteries, on average, outlast vehicles (15-20-10). However, the difference between supply and demand is smaller the longer the battery life expectancy compared to the vehicle life expectancy.

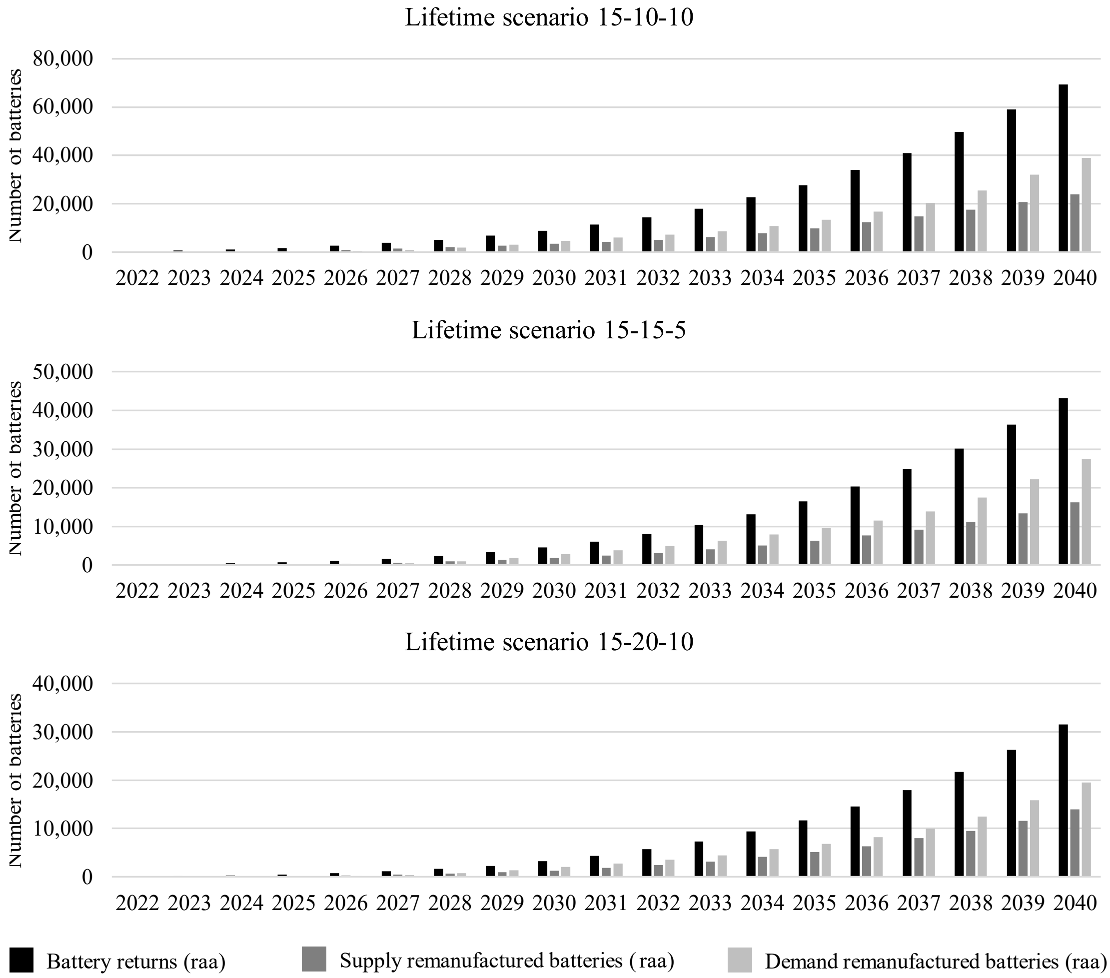


Figure A.8: Battery returns and supply of and demand for remanufactured batteries over time in selected scenarios. From 2030 onwards, remanufactured battery demand exceeds remanufactured battery supply for all lifetime scenarios in the raa case.

It might be surprising that there are fewer repurposed and remanufactured batteries in use the longer the battery lifetime is compared to the vehicle lifetime. This is owed to the limited simulation time of 26 years compared to the vehicle and battery lifetimes. In 26 years, a significant number of batteries will fail when lasting 10 years on average, even if the number of registered

EVs is small at the beginning of the considered period. About half of the 10-year-life-expectancy batteries that were brought to the market in 2030 will have returned by 2040, the end of the simulation period. However, when considering an average battery life of 20 years, only about half of the batteries that were newly registered in 2020 will have returned, and the assumed EV registrations in 2020 are much lower than those in 2030 (cf. section A.4.1). It can be concluded that the longer the average battery lifetime, the longer the delay in battery returns. This is relevant for companies considering an engagement in remanufacturing operations. The later batteries return, the later large-scale solutions for EoL battery remanufacturing, repurposing and recycling are requested.

Even though the total number of repurposed and remanufactured batteries in use is smaller in the timeframe under examination when batteries last longer, that does not mean that a smaller share of return batteries is suitable for reuse, on the contrary. As assumed in section A.4.1, 85% of the returning batteries that are not yet older than the expected battery lifetime and have not yet been remanufactured can be fed into the remanufacturing process, in which a further selection takes place. That means, a maximum of 85% of all returning batteries can enter the remanufacturing process. In the 15-10-10 and the 15-10-5 scenario, case *1a,* only 65% of all returning batteries take that path. In the 15-20-10 scenario, same case, the share is 84%. That means, in the latter case, most batteries return relatively young compared to their life expectancy.

Further KPIs are graphically depicted in the spreadsheet of the supporting information accompanying this paper.

A.5 Discussion

The proposed model allows estimating several performance indicators for different scenarios of the circular system of electric vehicles and their EV batteries. Based on separate lifetime expectancies for vehicles and batteries, and sales data for EVs, battery demand can be estimated as well as the supply of remanufactured batteries for automotive applications and repurposed batteries for non-automotive applications. Not only can this be determined as one final number at the end of a fixed period, but also can these KPIs be collected over time and displayed on a timeline (e.g., Figure A.8), which makes trends visible. These data might help to assess the overall reasonability of remanufacturing of EV batteries and draft planning of remanufacturing facilities since return rates and the effects of different scenario assumptions, e.g., concerning return battery quality, can be determined. The use of stochastic elements makes it possible to deal with high uncertainties, e.g., concerning the time of failure of vehicles and batteries.

However, to create scenarios, many assumptions about the future have to be made. Assumptions on battery and vehicle lifetimes, while being uncertain at this point, are probably at least tangible for a broad audience since it is easy to imagine that a vehicle fails after a certain period of time with some variance. Other variables, such as the share of cells that can be re-installed in automotive batteries, s_v, or the share of return batteries that are damaged beyond repair, (1-s_r), are much more elusive. While the uncertainty of different remanufacturing cases and different battery lifetimes is partially captured by the scenarios examined in the previous section, the parameters s_r, s_v and s_{sl} are not varied, although their values are equally uncertain. However, the way the simulation model considers the parameters above, their influence on the number of remanufactured batteries is linear, and therefore, the effect of varying these parameters is foreseeable.

Furthermore, the model assumes that all vehicles and batteries stay in the system until they are recycled. That means all batteries are available for remanufacturing if they fulfill the set prerequisites, and all owners of medium old vehicles with a failed battery want a replacement. Sensibly, the system represents one region, in the case study that is Germany. ICEVs, though, are often sold to other countries before they reach their End-of-Life. Only about 20% of the finally deregistered vehicles are scrapped in Germany; the rest is exported to other countries (EU and Non-EU) and re-registered (Umweltbundesamt, 2019). That means the “real” EoL occurs when the vehicle is out of the system. If the same holds for EVs, supply and demand for remanufactured batteries would perhaps change dramatically. Alternatively, one could see the whole European market and all OEMs (Original Equipment Manufacturers) as one system. Figure A.9 shows how this would affect the number of batteries that need any kind of EoL treatment (battery returns) as well as the potential supply and demand of remanufactured batteries. This could be helpful for independent remanufacturers that plan an international company network. However, batteries are dangerous goods for whose transport special requirements apply. Therefore, even in globalized markets, regional studies should not be neglected.

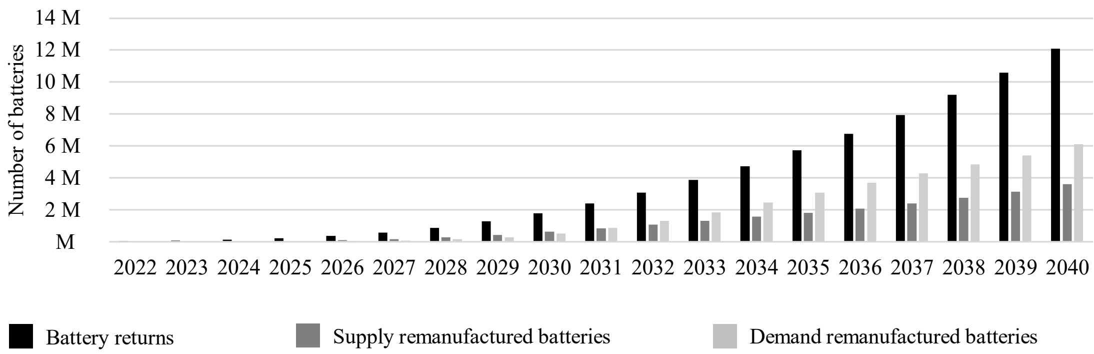


Figure A.9: Battery returns and supply and demand of remanufactured batteries in Europe up to 2040. Input data are expected BEV sales in Europe (EU, EFTA and UK) of all OEMs (Strategy&, 2021), average vehicle lifetimes of 15 years, and average battery lifetimes (new and remanufactured) of 10 years. Battery replacements after the warranty period are performed with remanufactured or new batteries. Other assumptions are the same as in section A.4.

Moreover, the greatest demand for spare batteries occurs when the battery life is, on average, much smaller than the vehicle lifetime. While that might be the current situation, it might change in the future. New technologies, e.g., solid-state batteries (Ding et al., 2019), might expand battery lifetimes, so that battery and vehicle lifetime converge, or batteries even outlast vehicles on average. But, as the 15-15-x and the 15-20-x scenario showed, remanufacturing potential still exists and particularly further second-life concepts such as the use as stationary energy storage (repurposing) would become more relevant. A greater barrier to remanufacturing might be expected improvements in Battery Management Systems (BMS) (Hu et al., 2019). With those improvements, cells will probably age more evenly, so that fewer well-functioning cells or modules could be reassembled to a remanufactured battery. It could be examined in further research if the decrease in supply of remanufactured batteries is proportional to the decrease in demand due to prolonged lifetimes of EV batteries.

Independent of the battery lifetime, it could be worth examining the possibility to not only employ used batteries for remanufacturing but also production scrap from new battery manufacturing. It seems to be a viable assumption that new batteries, which have been sorted out due to punctual faults, accumulate during manufacturing, and single modules or cells might be well-functioning and available for spare batteries.

In this paper, only the theoretical potential for using remanufactured batteries was examined. However, to depict a realistic solution to address increased resource consumption and impact, economic aspects and social acceptance need to be examined as well. If remanufacturing is too expensive compared to producing new batteries, it is unlikely it will be put into practice on a larger scale. It is important to note that the economic viability depends on the price for new raw materials as well as future production costs that might decrease due to economy of scale, which can change over time. Also the business model in which remanufacturing is realized will play a key role in the efficient implementation (e.g. remanufacturing in the context of product-service systems ranging from warranty services to leasing concepts etc.). Equivalently, remanufactured batteries can only be successful if consumers accept these products. It is conceivable that consumers do not trust the quality of a remanufactured battery and prefer new products. Hence, both warranties and lower prices for remanufactured batteries will be necessary for broad acceptance. Subsequently, legal aspects such as product liability can be a significant obstacle regarding the realization of remanufacturing in closed-loop supply chains. This is particularly true for business cases where the remanufacturing is not conducted by the OEM. Nevertheless, apart from the challenges and obstacles discussed, the simulation results show that remanufacturing has the potential for making electromobility more sustainable by decreasing the need for new spare batteries. Therefore, more engagement of battery and EV (re)manufacturers in investigating the technological potential of remanufacturing EV batteries would be desirable.

A.6 Conclusion

In this paper, a discrete event simulation approach is proposed, with which the theoretical potential of supply of cores for remanufacturing, the supply of remanufactured batteries, and the demand for those can be evaluated under different scenario assumptions. For the scenarios we examined, including different battery and vehicle lifetime assumptions, there was always demand for remanufactured batteries, even when technological developments would lead to higher *average* battery than vehicle lifetimes. This should alert remanufacturing companies since business opportunities could open up there. However, our approach also showed that probably not all batteries returning in good condition can be reused in a car after remanufacturing. This is not due to a lack of general demand for spare batteries but due to developments in battery technology that could lead to incompatibilities between batteries and vehicles of different technological generations. To our knowledge, our model is the first to estimate this amount of unusable batteries for remanufacturing due to lack of suitable demand.

However, the attractiveness of battery remanufacturing to companies is not only determined by the amount of potential demand and potential supply. To assess the technical and economic feasibility and the social acceptance of remanufactured batteries, further research is needed in the fields of technology development for low-cost automated disassembling, techno-economic assessment of remanufacturing, and consumer acceptance of remanufactured EV batteries.

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A.8 CRediT Authorship Statement

Sandra Huster: Conceptualization, Methodology, Writing – original draft. Simon Glöser-Chahoud: Conceptualization, Writing – review & editing, Supervision. Sonja Rosenberg: Conceptualization, Writing – review & editing. Frank Schultmann: Writing – review & editing, Funding acquisition.

A.9 Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

A.10 Supporting Information

In the supporting information, capacity scatter diagrams are introduced to illustrate the effects of inhomogeneous ageing of cells within a serial-circuit battery pack. Additionally, the simulation model is described in detail, and the developed scenarios are illustrated.

In a separate spreadsheet, raw data from the simulation experiments are provided as well as aggregation and analysis of the data. In this spread sheet, further KPIs derived from the aggregated data are depicted graphically.

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B Do Consumers Want Reconditioned Electric Vehicle Batteries? – A Discrete Choice Experiment

Authors: Sandra Huster, Sonja Rosenberg, Simon Hufnagel, Andreas Rudi, Frank Schultmann

Abstract

Reconditioning electric vehicle (EV) batteries for reuse as spare parts could extend the lifespan of EVs and reduce the environmental impact of battery production. However, this circular option's viability depends on consumer acceptance of reconditioned batteries. This study presents a discrete choice experiment among German residents to address this issue. A mixed logit behavioral model and Hierarchical Bayes estimation are used to evaluate the choice experiment. The experiment was conducted online and surveyed 1152 participants, with 837 providing sufficient data for analysis. The results indicate that there might be acceptance of reconditioned EV batteries as spare parts. A considerable number of respondents opted for this option when presented with the hypothetical choice of replacing a defective battery in their EV with a new or reconditioned spare battery, or scrapping the EV and purchasing a working vehicle. The study finds that the choice is primarily influenced by the expected battery lifetime and the associated costs. Ecological factors play a minimal role and are more of a bonus. The study also reveals that younger respondents and non-EV owners exhibit greater concern regarding the lifetime losses of reconditioned batteries compared to older respondents and EV owners. A self-assessment of the respondents concerning the most and least decisive battery characteristics shows a connection between stated importance of the attributes and the actual choice, but the connection is relatively weak. The results lead to the conclusion that industry and academic institutes should see EV battery reconditioning as an emerging research field that requests solutions for prolonging reconditioned batteries' lifetime while ensuring economical pricing to satisfy the demands of the consumers.

Keywords

Circular Economy; Discrete Choice; Remanufacturing; Customer Acceptance, Consumer Preferences

Nomenclature

Symbols

asc_{it}	alternative-specific constant of option i in choice situation t
b	superscript denoting battery characteristics, $b \in$ {cost savings compared to a new battery; battery life losses compared to a new battery; greenhouse gas savings compared to a new battery}
β	vector of all coefficients (population level)
β_n	vector of all coefficients for decision maker n
${\beta_y}^{bv}$	vector of coefficients for y regarding $bv \in$ {battery characteristics b; vehicle characteristics v}
$\beta_y^{bv,c}$	vector of coefficients for y regarding $bv \in$ {battery characteristics b; vehicle characteristics v} *and* consumer characteristics c
c	superscript denoting consumer characteristics, $c \in$ {age; income; education; residence; EV ownership; self-assessed importance of battery attributes b}
ε_{nit}	independent and identically distributed extreme value type I error term of decision maker n for choice option i in choice situation t
$f(\beta)$	density function of β
i	subscript denoting choice option, $i \in$ {new spare battery, reconditioned spare battery; none option}
j	number of alternative utility functions
$L_{nij}(\beta)$	logit probability of decision maker n for choice option i in choice situation t evaluated at β
n	subscript denoting decision maker, $n \in \{1, \dots, N\}$
N	number of decision makers n
P_{ni}	choice probability of decision maker n for choice option i
t	choice situation, $t \in$ {1, ..., T}
T	number of choice situations t
U_{nit}	utility of decision maker n from option i in choice situation t
$U_{j,nit}$	$j'th$ version of utility function U_{nit}
v	superscript denoting vehicle characteristics, $v \in$ {car price level}
x_{yt}	vector of all observable variables of y in choice situation t
x_{yt}^{bvc}	vector of observable variables of y in choice situation t regarding $bvc \in$ {battery characteristics b; vehicle characteristics v; consumer characteristics c}
y	subscript, $y \in$ {decision maker n; choice option i}

Abbreviations

AIC	Akaike information criterion
ANOVA	analysis of variance
BEV	battery electric vehicle
BIC	Bayesian information criterion
CO_2	carbon dioxide
DCE	discrete choice experiment
EV	electric vehicle
EVB	electric vehicle battery
GHG	greenhouse gases
HB	Hierarchical Bayes
MCMC	Monte Carlo Markov Chain
OEM	original equipment manufacturer

B.1 Introduction

Considering the pressing issue of climate change, it is essential to reduce greenhouse gas (GHG) emissions. Transportation is a significant contributor to carbon emissions, accounting for approximately one-fifth of all such emissions globally in 2021 (Crippa et al., 2021). There is a particular focus on transitioning this sector from predominantly internal combustion technology to less carbon-intensive alternatives. Electric mobility, which has gained increasing acceptance among policymakers, companies, and consumers, could be part of a viable solution for individual transportation. Policy-wise, many countries worldwide have enacted legislation banning internal combustion engine passenger cars in the future, implemented incentives to purchase electric vehicles (EVs), or established targets for EV quotas or charging infrastructure (IEA, 2020). Company-wise, the product range for EVs has increased over the last years (IEA, 2020), and some car manufacturers have announced plans to cease the development of internal combustion engine cars by the end of the decade (Ewing, 2021). At the consumer end, there has been a remarkable increase in global EV sales from about 2 million EV sales in 2018 to more than 10 million in 2022 (IEA, 2023).

It is widely recognized by various studies that EVs have a lower carbon footprint than those powered by internal combustion engines (e.g., Girardi et al., 2015; Hill et al., 2020; Verma et al., 2022).This advantage is expected to increase as the proportion of renewable energy sources in electricity generation grows (Burchart-Korol et al., 2018). Nevertheless, the production of electric vehicle batteries (EVBs) presents a challenge to their environmental friendliness as it is an energy- and resource-intensive process that can cause other forms of pollution (Dai et al., 2019). In the long term, it is crucial to develop less environmentally harmful batteries (Murdock et al., 2021). However, in the short and medium term, maximizing the effective use of EVBs is essential.

The service life of batteries within vehicles is limited. However, due to the uneven aging of battery cells and modules, uninstalled batteries from EVs still contain numerous well-functioning cells or modules that could be reused (Kampker et al., 2020). The reconditioning process is schematically illustrated in Figure B.1. Original equipment manufacturers (OEMs) and independent remanufacturers have begun or plan to manufacture reconditioned batteries that could be used as cost-efficient spare parts for older EVs (Autocraft Solutions Group, 2023; Stellantis N.V, 2023). For example, in 2022, Stellantis has remanufactured approximately 46% of all returning end-of-life batteries (1032 of 2261, Stellantis N.V, 2023), Mercedes Benz operates a remanufacturing plant without disclosing remanufacturing numbers (Mercedes-Benz Group, 2024), and Hyundai points out battery remanufacturing as a future path (Hyundai Motor Company, 2023). Such reusing endeavors could serve sustainability in three ways: First, the lifetime of existing vehicles can be extended since spare parts could be an economically viable solution for a longer time (Glöser-Chahoud et al., 2021). While electric cars are expected to last at least as long as internal combustion cars (Hoekstra and Steinbuch, 2020), which is approximately 14 years in Germany (Oguchi and Fuse, 2015), EVBs are expected to last for about 10 years (Schulz-Mönninghoff et al., 2021), so there is a potential lifespan mismatch. Second, fewer new spare batteries would be needed (Huster et al., 2022), resulting in a lower resource consumption for production. Third, the value induced by the manufacturing process for the battery cells is conserved, thus serving economic sustainability (Kampker et al., 2023).

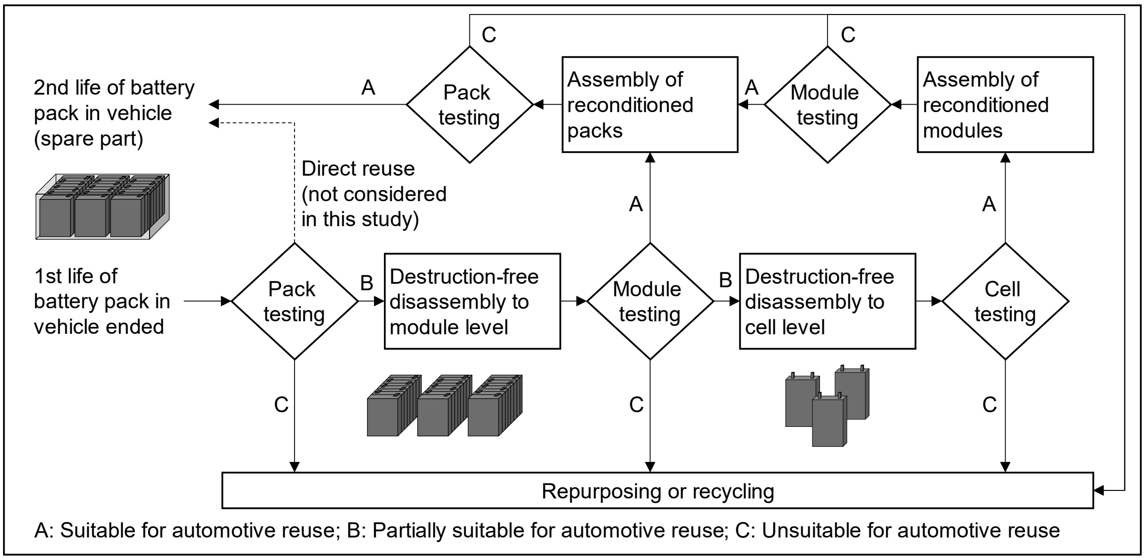

Figure B.1: Schematic representation of battery reconditioning (based on Kampker et al., 2020, and Glöser-Chahoud et al., 2021)

However, remanufactured, reconditioned, and repaired products, with the differences between the terms lying mainly in the quality and warranty of the end product (Ijomah et al., 2004), serve a purpose only if product demand exists. This demand exists only when there are batteries that fail before the rest of the vehicle, necessitating spare parts for the host vehicle. Simulations suggest a growing number of such vehicles in the future (Glöser-Chahoud et al., 2021; Huster et al., 2022). Another prerequisite is that customers accept reconditioned batteries. For other products such as consumer electronics, some customers prefer new products, even if the used products are remanufactured to a state as good as new (Abbey et al., 2015a). However, the market for remanufactured electronics is still expanding (Munde, 2024). Moreover, concerns regarding EVs and their batteries, such as price and performance, may also affect the acceptance of reconditioned EVBs (Stockkamp et al., 2021).

Research on reconditioned batteries is limited, as many publications have focused on recycling or repurposing EVBs for non-EV applications after their first use phase in an EV (Cong et al., 2021; Zhu et al., 2021). Consequently, consumer acceptance of reconditioned EVBs has not been extensively examined and fundamental questions remain unanswered. Specifically, the following research questions will be addressed:

- RQ1. Is there acceptance of reconditioned EVBs at all?
- RQ 2. What EVB attributes influence acceptance?
- RQ 3. Are there differences in acceptance among customers with distinct attributes, for example, regarding their demographics?

Previous research in the field of consumer acceptance of remanufactured products often employed discrete choice experiments (DCEs) (Hidrue et al., 2011; Helveston et al., 2015; Liao et al., 2018), sometimes also referred to as choice-based conjoint experiments (Ben-Akiva et al., 2019). While some authors argue that the concepts of DCEs and conjoint analysis should be strictly separated since they are based on different theoretical foundations (Louviere et al., 2010a), others regard choice-based conjoint as an “umbrella term” for economic stated choice experiments (Ben-Akiva et al., 2019). DCEs involve potential customers selecting from multiple sets of options that vary in certain attributes (Raghavarao et al., 2010). These experiments are usually based on Random Utility Theory and can estimate the utility function and decisiveness of single attributes and their levels in a population (McFadden, 1974). It should be noted that there are choice situations that cannot be modeled with the Random Utility framework, as Hess et al. (2018) have pointed out. For some applications, other frameworks might fit the choice problem better, for instance the Random Regret Minimization Model (Chorus et al., 2014). DCEs were chosen as the research method for this study because of their suitability for investigating consumer preferences concerning electric vehicle battery reconditioning and their wide application. Additionally, discrete choice experiment have been found to be a good choice for obtaining information about future behavior considering the alternatives of conducting a costly pilot project or collect the opinion of experts who could be biased (Quaife et al., 2018). However, findings about the external validity of discrete choice experiments has been mixed (Telser and Zweifel, 2007; Rakotonarivo et al., 2016; Quaife et al., 2018). The experiments were carried out via an online survey in Germany. The questionnaire is provided in the supplementary information.

The contribution of this study is threefold. First, it complements existing literature about consumers' views on circular products by adding perspective on EVBs. As Section B.2 will show, there is scarcity of research on consumer preferences for reconditioned EVBs, and this study seeks to overcome the limitations of existing literature, such as the lack of realistic choice options. Second, the findings of this study can support forecasting the demand for reconditioned batteries, which can assist OEMs and independent operators in determining the economic viability of building reconditioning capacity. Finally, by identifying the key battery attributes that most influence consumer perceptions of reconditioned batteries, this study can guide future research and development efforts aimed at improving the performance of reconditioned batteries. As such, this study can help to prioritize research budgets for both public and private entities.

The structure of the paper is as follows: In Section B.2, an overview of consumer preferences regarding remanufactured products and EVs is given, as well as a summary of existing literature regarding consumer preferences for reconditioned electric vehicle batteries. In Section B.3, theoretical foundation of discrete choice models is provided, followed by the specific implementation in this study. Additionally, the case study is described in Section B.3. The results are presented and discussed in Sections B.4 and B.5, and the study is concluded in Section B.6 with an outlook.

B.2 Literature Review

When examining consumer behavior, the methods at hand to obtain data are manifold and include qualitative approaches like forming focus groups or observation, and quantitative procedures like surveys or experiments (Chrysochou, 2017). The theoretical foundations of analyzing the obtained data are equally diverse and encompass the theory of planned behavior, the theory of reasoned action, utility theory and others (Belbağ and Belbağ, 2023). With regard to consumer choice of circular products, DCEs and conjoint analyses have gained popularity. They belong to the class of stated preference methods and therefore to the family of surveys (Alamri et al., 2023). For example, Koide et al. (2023) examined the acceptance of buying or leasing circulated refrigerators in Japan with a DCE. They used a multinomial logit model and estimated it with a Hierarchical Bayes approach. Their findings indicate that there are customer segments that leaned towards certain alternatives, namely brand-new refrigerators or subscriptions offers respectively, and others who based their decision on all or some of the attributes of the options. Similarly, Lieder et al. (2018) applied DCEs to investigate the acceptance of renting washing machines or paying per wash as opposed to purchasing washing machines, to enable product remanufacturing. With their survey in Stockholm, they found that service levels were the most decisive attribute, followed by the price and payment scheme. Environmental friendliness was the least decisive item. Hunka et al. (2021) used DCEs and Hierarchical Bayes analysis to evaluate consumers choice of reused and remanufactured mobile phones and robot vacuum cleaners in the United Kingdom. The importance of the examined attributes varied between phones and vacuum cleaners, but the price was the most important one for both products. The importance differed the most for the attributes battery life, appearance and ease of fixing. Further studies about consumers' perspectives on remanufactured products can be found in the literature review by Belbağ and Belbağ (2023). They provide a summary of the theories employed, the countries and product types for which analyses have been conducted, and the methodologies applied. Belbağ and Belbağ (2023) found that, besides experiments like DCEs, structural equation modeling and regression analyses are popular methods for examining consumer preferences towards remanufactured products.

DCEs have been used to predict EV adoption. For example, Liao et al. (2018) conducted a DCE in the Netherlands to analyze which the effect new business models, namely EV leasing and EVB leasing, have on the adoption of battery electric vehicles and plug-in hybrid electric vehicles. The availability of both EV and EVB leasing barely changes the attractiveness of EVs on the aggregate level compared to the case where ownership is the only option. However, a latent class approach reveals that some groups, especially the EV-affine group, are affected by the availability of different business models (Liao et al., 2018). Han and Sun (2024) examined the willingness to pay for EV attributes in China by fitting a multinomial logit model and a latent class model. The attributes were the EV purchasing price, maintenance cost, range, charging facility coverage, fast charging time, replaceability of the battery and vehicle-to-grid capability. They found that all attributes they examined had a significant influence on the willingness to pay. Han and Sun (2024) found that the willingness to pay for the attributes differ between distinct regions in China. Bhat et al. (2024) conducted a similar DCE in India where they examined the effect of different vehicle attributes, service attributes, supporting schemes like toll tax exemption, socio-demographic factors and latent factors such as environmental awareness on the intention to adopt EVs. They found significantly negative effects for EV purchasing prices, operating costs and charging time, and a significantly positive influence of driving range and availability of charging facilities. Some socio-demographic characteristics, like age, and latent characteristics also influenced the adoption intention (Bhat et al., 2024).

Examinations of consumer preferences for reconditioned EVBs have been relatively limited. Tondolo et al. (2021) were among the first to investigate the purchasing likelihood of reconditioned EVBs dependent on the price and the service provided, and the perceived risk and value. They employed the experimental vignette methodology with purchasing likelihood as the dependent variable surveyed on a seven-point scale, and price and service varying between the vignettes. The participants were United States nationals. By regression analysis, Tondolo et al. (2021) found that price and service of reconditioned EVBs interacted with regard to the purchasing likelihood, and a higher perceived risk had a negative impact on purchasing likelihood. Furthermore, they observed that a higher willingness to pay was associated with the offer of services such as free upgrades or roadside assistance. Chinen et al. (2022) surveyed respondents in China on their perception of remanufactured EVBs and employed structural equation modelling for analysis. They found that consumers' price consciousness and perceived benefits affect their purchasing intention, which in turn affects their willingness to pay and acceptance. However, willingness to pay was not surveyed for certain battery characteristics but was based on general beliefs about remanufactured batteries.

It remains unclear whether the survey participants in the EVB studies above were aware of alternatives to remanufactured or reconditioned products, such as new replacement products or early scrapping of the vehicle. It is generally recommended to include realistic options in choice experiments, which may include opting-out or maintaining the status quo (Adamowicz and Boxall, 2001; Determann et al., 2019). Not including such alternative options when realistic, may influence the obtained part-worth utilities or estimated willingness to pay, and therefore overestimate demand (Ryan and Skåtun, 2004; Campbell and Erdem, 2019). However, depending on the choice situation and the intended analysis, omitting none options, i.e., opting-out or maintaining the status quo, can lead to equal relative importance of attributes as including them (Veldwijk et al., 2014). Tao et al. (2022) partially addressed the lack of realistic choices with regard to reconditioned EVBs by determining consumer preferences for the alternatives "new spare battery", which 57% chose, "refurbished battery" [26%], and "directly reused battery" [17%]. They obtained this data via an online questionnaire in Japan and analyzed the data with a multinomial logit model. However, they did not consider the "none" option and assumed that all consumers would replace the EVB.

The authors are not aware of any other studies that have specifically addressed consumer acceptance or perception of reconditioned or remanufactured EV batteries. While previous studies have explored consumers' perspectives on other remanufactured or reconditioned products than EVBs, it is not possible to easily transfer these results. For instance, repulsion or disgust has been identified as a barrier to adopting remanufactured household and personal products (Abbey et al., 2015a; Lee and Kwak, 2020); however, this is not expected to apply to EVBs. All existing studies on EVBs present their findings across a sample of consumers without differentiating between consumer groups, such as demographic groups. As EV adoption rates vary across demographic groups (Yang and Tan, 2019; Shanmugavel et al., 2022), whether the same is true for the adoption of reconditioned EVBs remains an open research question. Additionally, it is unclear how consumer preferences are linked to specific battery characteristics, such as the cost of one unit of battery or the lifespan of one year.

B.3 Methods

First, this section presents background information on the application of discrete choice experiments in conjunction with behavioral models in the literature. Subsequently, the study design of the discrete choice experiment is introduced in this section, including the selection of items and the sample. The behavioral models for estimation and the focus of the analysis are then outlined.

B.3.1 Analysis of Discrete Choice Experiments

Discrete choice experiments can be assessed using various behavioral models, which are generally divided into logit and probit models (Ziegler, 2005). One foundational evaluation model upon which other models are built is the multinomial logit model (Louviere et al., 2010b). This model allows the estimation of utility as a function of the attribute levels of an alternative, with the population weight of certain attribute levels expressed as coefficients, and an error term (Hauber et al., 2016). However, this multinomial logit behavioral model has certain limitations. The most relevant limitation to this study is that it does not consider taste variation within the population or the correlation of unobserved factors over time (Train, 2009). The lack of taste variation stems from the coefficients of the attribute levels being fixed values (Train, 2009), meaning that the entire examined population has the same valuation of an attribute level, such as one unit of cost savings. While this assumption may be a simplification in general, it seems overly simplistic for the case of EVB replacement evaluation and unsuitable for the research questions proposed in Section B.1. The mixed logit model is an advanced logit model that addresses some of the limitations of the multinomial logit model. This model contains distributed coefficients, allowing for random taste variations within the population, and is robust to correlation in unobserved patterns over time (Louviere et al., 2010b; Hauber et al., 2016). In mixed logit models, the choice probability P_{ni} of decision maker n for choice option i among a set of I choices are denoted as

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta, \tag{1}$$

where β is the parameter vector, $L_{ni}(\beta)$ the logit probability evaluated at β, and $f(\beta)$ a density function (Train, 2009). In case a decision maker faces a sequence of choice situations t, either over months or years in a panel study, or within one questionnaire, the logit probability $L_{nit}(\beta)$ is typically represented as

$$L_{nit}(\beta) = \frac{e^{\beta_n x_{nit}}}{\sum_{j=1}^{I} e^{\beta_n x_{nit}}} \tag{2}$$

with $\beta_n x_{nit}$ being the observed utility share (Revelt and Train, 1998). As per Hensher and Greene (2003), the utility U_{nit} of decision maker n from option i in choice situation t can be expressed as

$$U_{nit} = \beta_n x_{nit} + \varepsilon_{nit}. \tag{3}$$

x_{nit} refers to the observable variables of i and n, such as the price attribute of option i or the age of decision maker n, in choice situation t. The vector of coefficients for individual n is denoted by β_n. Within the population, these coefficients are distributed according to the density function $f(\beta)$, which distinguishes mixed logit from multinomial logit. In the latter, β_n equals β_m for all individuals m and n of the population (Train, 2009). ε_{nit} represents an independent and identically distributed extreme value type I error term. While the decision maker is assumed to be aware of their coefficients β_n and error term ε_{nit}, the researcher knows only the values of x_{nit}. Furthermore, the researcher assumes certain distributions for the coefficients, often normal or lognormal distributions (Louviere et al., 2010b). By utilizing the knowledge of the observable variables, assumptions about the coefficient distributions, and integration of Equation 1, the coefficients can be estimated, for example, through simulation techniques (Hensher and Greene, 2003).

To gain more insight into the preferences of individual decision makers or groups of decision makers, such as those with similar age or educational backgrounds, one could apply a latent class approach. However, this method requires specifying the number of groups prior to estimation, and is not suitable for analyses in which individuals may belong to multiple classes (Hauber et al., 2016). Considering this study's objective of examining different preferences for reconditioned batteries among demographic groups and the presence of overlapping demographic markers, such as age and income, the Hierarchical Bayes (HB) approach appears to be a more appropriate choice. HB is an estimation method that has gained popularity in recent years. Instead of estimating the coefficients for the entire population, it estimates individual-level parameters which can be aggregated at the population level (Lenk, 2014). HB estimation can be applied to various behavioral models, such as multinomial or mixed logit models (Huber and Train, 2001). Bayesian methods require making assumptions about the parameters and their relative weights before estimation, which are referred to as *prior distributions* (Bolstad and Curran, 2016). These priors are then updated with observed data and normalized to ensure integration to one, resulting in *posterior distributions* that are the focus of estimation (Lenk, 2014). As it is unlikely that the posterior distribution for the entire parameter vector will have a simple form that can be easily drawn from, it is necessary to use sampling methods. In particular, Monte Carlo Markov Chain (MCMC) methods have been employed for HB sampling, such as Gibbs sampling and the Metropolis-Hastings algorithm (Train, 2009). With MCMC methods, draws from the posterior distribution can be taken for one parameter at the time. The means of these draws converge to be the posterior parameter estimates (Qian et al., 2003).

B.3.2 Study Design of the Discrete Choice Experiment

To address the research questions presented in Section B.1 through the use of a discrete choice experiment, it is first necessary to establish a setting in which potential customers can choose a reconditioned battery. As reconditioned products are typically utilized as spare parts, the scenario must involve the respondents owning an EV whose battery has failed. Given that battery exchanges are typically covered under warranty for a period of 8 years or 160,000 km (ADAC, 2022), the customer will only find themselves in a choice situation if their battery fails beyond repair after the warranty expires, meaning that their vehicle is at least 8 years old or has accumulated a mileage of 160,000 km or more. In this instance, the customer has three viable alternatives: first, to replace the faulty battery with a new spare battery to restore the car's functionality; second, to replace the battery with a reconditioned spare battery to restore the car's functionality; or third, to scrap the car and purchase a new or used vehicle that is in working order. Of course, the option of not replacing the car and simply discarding it would also be available. Given that the aim of this study is not to examine preferences for transportation modes, the option of switching to an alternative mode of transportation will not be included in the experiment.

In order to gain a deeper understanding of the factors that influence decisions beyond general beliefs about the available options, it is important to determine the attributes and their respective levels of the battery to be tested in the experiment. Consumers often consider the price, quality, and environmental friendliness of reconditioned products when making decisions (Abbey et al., 2015a; Wang et al., 2018; Aydin and Mansour, 2023). Additionally, concerns about the price and performance of new EVs and EV batteries (Li et al., 2017) and the environmental impact of EV batteries (Hall and Lutsey, 2018; Dai et al., 2019; Zhang et al., 2023) may indicate that these factors are also relevant for reconditioned batteries. As a result, the battery's price, its environmental sustainability, represented by GHG emissions, and its expected lifespan have been chosen as the battery attributes for this study. The lifespan is assumed to incorporate concerns about performance and quality, as the definition of lifespan used is that of most warranty schemes, which consider a battery State-Of-Health (SOH) of 70% as a threshold (ADAC, 2022). Thus, an expected lifespan of six years implies that the SOH is expected to be above 70% for six years. Additionally, the price of a new EV is taken into account in the analysis in order to determine whether the cost of acquiring a vehicle impacts the preference for or against reconditioned spare parts.

In determining the price levels for new EVs, the approximate basis prices of the Renault Twingo Electric, the VW ID.3 Pro, and the Mercedes EQA were utilized, which amounted to approximately 25,000 €, 35,000 €, and 45,000 €, respectively. Within one choice set, the car price is the same for all options.

The cost of a new battery was set at 10,000 € (corresponding to the approximate cost of 161 € per kWh of battery for large car manufacturers in 2022, BloombergNEF, 2023). The prices of reconditioned batteries were examined at different discount levels of 25%, 50%, and 75%, resulting in prices of 7,500 €, 5,000 €, and 2,500 €, respectively. The study looked at battery life expectancies of 10 years for new batteries (Chen et al., 2019; Bruno and Fiore, 2023), and 8, 6, 4, and 2 years for reconditioned batteries. The environmental impact of the batteries was assessed in terms of the GHG emissions, with levels of 4,350, 2,900, and 1,450 kg CO_2 equivalents, corresponding to the GHG emissions associated with production (approx. 75 kg CO_2 equivalents/kWh, Hoekstra and Steinbuch, 2020), and assumed reductions of one-third and two-thirds for reconditioned batteries. The emission reduction levels are within the range found for remanufactured products (Sundin and Lee, 2012). For example, roeren GmbH (2023) report 66% GHG savings for a remanufactured 4-cylinder combustion engine. The reduction levels might be conservative for battery reconditioning, since LKQ Europe (2022) assume more than 80% reductions in GHGs for business models including battery remanufacturing. The attributes and their levels are summarized in Table B.1. The characteristics and their levels of the battery were redefined to facilitate more comprehensive analysis. For instance, the price of the battery was transformed into the attribute "cost savings compared to a new battery [10%]", which allows for the evaluation of the utility gain for each unit of cost savings, i.e., 10% of the cost savings. Similarly, the environmental criterion of GHG emissions was transformed into "GHG savings compared to a new battery [10%]" to easily assess the influence of GHG savings of 10% on the utility of a reconditioned battery. The battery life expectancy is measured in "Battery life losses compared to a new battery [years]" so that the loss of one year in life expectancy compared to a new battery can be evaluated. The vehicle price was translated into an ordinal scale of "low", "medium", and "high", which was further transformed into "0", "1", and "2". This means that a cheap vehicle is always the reference point (0), and the results show the difference between the cheapest and the medium-priced vehicle as well as the difference between the medium-priced and the highest examined price level. The level transformations are not expected to change the results compared to using the original levels, as the transformations are linear, and the utility will be specified linearly as well (cf. Section B.3.3). Therefore, the transformations could have been performed either at this stage or later on when interpreting the results. The transformations are summarized in Table B.1.

Table B.1: Attribute levels of the discrete choice experiment before and after transformation

Attribute	Levels	Transformation for analysis	Levels after transformation
Battery price [€]	2,500; 5,000; 7,500; 10,000	Cost savings compared to a new battery [10%]	0; 2.5; 5; 7.5
Battery life expectancy [years]	2; 4; 6; 8; 10	Battery life losses compared to a new battery [years]	0; 2; 4; 6; 8
Greenhouse gas emissions [kg CO_2 equivalents]	1,450; 2,900; 4,350	GHG savings compared to a new battery [10%]	0; 3.3; 6.6
Car price [€]	25,000; 35,000; 45,000	Car price level [ordinal scale]	Low (0); medium (1); high (2)

As one aim of the study is to determine whether there could be acceptance of reconditioned EVBs, it is necessary to label the options. The labels are “New battery”, “Reconditioned battery”, and “Vehicle disposal” as the none option, in which no spare battery is installed, but the whole vehicle is replaced instead.

The number of attributes and levels shown in Table B.1 lead to many possible combinations per option. However, the number of feasible combinations is reduced due to some particularities of the examined product laid out above, for example, the limitation that reconditioned batteries will always have lower GHG emissions, a lower price, and a lower expected lifespan than the new counterpart, or that all options within one choice set should have the same car price. Still, not all remaining combinations can be examined, as the number of choice sets would become overwhelmingly large. There is no definitive answer when determining the optimal number of questions and, consequently, the maximum number of attribute combinations one can include in a survey. For example, Caussade et al. (2005) find nine to ten choice situations to be optimal, but their results also depend on the number of alternatives and levels presented. Chung et al. (2011) consider six choice sets with five options optimal concerning variance, while Bech et al. (2011) observe no significant change in variance for up to 17 choice situations in a three-alternative DCE with six attributes. Johnson and Orme (1996) analyzed 21 existing datasets from DCEs with eight to 20 choice tasks and three to six attributes and could not find a decline in reliability. A review by Bekker-Grob et al. (2015) discovered that four to six attributes and nine to 16 choice sets per respondent were common. However, some of these studies do not reveal whether the respondents were paid or otherwise incentivized. Reliability of the results is probably the main concern for incentivized studies, while unincentivized studies may additionally face a greater risk of participants exiting the survey early. To minimize the risk of early dropouts, a comparatively low number of 14 choice sets was chosen for this study. Ten test subjects pre-tested the survey, and they needed approximately ten minutes to complete the survey with 14 choice sets, which they subjectively rated as appropriate.

An efficient design of choice sets would fulfill the criteria of "level balance", "orthogonality", "minimal overlap", and "utility balance" (Huber and Zwerina, 1996). "Level balance" means that all attribute levels should appear equally frequently (Rose and Bliemer, 2009). "Orthogonality" describes the independence of the attributes (Mariel et al., 2021). "Utility balance" ensures that all options within a set are equally attractive, minimizing obvious preferences (Huber and Zwerina, 1996). However, simultaneously achieving these criteria can be challenging, and an orthogonal design may lead to unrealistic combinations (Mariel et al., 2021). Because of the particularities of EVBs, independence of the attributes is not given, which inevitably leads to a design violating orthogonality. Efficient designs could still be obtained by measures derived from the asymptotic covariance matrix of parameter estimates (Mariel et al., 2021). However, designs obtained this way are only optimized for a certain DCE model formulation (Rose and Bliemer, 2009). As will be shown in Section B.3.3, several utility functions encompassing different parameters and coefficients will be tested. Therefore, instead of optimizing the design for one of the utility formulations, the efficiency criteria of level and utility balance and minimal overlap were utilized to manually create a universal design, incorporating knowledge about the product. However, it is not ensured that the design is optimal for any or all of the utility functions tested with regard to measures as D-efficiency or others. The initial design was presented to ten test subjects in a small pilot study to ensure utility balance.

An example of a choice set is depicted in Figure B.2. The full questionnaire is provided in the supplementary information.

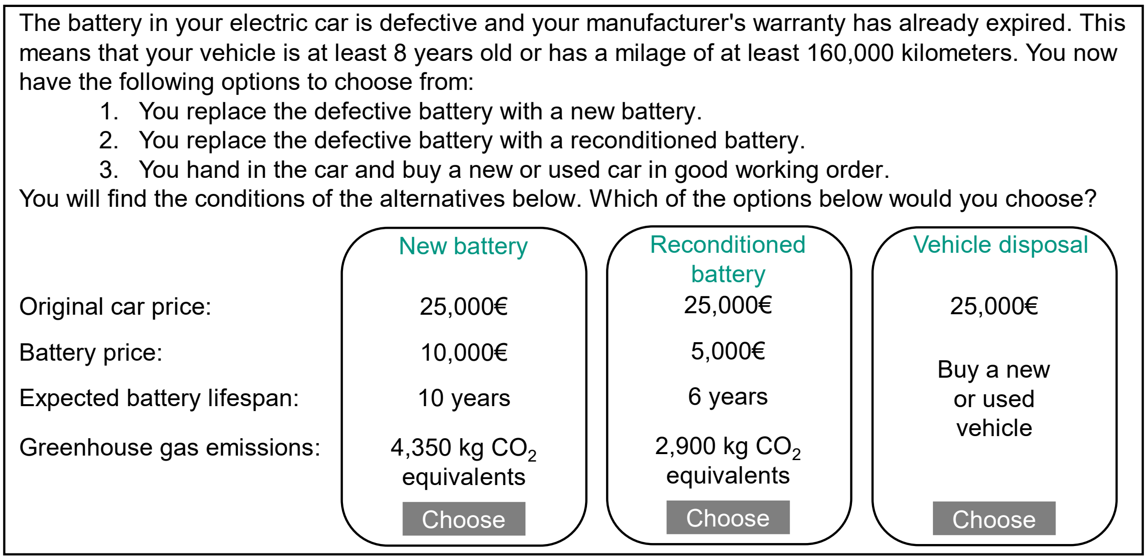

Figure B.2: Example choice set

The choice experiment was carried out as an online survey from November 2021 to January 2022 using the Sawtooth software. The survey link was distributed via German EV forums and a German YouTuber with a channel focused on battery-related topics (approximately 300,000 subscribers). Therefore, the regional focus of the study was Germany. Participation was voluntary and not incentivized. A total of 1,152 individuals participated in the survey, with 914 completing it. Of the 914 completed questionnaires, 837 respondents provided complete demographic information, including gender, age, education, household income, residence, and EV ownership to enable analysis by population characteristics. To enable best-worst scaling, respondents were additionally asked to rank the battery attributes (price, expected lifetime, GHG emissions) by indicating the most and least important attribute. A summary of the respondents' characteristics is provided in Table B.2, which includes information on the attribute class sizes, as well as numerical class names assigned to the attribute classes thought to have a linear relationship to the coefficients. These numerical class names are used as the x_{nit}'s in Equation 3 for later analysis. From Table B.2 it becomes clear that the sample is not representative of the German population, for instance with regard to gender. There may be a selection bias due to the distribution channels mentioned above, which will further be discussed in section B.5.

Table B.2: Respondents' characteristics

Attribute	Attribute class	Class size	Numerical class name
Age[1] [years]	≤29	64 [7.6%]	-
	30-39	165 [19.7%]	-
	40-49	198 [23.7%]	-
	50-59	265 [31.7%]	-
	60-69	129 [15.4%]	-
	≥70	16 [1.9%]	-
Gender[2, 3]	Male	827 [98.8%]	-
	Female	10 [1.2%]	-
Income [€]	≤999	23 [2.7%]	0
	1,000-1,999	88 [10.5%]	1
	2,000-2,999	187 [22.3%]	2
	3,000-3,999	181 [21.6%]	3
	4,000-4,999	179 [21.4%]	4
	≥5,000	179 [21.4%]	5
Education	Basic (secondary school for grades five to nine or ten)	217 [25.9%]	0
	Intermediate (A-levels or comparable)	189 [22.6%]	1
	Advanced (academic)	431 [51.5%]	2
Residence	Rural area	376 [44.9%]	0
	Small or medium town	211 [25.2%]	1
	Suburb of a metropolis	142 [17.0%]	2
	Metropolis	108 [12.9%]	3
EV ownership	No	427 [51.0%]	0
	Yes	410 [49%]	1
Most important attribute[1] (self-assessment)	Battery price	358 [42.8%]	-
	Battery life expectancy	377 [45.0%]	-
	Greenhouse gas emissions	102 [12.2%]	-
Least important attribute[1] (self-assessment)	Battery price	147 [17.6%]	-
	Battery life expectancy	96 [11.5%]	-
	Greenhouse gas emissions	594 [71%]	-

[1] No numerical class name because no linear change of coefficients is assumed;
[2] No completed survey forms for non-binary people;
[3] Insufficient data for non-male persons, therefore no analysis by gender is performed.

B.3.3 Estimation of the Behavioral Model

Equation 3 is specified for the described use case to estimate the mixed logit behavioral model. In the first instance, two fundamental formulations for the utility, $U_{1,nit}$ and $U_{2,nit}$, are contrasted, where n represents the decision-maker and i represents the option, i.e., a remanufactured, new, or no spare battery, and t the choice situation:

$$U_{1,nit} = asc_{\ it} + \sum_{\substack{Battery \\ characteristics\ b}} \beta_n^b \cdot x_{it}^b + \varepsilon_{nit}, and \tag{4}$$

$$U_{2,nit} = asc_{\ it} + \sum_{\substack{Battery \\ characteristics\ b}} \beta_n^b \cdot x_{it}^b + \beta_{in}^v \cdot x_{it}^v + \varepsilon_{nit}. \tag{5}$$

$asc_{\ it}$ denotes alternative-specific constants that account for non-included attributes (Tardiff, 1978) and can be interpreted as the population-wide preference for or against one option, for example, remanufactured spare batteries, independent of the option attributes. The alternative-specific constant for new batteries, $asc_{\ new\ battery}$, is kept at zero as a baseline. The attributes of a battery b include its price, the battery longevity, and the battery GHG emissions. v represents the vehicle characteristics, i.e., the vehicle price. The vehicles' coefficients β_{in}^v depend on the option i, and thus there are separate coefficients for reconditioned batteries, new batteries, and the none option. With this information, one can determine how a change in car size affects the overall preference for a particular option. As a reminder, a low-priced car serves as the reference point, with x_{it}^v set to zero for this category (cf. Table B.1).

The asc's and the vehicle cost-specific coefficients are assumed to follow a normal distribution, while the battery coefficients presumably follow a lognormal distribution ("Cost savings compared to a new battery" and "GHG savings compared to a new battery") or negative lognormal distribution ("Battery life losses compared to a new battery"). In this way, all decision makers have a positive valuation of savings and a negative valuation of losses.

With the utility functions $U_{1,nit}$ and $U_{2,nit}$, one can evaluate which model best represents the data. As $U_{1,nit}$ does not include coefficients for vehicles, and $U_{2,nit}$ does, a better fit of $U_{2,nit}$ would mean that explicitly separating the effect induced by the vehicle size adds value to the model. Therefore, the comparison of $U_{1,nit}$ and $U_{2,nit}$ helps determine the relevance of the vehicle price in estimating the demand for remanufactured batteries. The actual significance of the influence would be determined when analyzing the model results. There are numerous methods for selecting the most appropriate model from a range of alternatives. Two widely used measures from the class of penalized model selection criteria are the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) (Kuha, 2004). These measures are based on the log likelihood of the model and weigh it against its complexity (Kuha, 2004). Consequently, if two models have the same explanatory power but one model uses more attributes, making it more complex, the simpler model with fewer attributes will have a better BIC and AIC. This approach of penalizing complexity aims to prevent overfitting. Lower values for AIC and BIC are considered preferable as they represent a smaller information loss (Mariel et al., 2021).

The superior model is utilized to analyze statistically significant differences within the population based on age, income, and other characteristics by examining the coefficient means of subgroups using a one-sided (Welch) Analysis of Variance (ANOVA), following the approach Paetz (2020) applied. This technique is feasible since HB estimates coefficients at the individual respondent level. In essence, each characteristic that is being examined (cf. Table B.2) is treated as a categorical factor, and each respondent's coefficient estimates are considered as one realization of an experiment. To determine whether the mean of a specific coefficient, such as $\beta^{cost\ saving}$, differs between respondents belonging to different groups, for example, income groups 0 to 5, the variances of the betas within and between the income groups are compared with those of all other income groups. The results of an ANOVA indicate if the means of all groups are equal, or if at least one pair of means is unequal (Shingala and Rajyaguru, 2015). Prior to conducting the ANOVA, the normality and homoscedasticity assumptions are assessed using the Shapiro-Wilk test and the Levene statistic, respectively, at a significance level of 0.05. IBM's SPSS software is used to perform these tests and the ANOVA. In the event that the ANOVA reveals disparities among any of the classes, post hoc Games-Howell tests are conducted at a significance level of 0.05 for further examination. The Games-Howell test is a multiple comparisons test that enables the identification of which group means differ from each other, even in the absence of homoscedasticity (Lee and Lee, 2018).

In addition to conducting an ANOVA to test for differences in the coefficients based on one of the basic utility models, a third method for estimating utility, $U_{3,ni}$, is employed. This approach takes into account the individual respondents' characteristics c for the battery attributes. If the model based on utility function $U_{2,ni}$ outperforms the one that utilizes $U_{1,ni}$, the vehicle attributes are also included in the analysis.

$$U_{3,nit} = asc_{\ it} + \sum_{\substack{Battery \\ characteristics\ b}} \left(\beta_n^b + \beta_n^{b,c} \cdot x_{nt}^c\right) \cdot x_{it}^b \left[+ \left(\beta_{in}^v + \beta_{i\ n}^{v,c} \cdot x_{nt}^c\right) \cdot x_{it}^v\right] + \varepsilon_{nit} \tag{6}$$

In $U_{3,nit}$, there are two coefficients, $\beta_n^{b(v)}$ and $\beta_n^{b(v),c}$, which are used to describe the valuations placed on battery and vehicle attributes by the entire population, as well as the deviations of certain subpopulations from the population mean and their normal distribution. For instance, the population's $\beta^{cost\ savings}$ could follow a lognormal distribution with a mean of 2 and a standard deviation of 0.5. This indicates that a 10% reduction in battery costs would result in an average increase in utility of 2 utility units. However, for respondents in the age group of 20-30 years, the utility increase might be 0.7 units higher on average. This would be represented by $\beta^{cost\ savings, age\ 20-30}$ having a mean of 0.7 and $x_{nt}^{age\ 20-30} = 1$.

From Equation 6 and Table B.2 it becomes clear that, except for age, all customer characteristics are considered to add to utility linearly. For example, with regard to education that means $\beta_n^{b,education}$ is multiplied by zero for the basic education group, by one for the intermediate group, and by two for the advanced group (cf. Table B.2). There are other ways to specify utility, for example higher-order polynomials or semi-log transformations, which could accommodate for rising or decreasing influence of coefficients' levels (Han et al., 2022). However, only the simple linear specification was used, since other forms of interactions could also be uncovered by descriptive statistics obtained from utility functions U_1 and U_2.

The reason for conducting a double evaluation of the influence of respondent characteristics, once using ANOVA and once with a dedicated model, is to address the issue of HB estimation causing individual coefficients to shrink towards the population mean (Crabbe and Vandebroek, 2012). Consequential, differences between subgroups might be reduced. By introducing covariates for respondent characteristics, there are more potentially relevant subgroups to whose mean the covariates can shrink. The third behavioral model is then compared to those estimated using Equations 4 and 5, with the AIC and BIC serving as evaluation criteria.

The mixed logit models with HB estimation technique are calculated using R, version 4.2.2, and the R-Package "Apollo" (Hess and Palma, 2019). All priors for normally distributed coefficients were set to zero. The means of those following lognormal or negative lognormal distributions were set to -3 and 3 respectively, to start close to zero as well. The models were simulated using 100,000 burn-in iterations and 50,000 valid iterations in a MCMC simulation. The estimates were found to converge within the burn-in iterations upon visual inspection.

B.4 Results

Reconditioned batteries have been chosen by the participants of the survey in about half of the choice situations. A new spare battery and no spare battery, i.e., a replacement of the vehicle, were selected with approximately equal share (24% each). Figure B.3 reveals that this distribution of 52% choice of reconditioned batteries and 24% for both new batteries and the none option is not valid for all respondents. There is a small proportion of survey participants who never selected the reconditioned battery (4%), while 7% selected them in all or almost all cases (13 to 14 of 14 times). 5% would replace their car in (almost) all cases, while 40% would never choose that option. The new battery option was chosen zero times by 31% of the respondents, and 13 to 14 times by 1% of the respondents. Many participants made choices between one and twelve times for each option, indicating that the options' attribute levels (as shown in Table B.1) influenced their decision. Overall, research question 1 can be answered positively: It appears that there is acceptance of reconditioned batteries, albeit subject to specific conditions that require further investigation and clarification.

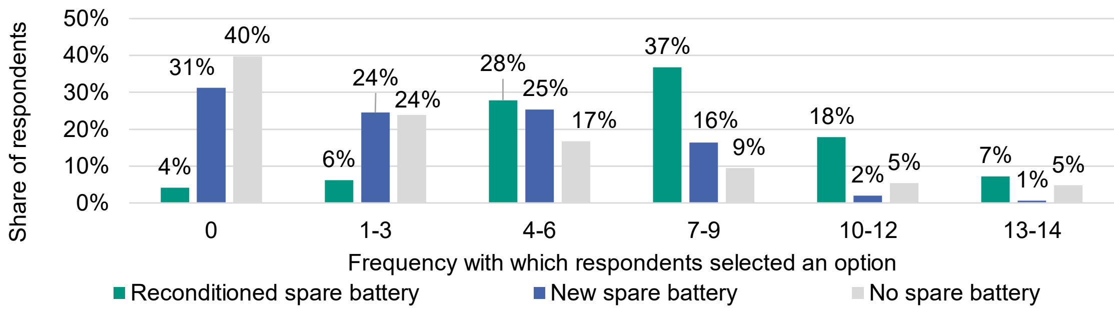

Figure B.3: Frequency of respondent selections of each option. Each respondent made 14 choices.

B.4.1 Results Concerning Battery and Vehicle Characteristics

In Section B.3, two initial models were developed to evaluate whether vehicle attributes should be considered in the analysis, based on the utility functions outlined in Equations 4 and 5. The model based on $U_{1,nit}$,, which did not include vehicle attributes, resulted in an AIC of 15,359 (BIC: 15,506), while model $U_{2,nit}$, which included the attributes, yielded an AIC of 14,811 (BIC: 15,134). As smaller values indicate a better model fit, $U_{2,nit}$ is deemed superior to $U_{1,nit}$. In accordance with Section B.3.3, a third mixed-logit model was estimated that incorporated coefficients for respondents' characteristics, based on utility function $U_{3,nit}$ as defined in Equation 6. However, this model yielded much larger AIC and BIC values (21,176 and 42,170), making it less suitable than the previously mentioned models. Consequently, both models $U_{1,nit}$ and $U_{3,nit}$ are disregarded, and the analysis proceeds with the model based on $U_{2,nit}$.

Table B.3 displays the coefficient posteriors of the mixed-logit model. The results indicate a positive alternative-specific constant for reconditioned batteries, which provides a base utility of 3.34 units relative to the "new battery" alternative. However, the standard deviation is relatively large at 2.47. Nonetheless, a normal distribution with a mean of 3.34 and a standard deviation of 2.47 still yields positive values in approximately 91% of the draws ($1 - F_{X\sim N(3.34, 2.47^2)}(0) \approx 91\%$). That means, in 91% of the cases a higher utility stems from choosing reconditioned battery compared to choosing a new battery, before considering specific battery and vehicle attributes. The alternative-specific constant for the "none" option presents a different picture. Although the mean is positive, providing an average utility of 0.89 relative to the "new battery" option, the standard deviation of 4.24 indicates that only 58% of the draws yield a positive part-worth utility ($1 - F_{X\sim N(0.89, 4.24^2)}(0) \approx 58\%$). Consequently, 42% of the draws are expected to produce a negative utility for the "none" option compared to the "new battery" option. A negative value means that the option is less favored than the baseline before considering specific option characteristics.

Table B.3: Posteriors of the mixed logit model with utility function $\boldsymbol{U_{2,ni}}$ (Equation 5)

	Mean	Standard Deviation
$\boldsymbol{asc}_{\boldsymbol{new\ battery}}$[1]	0.00	0.00
$\boldsymbol{asc}_{\boldsymbol{reconditioned\ battery}}$	3.34	2.47
$\boldsymbol{asc}_{\boldsymbol{none\ option}}$	0.89	4.24
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{new\ battery}}$	1.50	0.52
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{reconditioned\ battery}}$	1.13	0.46
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{none\ option}}$	-0.14	1.05
$\boldsymbol{\beta}^{\boldsymbol{battery\ cost\ savings}}$	1.18	0.86
$\boldsymbol{\beta}^{\boldsymbol{battery\ life\ losses}}$	-1.53	1.03
$\boldsymbol{\beta}^{\boldsymbol{battery\ GHG\ \ savings}}$	0.26	0.29

[1]: $\boldsymbol{asc}_{\boldsymbol{new\ battery}}$ is a non-random coefficient with the fixed value “0” as a baseline for the other asc’s

The cost of a vehicle can alter the appeal of various alternatives. As a reminder, the vehicle attributes contribute to the utility with the term $\beta_{i,n}^{v} \cdot x_{it}^{v}$ (cf. Equation 5), and x_{it}^{v} is coded as 0, 1 and 2 for the low-cost, medium-cost and the high-cost vehicles (cf. Table B.1). The car prices are the same for all options within one choice set. As automobile prices increase, the appeal of both new and reconditioned battery options also rises, with the mean beta coefficient for a new battery, $\beta_{new\ battery}^{car\ price}$, being approximately one-third higher than that of a reconditioned battery, $\beta_{reconditioned\ battery}^{car\ price}$. Specifically, a mean $\beta_{new\ battery}^{car\ price}$ of 1.5 means that the new battery option gains 1.5 utility units on average the higher the car price, and analogously, a mean $\beta_{reconditioned\ battery}^{car\ price}$ of 1.13 shows 1.13 utility unit gains on average the higher the car price. This indicates that the more expensive the vehicle, the more likely it is that the battery will be replaced with either a new or a reconditioned battery. Additionally, the more costly the car, the more respondents tend to favor new batteries. It is worth noting that the mean value of the car price attribute for the "none" option is close to zero, suggesting that the "none" option was not significantly impacted by the price of the vehicle.

The battery attributes also influence the utilities of the options ($\beta_{n}^{b} \cdot x_{it}^{b}$, cf. Equation 5). Among the various attributes of a battery, the loss of battery life compared to a new battery has the greatest impact on average utility. With a mean of -1.53, the coefficient of one unit of battery life loss (1 year or 10%) is approximately 30% higher than the beta mean for a 10% cost savings compared to a new battery and nearly five times the beta mean for a 10% GHG savings compared to a new battery. It should be noted that the coefficients of battery attributes follow lognormal distributions (as outlined in Section B.3.3), thus ensuring that the valuation of cost savings and GHG savings is always positive, while the valuation of life losses is always negative.

B.4.2 Results Concerning Observable Characteristics

The examination of coefficient means within subgroups to identify statistically significant differences in age, income, and other observable characteristics was conducted through a one-sided (Welch) ANOVA. The Shapiro-Wilk test and Levene's test at significance level 0.05 were utilized to assess the normality and homoscedasticity of the mean distributions (cf. Section B.3.3). Only 20% of the subgroups were found to follow normal distributions, with the remainder being classified as non-normal. One subgroup could be the means of $\beta^{battery\ cost\ savings}$ within the age group "30-39" (cf. Table B.2). However, an ANOVA has shown to be robust for non-normal data (Blanca et al., 2017), so non-normality does not contradict the usage of a normal ANOVA. Homogeneity of variances can be assumed for 82% of the attributes according to a Levene's test, i.e., there is no homoscedasticity for 18% of the attributes. This rules out a classic ANOVA since it is not robust under the violation of homoscedasticity (Bishop and Dudewicz, 1981). In this case, it is often recommended to use a Welch ANOVA instead (Jan and Shieh, 2014), which was done here. However, the classic ANOVA and the more robust Welch approximation lead to the same results concerning equality of means at the significance level of 0.05.

The results indicate that there are no discernible differences among participants with varying educational backgrounds. With regard to income and residence classes, only one coefficient stands out as significantly different. Specifically, for the income classes, it is the alternative-specific constant for the "none" option, and for the residence classes, it is the $\beta^{car\ price}_{reconditioned\ battery}$ that varies.

The most notable disparities between the coefficients' means are primarily evident in relation to the demographic characteristic of age (4 out of 8 coefficients, as demonstrated in Table B.4). $\beta^{car\ price}_{new\ battery}$ decreases with higher age, so that older respondents differentiate slightly less between the vehicle price classes when opting for a new spare battery. However, the decrease is not linear with age, and not all subgroups differ from all other subgroups in a statistically significant manner. A Games-Howell post hoc test reveals that the means of the youngest group ("≤29") deviate from those of the "40-49", "60-69" and "≥70" year old groups, while other deviations are not significant at the 0.05 level. A similar pattern is observed for $\beta^{car\ price}_{none\ option}$. Once again, significant differences occur between the youngest group ("≤29") and older groups, particularly the three groups between 30 and 69 years. The older groups base their decision for or against the none option less on the car price than the youngest group does. The mean values of the coefficients $\beta^{battery\ cost\ savings}$ and $\beta^{battery\ life\ losses}$ also differ between the age groups according to the Welch ANOVA. However, for the $\beta^{battery\ cost\ savings}$'s, that only applies to the two youngest groups ("≤29" and "30-39") compared to the oldest group ("≥70") in a statistically significant manner, as demonstrated by a Games-Howell post hoc test at the 0.05 significance level. With regard to the $\beta^{battery\ life\ losses}$'s, the youngest group's means are distinguishable from almost all other age groups' means ("40-49", "50-59", "60-69", "≥70"), and additionally significant differences occur between the age groups "30-39" and "≥70", and "50-59" and "≥70". Thus, in terms of age, the strongest influence is observed for the battery lifetime reductions, that younger respondents punished to a greater extent than older respondents.

Table B.4: Welch ANOVA for the respondents' attribute "age"and means of the coefficients within the age subgroups

	Welch ANOVA[1] Statistic[2]	Means for subgroup age [years]					
		≤29	30-39	40-49	50-59	60-69	≥70
$\boldsymbol{asc}_{\boldsymbol{reconditioned\ batt}}$	0.776	3.413	3.105	3.405	3.380	3.371	3.472
$\boldsymbol{asc}_{\boldsymbol{none\ option}}$	1.563	0.133	0.768	1.062	1.219	0.426	-0.006
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{new\ battery}}$	3.978***	1.554	1.506	1.491	1.507	1.466	1.456
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{reconditioned\ battery}}$	1.548	1.143	1.127	1.134	1.128	1.151	1.155
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{none\ option}}$	2.752**	-0.381	-0.162	-0.100	-0.136	-0.088	-0.122
$\boldsymbol{\beta}^{\boldsymbol{battery\ cost\ savings}}$	3.942***	1.303	1.227	1.155	1.190	1.082	0.841
$\boldsymbol{\beta}^{\boldsymbol{battery\ life\ losses}}$	6.731***	-1.858	-1.600	-1.460	-1.505	-1.436	-1.079
$\boldsymbol{\beta}^{\boldsymbol{battery\ GHG\ savings}}$	1.435	0.308	0.255	0.241	0.254	0.277	0.289

[1] Analysis of Variance; [2] Asymptotically F distributed; *significant at the level of 0.1; **significant at the level of 0.05; ***significant at the level of 0.01

Table B.5 indicates notable variations between EV owners and non-EV owners with respect to three coefficients. First, EV owners have a stronger preference for the "none" option compared to the "new" option than non-EV owners ($asc_{none\ option}$). Second and third, non-EV owners view each year of battery life losses from a reconditioned battery compared to a new battery as worse than EV owners, and they also derive slightly greater utility from less GHG-intensive options. As there are only two groups involved, i.e., EV owners and non-EV owners, post hoc tests are not applicable. Any statistically significant deviation in the coefficient means detected by the Welch ANOVA by default is indicative of differences between the two groups.

Table B.5: Welch ANOVA for the respondents' attribute "EV ownership" and means of the coefficients within the subgroups

	Welch ANOVA[1]	Means for subgroup electric vehicle ownership	
	Statistic[2]	No	Yes
$\boldsymbol{asc}_{\boldsymbol{reconditioned\ battery}}$	0.488	3.295	3.375
$\boldsymbol{asc}_{\boldsymbol{none\ option}}$	16.409***	0.345	1.405
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{new\ battery}}$	0.019	1.499	1.500
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{reconditioned\ battery}}$	2.391	1.139	1.129
$\boldsymbol{\beta}^{\boldsymbol{car\ price}}_{\boldsymbol{none\ option}}$	3.132*	-0.182	-0.104
$\boldsymbol{\beta}^{\boldsymbol{battery\ cost\ savings}}$	3.798*	1.209	1.138
$\boldsymbol{\beta}^{\boldsymbol{battery\ life\ losses}}$	12.756***	-1.604	-1.435
$\boldsymbol{\beta}^{\boldsymbol{battery\ GHG\ savings}}$	9.938***	0.280	0.238

[1] Analysis of Variance; [2] Asymptotically F distributed; *significant at the level of 0.1; **significant at the level of 0.05; ***significant at the level of 0.01

B.4.3 Results Concerning Self-Assessment of the Respondents

The study participants were asked to identify the most and least important battery attributes regarding their decision, which are non-observable and depend on their self-assessment. A Welch ANOVA was applied, revealing statistically significant differences in the coefficients' means of battery cost savings, battery life losses, and GHG savings between the groups who rated the attributes most, second-most, and least important (cf. Table B.6). The results indicate that respondents who rated battery price as the most important attribute derive greater utility from each 10% of cost savings compared to those who rated it least important. Similarly, those who considered battery life expectancy as the most important attribute place a higher value on each year of battery life loss than those who ranked it least important. Additionally, those who ranked environmental friendliness as the most important attribute place a higher value on every 10% of GHG savings compared to those who ranked it least important. However, the effect is smaller than expected, measured by the Marginal Rates of Substitution, i.e., the rates at which respondents are willing to trade one level of one attribute for a level of another one (Lancsar and Louviere, 2008; Mott et al., 2020). Even those who ranked environmental friendliness as the most important attribute, require 41% of GHG savings to compensate for one year (=10%) of battery life loss $\left(\left|{}^{-1.367}/_{0.335}\right| \approx 4.1\right)$. For those who rated battery price as the most important attribute, the intersection is at 66% GHG savings $\left(\left|{}^{-1.466}/_{0.221}\right| \approx 6.6\right)$, and 59% $\left(\left|{}^{-1.615}/_{0.276}\right| \approx 5.9\right)$ GHG savings for those who ranked battery life the most important attribute.

Similarly, the statement that battery price is the most important attribute does not imply that a 10% reduction in price is equivalent to a 10% loss in battery life. The respondents who ranked the battery price as the top priority actually place a 10% decline in battery life on par with a 11.7% price reduction $\left(\left|{}^{-1.466}/_{1.253}\right| \approx 1.17\right)$. Those who selected life expectancy as their primary concern require an average price reduction of 13.8% $\left(\left|{}^{-1.615}/_{1.168}\right| \approx 1.38\right)$ to gain equal utility.

Table B.6: Influence of self-assessment on coefficients' means

Self-assessment concerning importance of attributes		$\beta^{battery\ cost\,savings}$	$\beta^{battery\ life\,losses}$	$\beta^{battery\ GHG\,savings}$
Battery price	most important	1.253	-1.466	0.221
	2nd most important	1.188	-1.608	0.265
	least important	0.953	-1.460	0.341
Battery life expectancy	most important	1.168	-1.615	0.276
	2nd most important	1.205	-1.469	0.244
	least important	1.082	-1.350	0.256
Environmental friendliness	most important	0.922	-1.367	0.335
	2nd most important	1.063	-1.452	0.288
	least important	1.244	-1.564	0.240
Shaded values indicate the corresponding coefficients and attributes				

B.5 Discussion

The discrete choice experiment addressed the three research questions presented in Section B.1. Firstly, the study revealed that there could be acceptance of reconditioned EV batteries as spare parts. A considerable number of respondents opted for this option when presented with the hypothetical choice of replacing a faulty battery in their EV, outside of the warranty period, with a new or reconditioned spare battery, or scrapping the EV and purchasing a working vehicle. Secondly, the study found that the choice is primarily influenced by the expected battery lifetime and the associated costs. Ecological factors play a minimal role and are more of a bonus. Moreover, the study identified that general beliefs about the options, expressed as alternative specific constants, play a role and are partially dependent on the EV's original price. Thirdly, differences between potential customer groups with regard to observable factors are mainly related to the age of the respondents, and to respondents actually owning an EV or not. EV owners, who may face a less hypothetical choice situation than non-EV owners, were found to slightly prefer the "none" option, i.e., scrapping the vehicle and replacing it, over the "new" option. Additionally, they were less punitive towards reductions in the life expectancy of reconditioned batteries compared to new ones. This finding aligns with research that suggests that the fear of a limited range of EVs, which is closely associated with the expected battery lifetime, is more pronounced in individuals without EV experience (Rauh et al., 2020). The self-assessment of the respondents concerning the most and least decisive battery characteristics showed a connection between stated choice and stated importance of the attributes, however, the connection was relatively weak.

B.5.1 Comparison with Other Studies' Findings

The results mainly support the findings of other studies. The importance of price attributes has been found for EVBs (Tondolo et al., 2021), EVs (Bhat et al., 2024; Han and Sun, 2024) and non-EV related products (Klemm and Kaufman, 2024). Also the decisiveness of battery life has been pointed out before by Hunka et al. (2021) for remanufactured mobile phones, or the quality of circular products in the technology, household and personal care sector by Abbey et al. (2015a). The study found that the environmental attribute had a low influence, which aligns with Aydin and Mansour (2023), who determined the relative importance of CO_2 emissions compared to the other examined factors to be 3.4% only. Concerning the influence of socio-demographic factors, results in the literature have been mixed. Bhat et al. (2024) examined the adoption of EVs and found age and EV ownership to have significant effects, which is in line with the findings of this study. The results of Abbey et al. (2015b) indicate significant influence of age and number of children on the attractiveness of remanufactured products of the technology, household, and personal care segments. Some of the segments were also influence by other socio-demographic factors. For technological products, education and income did not show significant effects (Abbey et al., 2015b). Kim et al. (2014) identified significant influences of socio-demographics on the intention to purchase an EV for gender and education, and no significances for age and income.

B.5.2 Limitations

While the findings regarding the examined attributes are mostly in line with the literature, the attributes were limited to the vehicle price, the battery price, the battery life expectancy and the battery GHG intensity. There may be other attributes that also influence the decision making of consumers. For example, Tondolo et al. (2021) found the purchasing likelihood of EVBs to be higher when service was included. On the other hand, Liao et al. (2018) report only minor effects on EV attractiveness when leasing options were present. The effect of service offers or alternative business models in combination with the examined attributes remains an open question. The same holds for other potential attributes like policy interventions, that were examined for example by Li et al. (2022) or Wang et al. (2017) with regard to EV adoption.

Further potential limitations may exist concerning the method of the survey and the analysis. This study employed a mixed logit behavioral model and Hierarchical Bayes estimation based on a stated choice study. The data basis may be enhanced by combining it with data about revealed preferences, i.e., observing peoples' choice behavior, as for example Brownstone et al. (2000) did. As the offers for reconditioned EVBs are rare right now, the data basis would also be limited, but that could change in the future. Additionally, applying a mixed logit model requires making assumptions about the form of the density functions of coefficients. In this study, all coefficients related to costs and quality losses were defined to follow a negative lognormal distribution, all coefficients relating to GHG saving were assumed to follow a lognormal distribution, and all other coefficients were modeled as normal distributions. While those are common distributions (Hensher and Greene, 2003; Train, 2009), it has not been investigated if others fit the use case better. Moreover, there is no standard way on how to define utility functions. Here, three forms were tested and the selection criteria BIC and AIC were used to choose the best one of the three. However, there are many more ways utility could be defined, potentially affecting the results. Furthermore, different approaches to reveal heterogeneity could be applied. In this study, socio-demographic markers and the self-assessment of respondents were used for a priori segmentation. A latent class approach could be used to find segments instead (Eggers et al., 2022).

One fundamental question remains regarding the scope of the results. The study utilized a discrete choice survey, which was completed by 1,152 participants, of whom 837 provided complete information for further analysis. While this sample size is reasonable, as Johnson et al. (2013) found that the precision of studies typically does not increase significantly beyond 300 observations, it is important to note that the analysis entailed sub-groups of much lower size (cf. Table B.2). Consequently, the results for these smaller groups must be interpreted with caution. Additionally, the sample is not representative of the German population. Probably due to the distribution channels of the survey link, i.e., EV forums and a YouTube channel for battery related topics, and its target group, about half of the respondents own an EV, and about 98% are male. However, one could argue that this technically interested group that networks in EV forums and watches technical battery videos could be the early adopters of reconditioned batteries, who may be influential in shaping the opinions of other car owners. Nonetheless, further research is necessary to validate the findings with a more diverse and representative sample. Moreover, such further research could be a panel and uncover whether there are developments in customers' preferences over time, since this study only covers a single survey.

B.5.3 Impact of Stakeholders

It should be noted that the success of reconditioned batteries as spare parts does not only depend on customer acceptance. It is essential that workshops are aware of the option of reconditioned batteries, endorse it, and present it to customers. This option is contingent upon the availability of reconditioned batteries in the market, which relies on OEMs and potentially other market players such as independent third-party refurbishing companies in the future.

Currently, recycling is the default battery End-of-Life option in the EU, as it is required by law, and recycling an EV battery costs more than selling the regained raw materials yield (Gernant et al., 2022). OEMs are legally obligated to take back used EV batteries and cover the costs for recycling (European Parliament and European Council, 2023). Consequently, as long as recycling remains unprofitable, third parties are likely to accept the enforced offer and return used batteries to the OEMs, who then decide whether to recycle them directly or to recondition or repurpose them first. Therefore, OEMs are currently the key players in deciding for or against reconditioning. They also control their service network of workshops and can influence whether or not their workshops offer reconditioned spare parts. When recycling becomes profitable, control over End-of-Life batteries may shift. If a third-party firm reconditions or repurposes an EV battery, it assumes responsibility for the final treatment, i.e., recycling, according to the new EU battery regulation (European Parliament and European Council, 2023). Thus, the profitability of recycling could enable other second-life strategies. On the other hand, when recycling becomes profitable, it could be a strong alternative to second-life concepts due to the lower economic risk. Furthermore, the introduction of EU quotas for secondary raw materials in battery production, which will take effect in 2031 (European Parliament and European Council, 2023), may favor recycling over reconditioning. It is evident that political will, as demonstrated through the enactment of legislation, plays a significant role in determining the End-of-Life pathways for EV batteries.

B.5.4 Implications for Stakeholders

This study indicates that there may be demand from the customer side when the batteries are durable and competitively priced. In case policy makers want to foster the spread of reconditioned EVBs, these are the starting points for action. Quality could be promoted by funding research projects dealing with developing EVB reconditioning processes. Another step for quality promotion has already been done by the EU battery regulation by defining the term “remanufacturing” so that remanufactured batteries must have a capacity of at least 90% of the original battery. In this way, customers can be certain about the quality if the EVB is labelled “remanufactured”. Other terms, like reconditioning or refurbishment, are not protected. The price of reconditioned EVBs can be impacted by governments by various means. For example, they can provide subsidies for end customers in the form of a circularity premium or financially support reconditioning activities within the industry. Additionally, governments can invest in research and development to improve cost-efficient processes. Instead of lowering the costs and improving the quality of reconditioned EVBs, policy makers can also focus on changing customer perception of reconditioned batteries. For example, they could support business models that rent out reconditioned spare batteries, which could reduce the importance of battery longevity and overall costs. Governments could, for instance, tax those circular products less, create suitable legislative frameworks, or make use of circular battery options in public vehicle fleets.

OEMs and reconditioners could also promote reconditioned batteries without government support. To successfully introduce reconditioned batteries to the market on a large scale, this study suggests they concentrate their research and development efforts on the aspects of battery longevity and cost competitiveness, and on batteries for more expensive cars. The results of this study can also be used to target advertising to different demographics, particularly younger consumers who place a high value on battery life expectancy.

Lastly, end customers could evaluate their decision making based on the study results. Although it may seem intuitive that a longer EVB lifespan is always preferable, it could be argued that for vehicles aged eight years or more, an EVB with a like-new lifespan may not always be essential. By taking a step back and reflecting on their decision-making process, end users may gain a different perspective and potentially alter the outcome.

B.6 Conclusion

The findings of the study indicate that the durability of batteries is the primary concern for consumers when deciding on the replacement of defective EV batteries, followed closely by the batteries' price. This is particularly true for respondents who are younger and those who do not own electric vehicles. The significance of ecological sustainability in the purchasing decision is relatively minor, even among those who consider environmental friendliness to be the most important attribute in their decision-making process. The vehicle price segment should also be taken into account, as the results show that the likelihood of replacing a battery with either a new or reconditioned battery is greater in more expensive vehicles. However, the more costly the car, the more respondents tend to favor new batteries.

Future research may supplement the outcomes of this study by implementing a more comprehensive and diverse survey sample, and by collecting data from additional countries for cross-cultural comparisons. Additionally, research could contribute to the topic of acceptance of reconditioned batteries by broadening the scope from consumers to other stakeholders in the battery value chain, like workshops.

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B.8 CRediT Authorship Contribution Statement

Sandra Huster: Writing – original draft, Formal analysis, Conceptualization. Sonja Rosenberg: Writing – review & editing. Simon Hufnagel: Investigation. Andreas Rudi: Writing – review & editing, Project administration. Frank Schultmann: Writing – review & editing, Supervision.

B.9 Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used the tool “Paperpal” in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

B.10 Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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B.12 Appendix A. Supplementary Data

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C Will Electric Vehicle Battery Reconditioning Succeed? – A Flexible Simulation Approach Considering Stakeholders' Interests

Authors: Sandra Huster, Raphael Heck, Andreas Rudi, Sonja Rosenberg, Frank Schultmann

Abstract

The increasing adoption of electric vehicles will generate substantial quantities of end-of-life batteries, necessitating effective management strategies beyond recycling. Reconditioning these batteries for reuse in vehicles or alternative applications presents a promising yet underexplored pathway. This study introduces a flexible simulation model combining discrete event and agent-based elements to estimate the long-term demand and supply of reconditioned electric vehicle batteries up to 2050. The model considers economic and regulatory factors, integrating the interests of key stakeholders, including original equipment manufacturers, recyclers, reconditioners, and consumers.

A German case study demonstrates the viability of reconditioning, highlighting its niche role compared to recycling and repurposing. Key findings reveal that original equipment manufacturer decisions, particularly the use of reconditioned batteries in warranty cases, significantly influence market dynamics. Consumers' demand for reconditioned batteries depends on their quality, price, and green-house gas savings compared to new batteries. The study also examines the impacts of the EU Battery Regulation's recycled content mandates.

The results underline the importance of aligning stakeholder strategies and regulatory frameworks to optimize end-of-life battery management. Promoting reconditioning can enhance circular economy practices while reducing environmental impacts, though challenges remain in aligning supply with demand and ensuring economic feasibility.

Keywords: discrete event simulation, agent-based modeling, stakeholders, remanufacturing, repurposing, batteries

Abbreviations: AB: agent-based; BEV: battery electric vehicle; DES: discrete event simulation; GHG: greenhouse gas; EU: European Union; EV: electric vehicle; EVB: electric vehicle battery; EoL: end-of-life; KPI: key performance indicator; LCA: life cycle assessment LFP: lithium iron phosphate; MFA: material flow analysis; NCA: nickel cobalt aluminum oxide; n.d.: not defined; NMC: nickel manganese cobalt oxide; OEM: original equipment manufacturer

C.1 Introduction

The growth in electric vehicle (EV) sales will result in a substantial quantity of end-of-life (EoL) electric vehicle batteries (EVBs) in the future (Engel et al., 2019). The International Energy Agency assumes that the global stock of battery electric and plug-in hybrid electric vehicles will rise from approximately 30 million in 2022 to 250-375 million, depending on the policy scenario (IEA, 2023a). As EVBs contain both hazardous and valuable materials (Chen et al., 2019), regulations worldwide mandate the collection and ultimate recycling of these batteries (European Parliament and European Council, 2023a; Ji, 2024), i.e., reprocessing them on a material level (European Comission, 2008). In light of those regulations, the global EVB recycling market is projected to grow from 0.54 billion US dollars in 2024 to 23.72 billion US dollars by 2023 (MarketsandMarkets, 2025). However, prior to final recycling, EoL EVBs may be reused for a different application, such as a stationary energy storage system, or as spare parts for older EVs (DeRousseau et al., 2017). The utilization in an application other than the original one is generally referred to as repurposing, and different terms are common for re-utilization in the same application (Potting et al., 2017). Remanufacturing is generally used when a product is brought back to a state as-good-as-new, while reconditioning or refurbishment describe the process of restoring a product to a satisfactory working condition (Ijomah et al., 2004; Potting et al., 2017). Since EVBs cannot be restored to a like-new condition (Autocraft Solutions Group, 2023), the term “reconditioning” will be used in the following. The closed-loop system for electric vehicle batteries, including recycling, repurposing and reconditioning, is schematically illustrated in Figure C.1, and an overview of the terms is given in Table C.1.

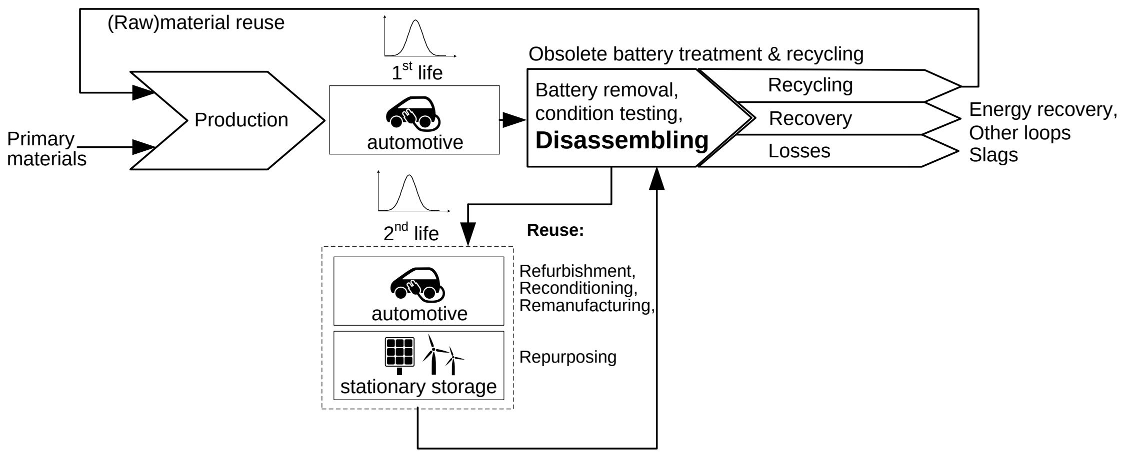


Figure C.1: Simplified closed-loop system for electric vehicle batteries. Reprinted from Glöser-Chahoud et al. (2021), with permission from Elsevier

Table C.1: Overview of circular economy terms

Term	Definition
Recovery	„Incineration of materials with energy recovery" (Potting et al., 2017)
Recycling	„[Any] recovery operation by which waste materials are reprocessed into products, materials or substances whether for the original or other purposes" (European Comission, 2008)
Repurposing	„Use discarded product or its parts in a new product with a different function" (Potting et al., 2017)
Reconditioning/ refurbishment	„The process of returning a used product to a satisfactory working condition that may be inferior to the original specification" (Ijomah et al., 2004)
Remanufacturing	„The process of returning a used product to at least OEM original performance specification from the customers' perspective" (Ijomah et al., 2004)

The treatment of EoL EVBs is of critical importance, as the production of lithium-ion batteries consumes significant amounts of raw materials and energy, resulting in a high environmental footprint. For example, producing 1 kWh of a NMC622 battery (nickel, manganese and cobalt in the ratio of approximately 6:2:2) requires 104 g of lithium, 525 g of nickel, 176 g of cobalt, and 164 g of manganese (Maisel et al., 2023). For a typical EV battery of around 60 kWh, this results in the use of over 6.2 kg of lithium, 31.5 kg of nickel, 10.6 kg of cobalt, and 9.8 kg of manganese.

Recycling is an essential EoL treatment that allows the recovery of those valuable materials, which can then be used in the production of new batteries (Gaines et al., 2021). This process is especially relevant in view of the growing demand for battery raw materials. An advantage of recycling lies in the potential to produce technologically updated batteries with improved performance (Ma et al., 2021). However, recycling also entails the complete dismantling and processing of the battery, meaning that all the energy and emissions embedded in the original manufacturing process are effectively lost. From a sustainability standpoint, utilizing a battery for as long as technically feasible before recycling may be more desirable. This approach is also reflected in the European Union's waste hierarchy, which prioritizes preparation for reuse over material recycling (European Comission, 2008).

Repurposing is one such EoL strategy that aims to maximize the utility of used EVBs. From a life cycle assessment (LCA) perspective, repurposing is beneficial: it avoids the energy-intensive processes of material processing, resulting in minimal additional environmental burdens (Koroma et al., 2022). Moreover, by substituting the need for newly manufactured stationary battery systems, repurposing indirectly lowers pressure on battery production supply chains (Aguilar Lopez et al., 2024). One limitation, however, is that materials in repurposed batteries remain tied up in use and are therefore not immediately available for recycling and re-entry into battery manufacturing (IEA, 2020).

Reconditioning offers a similar set of advantages. Like repurposing, reconditioning requires little energy and new material input (Kampker et al., 2020). In addition to prolonging the life of the battery, reconditioning may provide cost-effective spare parts for aging EVs, thereby extending the useful life of the vehicles themselves (Huster et al., 2022). This in turn reduces the need for new EVs and new EVBs, leading to further environmental benefits. Furthermore, reconditioned batteries can be used in warranty cases by OEMs, reducing their costs significantly (Sainz, 2023). Battery reconditioning is for example already performed by Stellantis or Autocraft Solutions (Autocraft Solutions, n.d.; Stellantis, 2023).

Although recycling may be more or less profitable or costly depending on the cathode material and the recycling location (Lander et al., 2021), it remains the default option and is mandated by law as the final treatment for waste batteries. Repurposing or reconditioning, conversely, necessitate active decisions to pursue this alternative. For repurposing, these decisions primarily involve business entities, such as the original equipment manufacturer (OEM), which may receive old EVBs as part of the mandatory take-back system, and energy providers who operate power plants requiring energy storage systems (Schulz-Mönninghoff and Evans, 2023). These business entities are likely rational economic actors whose actions are governed by economic considerations and legal requirements. Reconditioning, however, involves additional stakeholders, including private customers who can opt for or against a reconditioned spare battery and who may have a more personal attachment to their vehicles than business entities (Gauer et al., 2023), as well as workshops that may or may not offer reconditioned spare parts. Given the multitude of stakeholders involved in EVB EoL treatment decisions, predicting market trends proves challenging, particularly in the reconditioning sector.

Nevertheless, it is imperative to obtain accurate estimations of EoL EVB streams, as the construction of treatment facilities is capital-intensive, and the optimal development of capacity is heavily dependent on the quantities of EoL EVBs (Rosenberg et al., 2023). These quantities, however, are influenced by multiple factors. For instance, the sales figures of new EVs play a significant role (Huster et al., 2023a), but they can fluctuate rapidly, such as when subsidies are discontinued, as observed in Germany (Crownhart, 2024), or when competitors enter the market and acquire market shares (Dau et al., 2022). Furthermore, legal requirements that affect EoL treatment options can be subject to change, as exemplified by the EU Battery Regulation.

There are estimates about EoL quantities from consulting firms (e.g., Breiter et al., 2023; Haas et al., 2023) and scientific institutions (e.g., Sanclemente Crespo et al., 2022; Skeete et al., 2020). However, the assumptions are often only partially disclosed, and frequently these estimates focus on EoL quantities for recycling and omit other EoL pathways. Notably, estimates that include battery reconditioning are infrequent (c.f. Section C.2 for a more detailed overview). To date, no model adequately captures the complexity of the environment for EoL pathway selection, particularly with regard to stakeholders' interests. This paper aims to address this gap by introducing a flexible, parameterizable simulation model to estimate the demand and supply of reconditioned EVBs in the long term (up to 2050). The model primarily adheres to the discrete event simulation paradigm, but also incorporates agent-based elements. It considers the economic interests of OEMs, recyclers, repurposers, and reconditioners, and consequently also estimates battery quantities for recycling and repurposing as a by-product. Customer preferences towards reconditioned spare batteries are taken into account, as well as recycling quotas as imposed by the EU Battery Regulation. By offering a comprehensive view of the supply and demand dynamics within this ecosystem, the study also investigates potential market mismatches and the influence of key players, such as OEMs, consumers, and policymakers, in shaping the future of battery reconditioning. This approach is novel in its inclusion of diverse stakeholder interests, making it one of the first studies to holistically evaluate economic, social, and regulatory factors that could drive the adoption of reconditioned EVBs. The model is intended for OEM use and encompasses parameters that can be controlled by OEMs, as well as those that are beyond their control.

The remainder of the study is structured as follows: First, an overview of literature concerning reconditioning supply and demand estimation is given. Afterwards, in Section C.3, the stakeholders and the discrete event and agent-based simulation model is described. Additionally, a case study examining the German BEV market is introduced. In Section C.4, the findings of the case study are presented, followed by a discussion in Section C.5. Finally, Section C.6 provides concluding remarks.

C.2 Literature

The literature about EoL EVB forecasting predominantly focuses on recycling as the sole viable option. For instance, Shafique et al. (2023) used material flow analysis to estimate the recovery potential of materials from nickel manganese cobalt oxide (NMC) batteries globally up to 2038; while Wasesa et al. (2022) evaluated the lithium-ion battery recycling supply chain up to 2035 in Indonesia with a combination of system dynamics and an agent-based approach. Literature incorporating repurposing options is less prevalent and primarily employs material flow analyses. For example, Wu et al. (2020) estimate the EVB return quantities for recycling and repurposing for different provinces in China. The repurposing supply is determined by assuming that all lithium iron phosphate (LFP) batteries are suitable for repurposing (Wu et al., 2020). Yang et al. (2024) also estimate EVB return quantities for recycling and repurposing on province level in China. They assume a certain proportion of the EoL LFP batteries to be suitable for repurposing, evolving from 25% in 2022 to 80% in 2030. Fallah et al. (2021) determine the usable repurposing capacity of EVBs in Ireland as a proportion of EoL returns, commencing with a rate of 0% in 2010 and increasing this rate by +10% or +20% in a low or high scenario, while assuming a remaining battery capacity of 80%. In their estimation, they consider that repurposing increases the remaining value of an electric vehicle, thereby altering the costs. They examine the effect of repurposing on the demand for new electric vehicles under changing political conditions with regard to motor and vehicle registration tax, grants, and the ban of internal combustion vehicles (Fallah et al., 2021). Sanclemente Crespo et al. (2022) employ a product flow analysis for estimating EVB repurposing quantities and secondary material supply from recycling in Catalonia, Spain. For estimating repurposing quantities, they also assume certain rates of the collected EoL EVBs, starting from 10% in 2017 and rising to 25% to 75% in

2030, depending on the scenario. Demand for secondary storage is not considered. Pratap et al. (2024) utilize a system dynamics model to determine the raw material recovery potential from EoL EVBs in India while considering repurposing as an EoL option that delays recycling. They incorporate the financial aspect of the repurposing-vs.-recycling decision by setting repurposing and recycling costs and prices dynamically based on the collection quantities, and deciding on capacity expansion or contraction based on those costs. Demand is assumed to be a fixed value, corrected by a compound annual growth rate of 30% (Pratap et al., 2024). Similarly, Seika and Kubli (2024) use system dynamics to estimate recycling and repurposing EVB quantities in Switzerland, considering the costs and profits of recycling and repurposing for decisions about capacity expansions or contractions. They investigate how the mandatory recycled materials shares imposed by the EU Battery Regulation affect those quantities.

A limited number of studies provide predictions regarding reconditioning quantities. Table C.2 presents an overview of these studies. Notably, most research utilizes material flow analysis to estimate reconditioning quantities and focuses on determining supply. Supply is predominantly estimated as a fixed percentage of either all returning EVBs (e.g., Busch et al., 2014; Standridge et al., 2014) or of those returning during the warranty period (Abdelbaky et al., 2020) or up to a certain use time (Kastanaki and Giannis, 2023). Only some of the studies consider demand (five out of eight, cf. Table C.2). Busch et al. (2014), Duarte Castro et al. (2021) and Standridge et al. (2014) assume that reconditioned batteries are utilized in new electric vehicles, therefore substituting new battery demand. Huster et al. (2022) estimate demand based on the lifetime mismatch between vehicles and batteries. They assume that reconditioned batteries are only used as spare parts for vehicles up to a certain lifetime, whose battery failed prematurely. Tao et al. (2022) also incorporate consumers' preferences in their demand estimation. Based on survey results, they concluded that 57% of customers prefer to replace their faulty EVB with a new one, 26% with a reconditioned one, and 17% prefer a direct reuse battery. In a high circularity scenario, they assume an increased demand for reconditioned and reused batteries, and also posit that reconditioned batteries can be utilized in new vehicles. However, it remains unclear how batteries are deemed suitable for reconditioning in their simulation model. Apart from private consumers, the only stakeholders included in one of the studies is politics, by considering legislation in the form of recycling efficiency targets set by the EU Battery Regulation for lithium, nickel, cobalt and copper (Kastanaki and Giannis, 2023). This refers to the recycling efficiencies for EoL EVBs, not to the minimum recycled content mandated by the same regulation for lithium, nickel and cobalt from August 2031 onwards.

Table C.2: Studies estimating EVB reconditioning quantities

Publication	Method	Description	Determination of reconditioning supply	Determination of reconditioning demand	Stakeholders	Different cathodes
Abdelbaky et al. (2020)	MFA	Estimate EVB recycling potential in the EU up to 2040, considering remanufacturing and repurposing	Fixed percentage of failures during warranty (30% - 70%, depending on the scenario)	n.d.	n.d.	No
Bobba et al. (2019)	MFA	Estimate stocks and flows of EVBs after their removal from electric vehicles in Europe up to 2035	Fixed percentage of returning EVBs (20% in a high-reuse scenario)	n.d.	n.d.	Yes
Busch et al. (2014)	MFA	Estimate stocks and flows of EVBs and other vehicle parts in the UK up to 2050	Fixed rate of 95%	Remanufactured EVBs are used like new ones à reman demand equals new demand	n.d.	No
Duarte Castro et al. (2021)	MFA	Estimate stocks and flows of EVBs in Brazil up to 2030	80% of all EVBs that return because of vehicle failure, not battery failure.	Remanufactured EVBs are used like new ones à reman demand equals new demand	n.d.	Yes
Huster et al. (2022)	DES	Estimate EVB reconditioning potential in Germany, considering recycling and repurposing up to 2040	Fixed percentage of returning EVBs	Vehicles up to a certain age with a failed battery after the warranty period (à reconditioned batteries are only used as spare parts)	n.d.	No
Kastanaki and Giannis (2023)	MFA	Estimate EoL EVB quantities for reconditioning, repurposing and recycling in the EU up to 2040	50% of the batteries that fail after five or less years of use	n.d.	EU Battery Regulation (recycling targets)	Yes

Table C.2 (continued)

Publication	Method	Description	Determination of reconditioning supply	Determination of reconditioning demand	Stakeholders	Different cathodes
Standridge et al. (2014)	MFA	Estimate EoL EVB quantities for reconditioning, repurposing and recycling up to 2030	Fixed percentage of returning EVBs (scenarios from 0% to 85%)	Remanufactured EVBs are used like new ones à reman demand equals new demand	n.d.	No
Tao et al. (2022)	Life cycle and market simulation	Estimate EoL EVB quantities for direct reuse, reconditioning, repurposing and recycling in Japan up to 2050, quantified by CO_2 emissions	Unclear	26% of the replacement cases are fulfilled with reconditioned batteries and 17% with direct reuse batteries. In a high scenario, reconditioned EVBs are also installed in new vehicles	Consumers (preference for battery replacement with new, direct reuse or reconditioned batteries)	No
This study	DES and AB	Estimate EoL EVB quantities for reconditioning, repurposing and recycling in Germany up to 2050	Dependent on demand and on financial viability for OEM, considering the alternatives recycling and repurposing, and reduced demand for new replacement batteries. Fixed percentage of batteries is unsuitable for reconditioning	Dependent on car workshops and on consumers' preferences, which in turn depend on the price, quality and environmental footprint of reconditioned batteries. Demand can also stem from OEMs' warranty cases	Consumers (preferences for battery replacements with new or reconditioned batteries or replacement of the whole car); OEM (also in the function of a repurposer and reconditioner); Recycler; EU battery regulation (recycling targets and recycled materials in new batteries targets)	Yes

AB: agent-based simulation; DES: Discrete-event simulation; EoL: End-of-Life; EVB: electric vehicle battery; MFA: material flow analysis; n.d.: not defined

It can be concluded that the supply of reconditioned EVBs is predominantly considered a technical issue, wherein a specific percentage is deemed suitable for reconditioning, and demand is either disregarded or assumed to be virtually unlimited if it substitutes demand originating from new vehicles. While the technical challenge undoubtedly exists (Kampker et al., 2020), decisions about reconditioning should also incorporate stakeholders' perspectives (Akano et al., 2021; Lieder et al., 2017). Tao et al. (2022) initiated this approach by including consumers' preferences concerning the replacement of a faulty battery with a new, reconditioned or directly reused battery. However, these preferences are represented as fixed proportions and are independent of the characteristics of the alternatives.

Qualitative studies have explored stakeholder perspectives regarding EV battery reconditioning and remanufacturing. For instance, Chirumalla et al. (2022) and Olsson et al. (2018) examine the roles of key stakeholders in the EV battery value chain, emphasizing the importance of collaboration across industries such as OEMs, recyclers, and energy storage providers. Wrålsen et al. (2021) identify governments and vehicle manufacturers as the most critical stakeholders, while also discussing the regulatory and financial barriers that impact circular business models for lithium-ion batteries. Kadner et al. (2021) extend this by including repair shops and logistics providers, highlighting the complexity of the roles these actors play in battery end-of-life management. Slattery et al. (2024) focus on the EV battery reuse and recycling network in North America. They discuss the role of various stakeholders, including manufacturers, remanufacturers, and policymakers, and the challenges in creating a closed-loop value chain for EV batteries. Their study emphasizes the importance of collaboration between these stakeholders to overcome barriers such as safety, transportation, and access to critical information.

Besides EV batteries, Abdul-Kader and Haque (2011) have examined stakeholder relations in the remanufacturing of tires using an agent-based simulation approach. Their study models the economic implications of remanufacturing processes and the involvement of different stakeholders such as tire manufacturers, recyclers, and consumers. Akano et al. (2021) explore decision-making factors in remanufacturability, focusing on the needs of primary stakeholders like OEMs and consumers. Kalverkamp and Raabe (2018) examine the automotive remanufacturing system, analyzing stakeholder interactions within the reverse logistics framework and highlighting the challenges faced by remanufacturers in balancing economic, environmental, and societal objectives. Their work adds to the broader understanding of the remanufacturing market, which could be useful in the context of EV battery reconditioning.

The present study extends existing quantitative approaches by including the consumers' and car' workshops' interests for or against reconditioned batteries in the demand estimation. Consumers' preferences are contingent upon the characteristics of reconditioned batteries with respect to price, quality, and environmental impact. Additionally, warranty cases may contribute to the demand for reconditioned batteries. The supply of reconditioned batteries considers the profitability for the OEM, the recycler, the reconditioner, and the repurposer, as well as potential lost sales of new spare batteries from the OEMs' perspective, in the event that reconditioned batteries are also supplied. Legislation is partially incorporated by considering recycling efficiencies and minimum recycled content of new batteries, as mandated by the EU battery regulation. To the best of the authors' knowledge, this study is the first to comprehensively examine the supply and demand of reconditioned batteries within the network of stakeholders with partially conflicting interests. The approach contributes to environmental management literature by expanding the technical focus of reconditioning research to include an economic perspective (OEM, recycler, repurposer, reconditioner) and a social perspective (consumers).

C.3 Materials and Methods

To gain insights into stakeholders' interests, a comprehensive literature review was conducted, supplemented by 19 interviews and two surveys. Utilizing the information obtained from these sources, a flexible simulation model incorporating discrete event and agent-based elements was constructed. The model's flexibility is attributed to its 49 input parameters, enabling comprehensive depiction of future scenarios.

C.3.1 Stakeholders

The interview participants comprised representatives from automotive OEMs (2), recycling companies (2), scrap yards (5), and workshops (10). The OEMs, recyclers, and one of the scrap yards were also involved in repurposing activities. The surveys were conducted among workshops (58 complete responses, cf. Huster et al., 2024a) and with potential customers of reconditioned batteries (837 complete responses in a discrete-choice experiment, cf. Huster et al., 2024b). For the literature review regarding legal requirements, the European Union (EU) battery regulation served as the primary source, thereby establishing the regional focus of the study on the EU.

The stakeholders can be categorized into four distinct groups: business entities, workshops, customers, and legislative bodies.

C.3.1.1 Business entities

These encompass the OEMs, recyclers, reconditioners, and repurposers. The primary finding from the interviews was that, within the constraints of legal requirements, economic viability is the principal objective. Environmental sustainability was also identified as a decision criterion, albeit with the limitation that environmental and economic sustainability should be congruent.

C.3.1.2 Workshops

Although workshops are also business entities, they are categorized separately. The interviews and the survey indicated that the attitude regarding reconditioned spare parts for some workshops is influenced by opinions about those parts rather than factual information (Huster et al., 2024a). Consequently, factors beyond economic considerations may influence a workshop's decision to offer or not offer reconditioned spare EVBs.

C.3.1.3 Customers

Data regarding customers' spare battery preferences were obtained through a discrete-choice experiment involving 837 participants, with the results published in Huster et al. (2024b). The choice options presented were “buy a new battery”, “buy a reconditioned battery” or “buy a new car”. These options varied in terms of price, life expectancy, and the greenhouse gas (GHG) intensity of new and reconditioned batteries, as well as the new vehicle price. As a result, the utility functions of the three options was retrieved (Huster et al., 2024b).

C.3.1.4 Legislative bodies

While numerous national and international regulations may influence the EoL pathway of an EVB, the EU Battery Regulation, which was ratified in August 2023, is considered one of the most significant in Europe. This regulation applies to all types of batteries and encompasses the entire battery life cycle from production to recycling. With regard to EoL, the regulation imposes extended producer responsibility (EPR) on manufacturers, making them responsible for an adequate EoL treatment. However, it does not entitle the producers to the EoL batteries. Instead, end consumers are required to return them to certified collection points, which in turn must ensure the batteries are treated within the boundaries of the law. This treatment can be conducted by the producer or by third parties. Furthermore, the EU Battery Regulation mandates certain minimum material recovery shares from 2031 onwards, as well as minimum recycled content in new battery cells from August 2031 onwards. For EVs, the initial minimum recycled content shares are 16% for cobalt (Co), 6% for lithium (Li), and 6% for nickel (Ni). These thresholds will increase five years later to 26% (Co), 12% (Li), and 15% (Ni). It is noteworthy that battery manufacturers are not required to obtain recycled materials for new battery production from their own batteries. In addition to recycling quotas, the EU Battery Regulation also outlines requirements for reuse, remanufacturing, and repurposing, as well as the preparation of these EoL pathways. For instance, it transfers the EPR from the original economic operator who placed the battery on the market to the operator who places the second-life battery on the market. In return, remanufacturers are granted access to relevant information about the battery's composition and condition through the Battery Passport (European Parliament and European Council, 2023a). The significant transfer of responsibilities to the second-life operator suggests that reconditioning and repurposing are likely to be carried out by or in collaboration with OEMs.

C.3.2 Simulation Model

As stated in Section C.1, the aim of this study is to create a flexible simulation model to estimate the demand and supply of reconditioned EV batteries up to 2050 under various future scenarios. For achieving this, a simulation model is constructed using the Java-based simulation software AnyLogic University 8.9.0. AnyLogic supports discrete event, agent-based, and system dynamics simulation paradigms, as well as the integration of these approaches. To capture detailed supply chain effects at an entity level, the discrete event paradigm is selected as the predominant logic. To incorporate effects arising from stakeholders' actions and interactions, agent-based elements are included. The general simulation logic is depicted in Figure C.2. A predecessor model, comprising only the entities "vehicle" and "EVB", has been published in Huster et al. (2022), and an extension including customers' preferences is presented in Huster et al. (2023b).

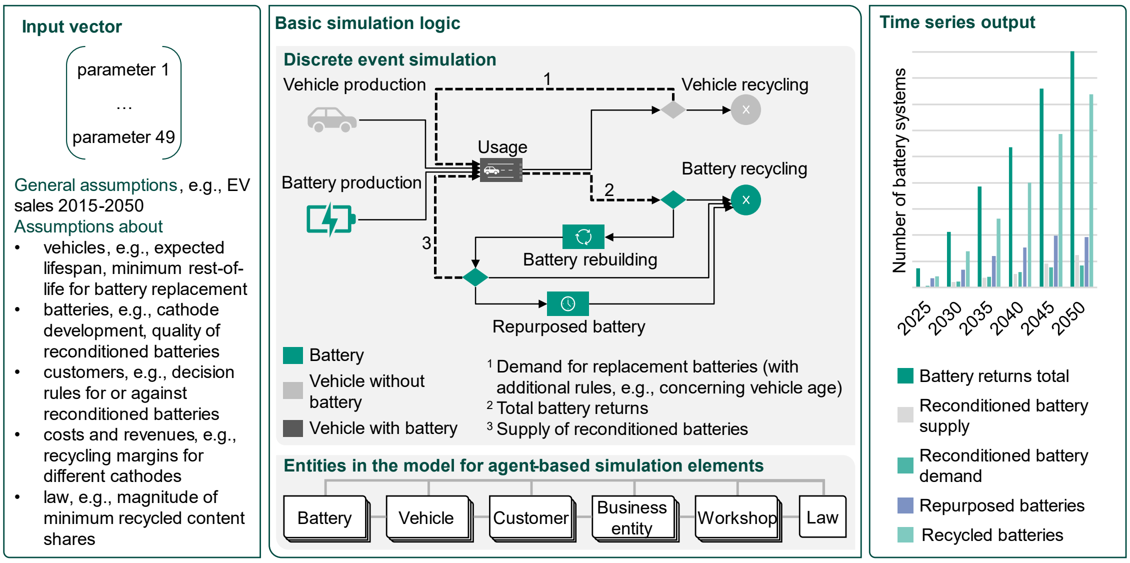


Figure C.2: General simulation logic (partially adapted from Huster et al. (2022)

The model employs a 49-parameter vector as input. These parameters characterize the overall environment, including historical and anticipated EV sales data through 2050, hypotheses regarding the onset of battery reconditioning feasibility, and stakeholder-related factors. A thorough explanation of each parameter is accessible in the Supplementary Material.

The discrete event simulation methodology initiates with the production of batteries and vehicles, which are subsequently integrated to form an EV. This is followed by a utilization phase, which may conclude due to the failure of either the vehicle or its battery. The longevity of both components is governed by independent lifetime distributions, with battery lifespan further influenced by the specific battery type employed. Upon the failure of either component, both are processed through the next stage of the simulation model. At this juncture, the vehicle may receive a replacement battery or be retired, contingent upon its operational status or the user's decision regarding battery replacement. The battery may undergo recycling, be repurposed for alternative applications, or undergo reconditioning for use as a spare unit. These decision-making processes involve varying degrees of stakeholder participation.

C.3.2.1 Business entities and workshops

As delineated in Section C.2.1, the business entities are presumed to make decisions based the economic viability of recycling, repurposing and reconditioning, each expressed as a percentage of the sales price of new EVBs. The margin and cost curves are established by values for the years 2023 and 2050, with linear interpolation for the intervening years. By setting the margins and costs in relation to the new sales price, the actual development of prices and costs, which depend on various factors including volatile raw material prices and difficult-to-predict energy costs, are excluded from consideration. Discounting thus becomes unnecessary. However, it is important to recognize both the advantages and limitations of using the "percent of new price" approach. On the one hand, this method simplifies the modeling process by providing a consistent metric that allows for easy comparisons between different EoL options, regardless of fluctuations in raw material or energy prices. By linking costs directly to the sales price of new EVBs, it also makes it easier to track changes over time without having to account for complex price dynamics. On the other hand, this approach assumes that all EoL options are equally sensitive to changes in raw material prices or other economic factors, which may not be the case in practice. For example, reconditioning may not be as directly impacted by raw material price increases as recycling, which heavily depends on the value of recovered materials.

While recycling and repurposing inputs are expressed as margins, the parameter for reconditioning is represented as costs. This distinction is made because the sales price of reconditioned batteries is a significant determinant of customer demand for replacement batteries after the warranty period (Huster et al., 2024b), and this way, the reconditioning entity can steer demand by setting the price for reconditioned batteries. As the EU Battery Regulation transfers numerous responsibilities of the original producer to the reconditioner, it seems likely that reconditioning is mainly done by OEMs or contract reconditioners. Consequently, reconditioned original EVBs compete with new original EVBs in the spare parts market. With the input parameters of new sales margin, recycling margin, repurposing margin, and reconditioning costs, the OEM can determine whether to offer reconditioned EVBs and how to establish the sales price of reconditioned batteries to maximize revenues. The considered sales prices are 30%, 50%, and 70% of the new sales price, and they are determined annually based on which sales price would have been most advantageous in the previous year. This approach fully utilizes the willingness-to-pay of customers for new and reconditioned batteries while acknowledging the trade-off that occurs because some customers may not purchase a spare battery if the price is too high.

The decision regarding EVB replacement after the expiration of the battery warranty lies with the vehicle owner, while the OEMs determine the EVB selection in warranty cases. Warranty provisions typically specify that replacements should restore the vehicle to a condition appropriate for its age (Mercedes-Benz, n.d.), implying that customers are not entitled to a new battery in warranty cases, and a reconditioned battery may suffice. The simulation model allows for the option of OEMs utilizing reconditioned batteries in warranty cases when reconditioning is cheaper than manufacturing new batteries. Upon expiration of the warranty period, workshops also gain influence in the replacement decision. Given that some workshops even oppose parts that are remanufactured to a state as-good-as-new (Huster et al., 2024a), the model incorporates a specified percentage of workshops offering or not offering reconditioned EVBs as an input parameter. This approach assumes that customers do not actively seek workshops offering reconditioned EVBs but rather maintain their relationship with their trusted workshop. This assumption can be adjusted by setting the proportion of workshops offering reconditioned batteries to 100%. The input parameters for business entities and workshops are depicted in Figure C.3.

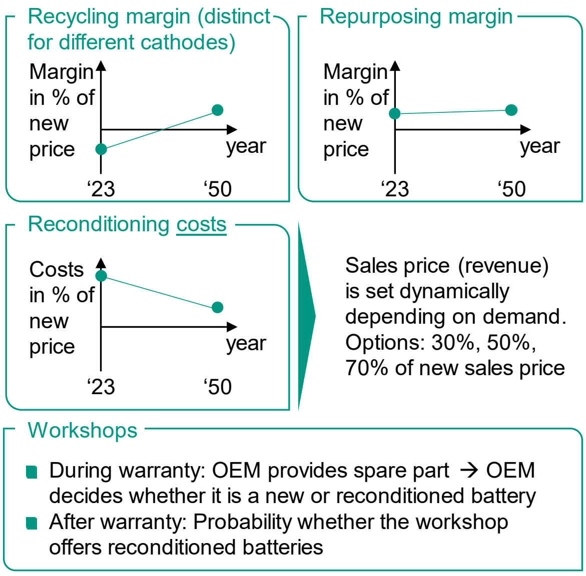


Figure C.3: Input parameters for business entities and workshops

C.3.2.2 Customers

Consumers determine battery replacement options in the event of EVB failure post-warranty expiration, in conjunction with workshops as laid out in Section C.3.2.1. The available three alternatives are replacing the failed EVB with a new or reconditioned unit, or replacing the entire EV. Pertinent model inputs for this decision-making process encompass the lifetime loss and GHG savings of reconditioned EVBs compared to new ones, as well as the vehicle size as a proxy for vehicle price. Vehicle sizes are categorized in the model as proportions of small, medium-sized, and large vehicles. With this information, the utility of all replacement options is evaluated in each choice scenario. In instances where a reconditioned battery demonstrates the highest utility but is unavailable, a new battery may be chosen if this option provides higher utility for the specific consumer than replacing the entire EV

Should the user of the simulation model be interested in the model outcome *without* considering consumers' utilities, it is also feasible to assume that all consumers opt for a new battery, all select a reconditioned battery, or all choose the EV replacement option.

C.3.2.3 EU Battery Regulation

The EU battery regulation requires specific minimum recycled content shares for newly produced EVBs from August 2031 onwards, as laid out in Section C.2. While the regulation does not specify the source of these recycled materials, the simulation model incorporates an option to derive them from EVBs within the simulated environment. This feature necessitates the recycling of a sufficient number of batteries to obtain the requisite amounts of recycled cobalt, lithium, and nickel for new battery production. As a result, recycling may be mandated even when repurposing or reconditioning would be more economically viable.

The model also enables the assessment of increased recycled content share requirements for cobalt, lithium, and nickel in the reference years 2031 and 2036.

For assessing the impact of recycled content shares, the composition of batteries is critical. Three battery technology development scenarios are implemented in the model, from which the user can select: a scenario where NMC cathodes maintain long-term dominance (scenario name NCx); an LFP-dominant scenario (scenario name LFP); and a scenario in which solid-state batterie, namely lithium sulphur and lithium air batteries, take over significant market share from 2030 onwards (scenario name: Li-S & Li- Air) (Xu et al., 2020). The cathode scenarios are depicted in the Supplementary Information.

C.3.2.4 Outputs

The model outputs are of a time series nature with a five-year resolution. For the years 2025, 2030, 2035, 2040, 2045, and 2050, the total EVB returns, the EVB returns from vehicles (excluding returns from repurposing), the supply and demand of reconditioned EVBs, the quantity of repurposed EVBs, and the quantity of recycled EVBs are determined. Additionally, aggregated key performance indicators (KPI) over the entire simulated period for all the aforementioned categories are recorded. At an aggregated level, the quantity of recycled batteries is further subdivided into different cathode technologies, such as NMC111 or NMC622 (i.e., nickel, manganese and cobalt in a ratio of 1:1:1 or 6:2:2, Myung et al., 2017), to facilitate environmental analysis and resource planning.

C.3.3 Case Study

The model is applied to various parameter combinations for demonstrative purposes. Initially, a base case is established. Subsequently, parameters are varied for sensitivity analysis.

The base case aims to create a plausible scenario for the development of the German EVB EoL market. However, due to the lack of available data on actual values, some parameters must be estimated. The historical and projected Battery Electric Vehicle (BEV) sales data for Germany are utilized as input for the simulation model (cf. Figure C.4a). The simulation period spans 36 years, commencing from 2015. Initiating the simulation from a period when EVs began entering the market ensures that the model replicates the actual market development. Furthermore, a cathode scenario is assumed in which LFP cathodes will gain a significant market share ("LFP scenario", Xu et al. (2020), cf. Figure C.4b). The robustness of this assumption is tested later on in the parameter variation by assuming the NCx scenario and the solid-state scenario Li-S & Li-Air (cf. Section C.3.2.3). Vehicles are assumed to have an average life-span of 14 years (Oguchi and Fuse, 2015), while batteries are expected to last 10 years (NMC and NCO cathodes, Shafique et al., 2023)) and 12 years (other cathodes, based on Ding et al. (2019)). However, both for vehicles and batteries, higher and lower life expectancies can be found in the literature. For example, Ai et al. (2019) assume the lifetime of EVBs of unspecified cell chemistry to evolve from 5.5 to 12.5 years until 2035, Drabik and Rizos (2018) estimate an average EVB lifetime in an EV to be 8 years, most likely referring to NMC cathodes, and Schoch, (2018) claim that with optimized charging, NMC batteries might last 25 years. LFP and more advanced battery chemistries are generally assumed to have a higher lifespan than NMC batteries (Ding et al., 2019; Zhang et al., 2018). To account for the variability of assumptions, a longer and shorter battery life expectancy of two years for all chemistries is tested in the parameter variation section C.4.2. The warranty period is set to the standard duration of 8 years (ADAC, 2022), and the production scrap is set at 10% (Koenig, 2024), which also accounts as recycled content as it is reintroduced into production. Warranty replacements are presumed to be executed exclusively with new batteries. However, this is relaxed when varying the parameters in Section C.4.2. Reconditioned batteries are unable to achieve a like-new condition (Autocraft Solutions Group, 2023). Since, to the authors' knowledge, it is not specified how much the condition of a reconditioned battery differs from that of a new battery, various lifetime reductions are tested. In the base case, a lifetime reduction of 4 years is assumed for all cell chemistries, and a reduction of 2 or 4 years is tested in the parameter variation section. The CO2 emissions are estimated at 50% of those of a new battery (Arnold et al., 2021), but higher and lower values (30% and 50%) are also tested. The sales margin for new batteries is set to 20% in the base case (Zhang and Yang, 2023) and subject to variation in the sensitivity analysis, and the cost for reconditioning is assumed to be 40% of the new sales price (Colledani et al., 2014). Minimum proportions of recycled cobalt, lithium and nickel from 2032 and 2036 onward are determined by the EU battery regulation (European Parliament and European Council, 2023a). For the parameter variation, cases where the recycled content is sourced from outside the system boundaries are tested, and cases where the recycled content quotas are doubled. Additional assumptions are delineated in the Supplementary Information.

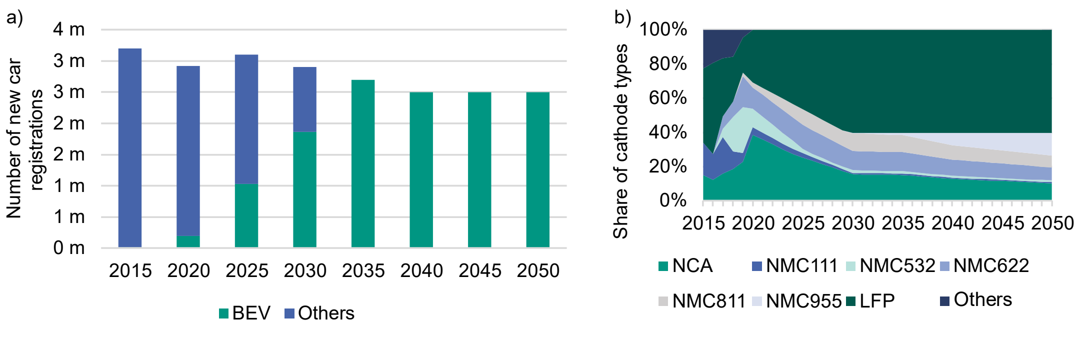


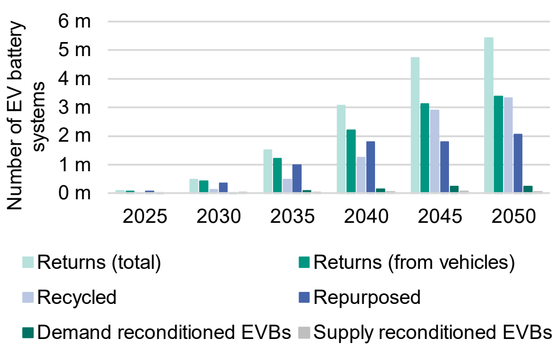
Figure C.4: Car registrations and cathode scenario. a) Number of new car registrations. For 2015 and 2020, the actual sales values are used (Kraftfahrt-Bundesamt, 2022). From then on, the total vehicle sales up to 2040 are assumed as predicted by Deloitte (2020) and kept constant for the following periods 2045 and 2050. From 2035 onwards, only BEVs are assumed to be newly registered due to the EU directive to only allow locally emission-free vehicles from then on (BMUV, 2023). The BEV sales values in between (periods 2025 and 2030) are linear interpolations. b) Cathode scenario, which is the LFP-dominant scenario of Xu et al. (2022), CC BY 4.0

C.4 Results

C.4.1 Base Case

The base case of the case study, as laid out in Section C.3.3 yields the outputs as depicted in Figure C.5. As expected, in 2025, only minimal quantities of EV batteries will be returned. Approximately 1.5 million EV batteries will be returned from 2035 onwards, with the number increasing to 5.4 million in 2050. This includes returning EV batteries from vehicles and after a second use phase in a non-automotive application. Return numbers from vehicle use reach a plateau from approximately 2045 onwards at about 3.1-3.4 million batteries, which equates to approximately 235-260 GWh of battery capacity, assuming 50 kWh batteries for small vehicles, 75 kWh for medium-sized vehicles, and 100 kWh for large vehicles. In the base case, repurposing is the predominant EoL strategy up to 2040, followed by recycling, and far behind, reconditioning. From 2045 onwards, more EoL batteries are recycled than repurposed, due to the high number of returning repurposed batteries. In all years, there is some demand for reconditioned EV spare batteries (up to approx. 240,000 in 2050). However, the supply peaks at approx. 50,000. It is plausible that the demand consistently exceeds the supply, as some consumers who would purchase a reconditioned battery would also consider purchasing a new spare battery with a potentially higher margin for the OEM. To mitigate cannibalization effects, it is sensible from an OEM perspective to attempt to maximize the willingness-to-pay with new batteries initially. Additionally, there may be a temporal mismatch between demand and potential supply that partially accounts for the discrepancy between supply and demand figures.

On an aggregated level of all years of the simulation (2015-2050), about 75.8 million EV batteries (5,760 GWh) are manufactured, of which 65.3 million (4,960 GWh) are returned in the examined time frame. Corresponding with the assumed new cathode production (Figure C.4b), the majority of recycled batteries are LFP batteries, followed by NCA, NMC622, and NMC811 cathodes.



Aggregated over all years:

- Returning EV batteries (from vehicles and second -life applications: 65.3. m (4,960 GWh)
- Reconditioned EV battery supply: 0.85 m (65 GWh)
- Reconditioned EV battery demand: 3.2 m (240 GWh)
- Recycled NCA EV batteries: 9.0 m (605)
- Recycled NMC111 EV batteries: 0.7 m (50 GWh)
- Recycled NMC532 EV batteries: 1.0 m (75 GWh)
- Recycled NMC622 EV batteries: 5.2 m (395 GWh)
- Recycled NMC811 EV batteries: 2.8 m (210 GWh)
- Recycled NMC955 EV batteries: 0.35 m (25 GWh)
- Recycled LFP EV batteries: 14.2 m (1,075 GWh)
- Manufactured EV batteries: 75.8 m (5,760 GWh)

Figure C.5: Results of the base case

C.4.2 Parameter Variation

The influence of parameter changes on the demand and supply of reconditioned spare batteries varies significantly (cf. Figure C.6). While eliminating the minimum recycled content share in new batteries (Figure C.6, "Min. recycled content: 0") or doubling it compared to the current EU Battery Regulation requirements (Figure C.6, "Min. recycled content share: doubled") has minimal effect on the aforementioned KPIs, other parameters, such as the assumption that all consumers select reconditioned batteries as spare parts for battery replacements after the warranty period (Figure C.6, "Every customer chooses a reconditioned spare battery"), substantially increase both demand and supply (+320% and +230%). While, in the base case, consumer decisions follow the results obtained in Huster et al. (2024b), the assumption that all consumers opt for reconditioned spare batteries would imply a drastic change in consumer behavior toward reconditioned spare parts, potentially due to price incentives or environmental awareness campaigns (cf. Section C.5). The majority of parameters fall between these extremes, ranging from hardly any effect to a large effect.

In the event that the average battery lifetime is two years longer or shorter than in the base case (Figure C.6, "Battery life expectancy +2 [-2] years"), demand and supply fluctuate by approximately 25% in the anticipated direction, which is an increase of 25% if the battery has a shorter lifespan, and a decrease of 25% in the opposite scenario. In case the vehicle is more durable than expected (+2 years, 16 years in total), demand and supply increase by approximately 40%, as the timeframe in which consumers may replace batteries after the warranty period expiration extends. Similarly, if cars are only eligible for battery replacement up to a remaining useful life of six years instead of four years (Figure C.6, "Min. car rest of life: 6 years"), supply and demand of reconditioned batteries decreases by about 35-40%, while they increase by 40-45%, if vehicles with a remaining useful life of two years remain eligible for battery replacement (Figure C.6, "Min. car rest of life: 2 years"). An extension of the warranty period by two years results in approximately 40% less demand for reconditioned spare batteries, and a reduction by two years leads to an increase in demand of similar magnitude (Figure C.6, "Warranty period: 10 years [6 years]").

As a reminder, the base case assumes that OEMs do not use reconditioned spare batteries for warranty cases, even if the reconditioning costs are below the manufacturing costs for new batteries. Altering this assumption results in an increase in demand for reconditioned batteries by nearly 900%, and an increase in supply by almost 300% (Figure C.6, "Reconditioned batteries during warranty"). In absolute numbers, this translates to a requirement of 12.2 million reconditioned EVBs instead of 3.2 million units, and a supply of 8.35 million reconditioned EVBs instead of 0.85 million batteries. With regard to warranty cases, only two-thirds of those intended to be fulfilled by reconditioned batteries receive suitable supply. This discrepancy is attributed to a temporal mismatch of supply and demand of suitable batteries of the right cathodes. It becomes evident that the OEMs' decisions regarding the use of reconditioned spare parts during the warranty period are crucial for assessing the significance of reconditioning in the future.

Further parameters that were varied include the CO2 savings of reconditioned batteries compared to new batteries (Figure C.6, “CO2 savings reconditioning: 30% [70%]”), and the average lifetime loss compared to new batteries (Figure C.6, “Quality loss reconditioning: 2 years [6 years]”). A decrease in CO2 emissions by 20 percentage points (from 50% savings to 70% savings; 40% increase) results in an increase in demand of approximately 10%, while an increase in emissions of the same magnitude reduces the demand by 10%. A reduction in battery life expectancy of reconditioned batteries of six years instead of four years in the base case (+50%) decreases the demand by approximately 20%, whereas a reduction of two years instead of four years leads to an increase in demand by 45%. Consequently, the quality of reconditioned EVBs significantly influences their demand and supply.

While most parameter variations change supply and demand for reconditioned batteries in the same magnitude, there are some parameters whose variation changes one of the KPIs more than the other. For instance, modifying the assumptions regarding the sales margin by 50% does not affect the demand for reconditioned batteries but influences the attractiveness of supplying reconditioned batteries for the OEM (+8% [-8%]), in the event that the sales margin decreases [increases].

In the base case, a cathode scenario is assumed in which LFP will be dominant with about 60% market share from 2030 onwards (cf. Figure C.4 b). As mentioned in Section C.3.2.3, two other scenarios can be chosen, namely the *NCx* and the *Li-S & Li-Air* scenario (cf. Supplementary Information Figure S1). In the *NCx* cathode scenario, the demand for reconditioned batteries rises by approximately 17%, while the supply decreases by 6%. This can be explained, first, by the shorter lifetime that is assumed for NMC and NCA batteries compared to LFP batteries. It leads to more early battery failures compared to the vehicle life, so that the demand for spare batteries (new or reconditioned), rises. However, NMC batteries contain more valuable materials than LFP batteries, so that recycling might be more favorable than reconditioning, hence the slight decline in reconditioned battery supply. The *Li-S & Li-Air* scenario depicts the case where solid-state batteries enter the market in 2030 and gain a market share of about 60% from 2040 onwards (Xu et al., 2020). As Figure C.6 shows, the demand for reconditioned batteries increases by 12%, and the supply by 4%. The higher demand can again be explained by the shorter assumed lifetime of NMC and NCA batteries, that per scenario assumption have a higher market share for longer than in the *LFP* scenario. This time, the supply partially follows the demand, since Li-S and Li-Air batteries, like LFP batteries, contain only a limited amount of valuable materials.

Workshops also have a significant influence on the adoption of reconditioned batteries. If instead of 50% of the workshops, as assumed in the base case, 30% [70%] offer reconditioned spare batteries, supply and demand decrease [increase] proportionally by approximately 40%.

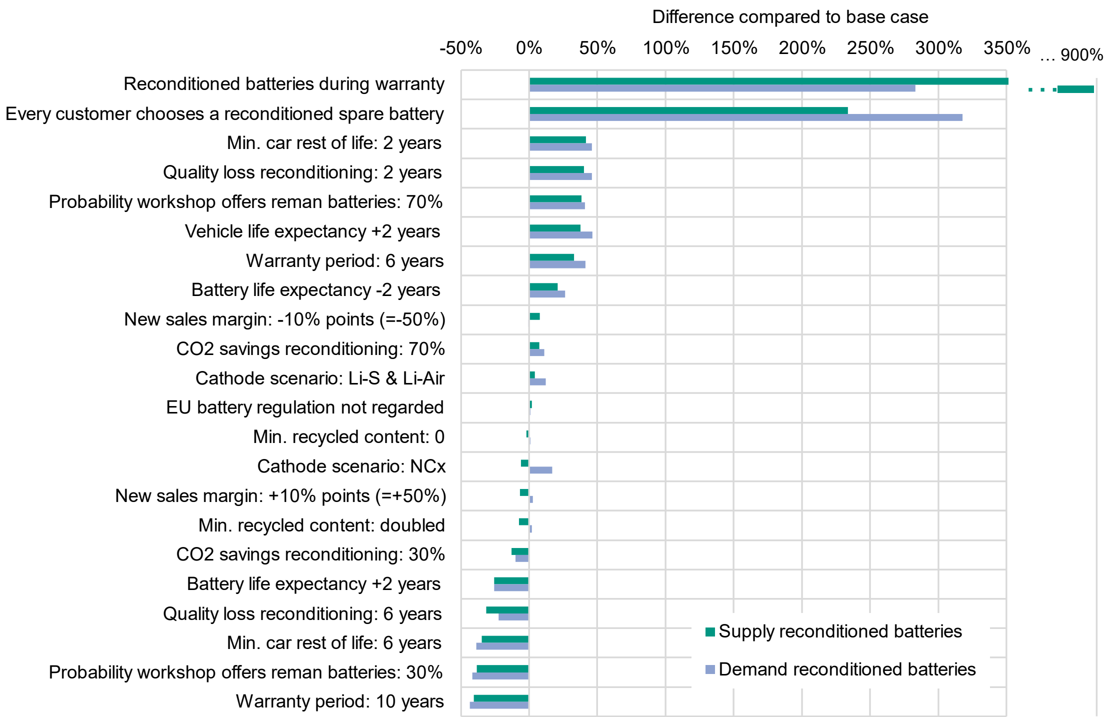


Figure C.6: Difference of supply and demand for reconditioned batteries compared to the base case for certain parameter variations

While the factors discussed above are static throughout the simulation, time-dependent variables can also change, which is particularly useful for assessing the impact of disruptive events, such as a sudden shock in BEV registrations caused by tariffs or disruptions in the supply chain due to pandemics or political conflicts. To illustrate this, a scenario is examined where BEV demand experiences a sharp decline, halving from 2030 to 2031. After five years, the demand is assumed to return to its 2030 level, and five years after that, the base case and demand shock scenarios are assumed to realign. This is shown in Figure C.7a. Overall, the "EV shock scenario" results in a 13% decrease in EV sales compared to the base case. Figure C.7b illustrates the corresponding effect on the supply and demand for reconditioned batteries. Given the long lifespan of both EVs and their batteries, and the distribution of their assumed lifetimes, the steep decline in demand is gradually smoothed out. The most significant impact occurs in 2045, when both demand and supply are approximately 35% lower than in the base case. In total, the demand shock could lead to a 20% reduction in the supply and demand for reconditioned batteries, a decline that is greater than the reduction in EV sales.

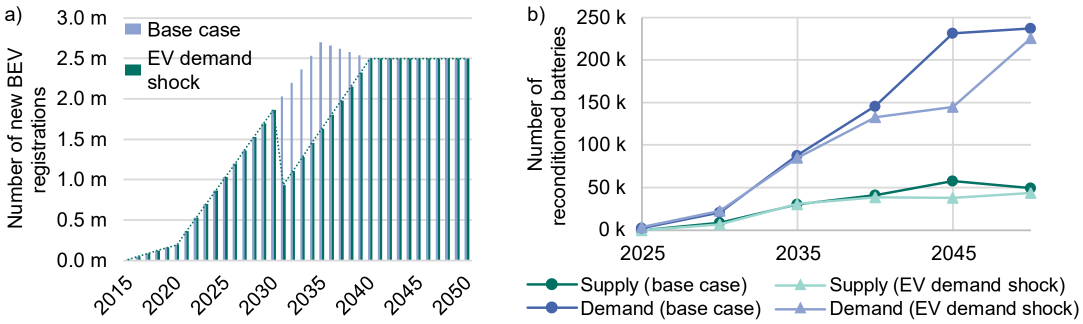


Figure C.7: Demand shock. a) BEV new registrations in case of a demand shock in 2031 and a 5-year recovery period. b) Resulting supply and demand for reconditioned EVBs

While the focus of this research is on the demand and supply of reconditioned batteries, it is pertinent to address an observation regarding the number of recycled EVBs that emerges when considering scenarios where the recycled content quotas of the EU Battery Regulation are doubled or disregarded entirely. In the absence of recycled content quotas within the system boundaries, no significant changes in the number of recycled batteries are observed (cf. Figure C.8). This indicates that with the minimum recycled contents mandated by the EU from 2031 and 2036 onwards, no batteries would be recycled prematurely instead of being reused, assuming the other parameters of the base case prove accurate. Conversely, if the minimum recycled content quotas were doubled (i.e., 32%/12%/12% for Co/Li/Ni from August 2031 onwards and 52%/24%/30% for Co/Li/Ni from August 2036 onwards), a notable shift in recycling quantities becomes apparent. In 2035, shortly after the introduction of minimum recycled material shares, 26% more EVBs require recycling compared to the base case. This implies that to meet the demand for recycled content in new battery production, end-of-life batteries that would otherwise be economically viable for reuse in other applications must be recycled. The earlier recycling of some EVBs up to 2040 results in fewer battery systems being recycled later (2045-2050) than in the base case for two reasons:

First, in the more distant future, the numbers of returning and manufactured battery systems approach parity, and sufficient batteries return for final recycling from all previous applications to fulfil the demand for recycled materials. Consequently, early recycling at the expense of second-life applications would no longer be necessary. Second, batteries that would have been utilized for second-life purposes in the base case would have already been recycled earlier in the high recycled content scenario. Therefore, the recycling quantities would shift from a later point in time to the nearer future.

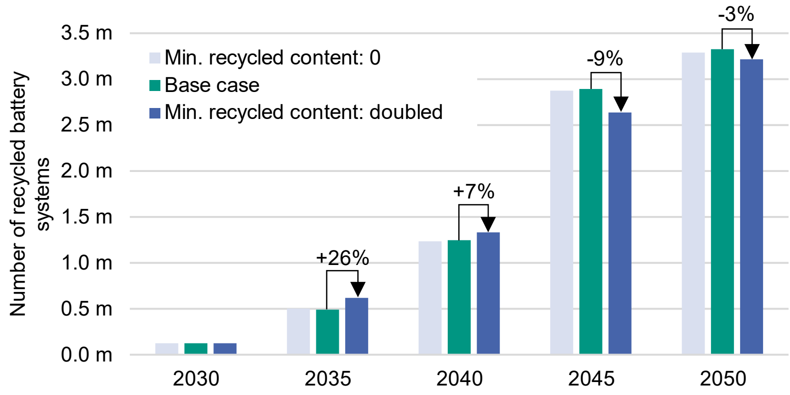


Figure C.8: Change in the number of recycled battery systems if there is no mandatory share of recycled materials in new batteries and if the target recycled content is twice as high as the EU Battery Regulation demands

C.5 Discussion

C.5.1 Evaluation and Stakeholder Recommendations

Regarding the low numbers of reconditioned batteries in the base case and most other cases of the case study, the question arises whether or not reconditioning is a relevant EoL option that should be further examined. The demand for reconditioned EVBs is projected to be approximately 20,000 in 2030 and 240,000 in 2050, with a supply of only 8,600 reconditioned EVBs in 2030 (50,000 in 2050), assuming the base case scenario. These figures align with the estimates of Kastanaki and Giannis (2023), who project an annual supply of reconditioned EVBs in Germany ranging from 7,000 to 29,000 from 2024 to 2034. It is important to note that these numbers pertain to the entire German market. In a scenario focusing on a single OEM with, for instance, a 10% market share, these figures would decrease proportionally. Nevertheless, if OEMs intend to promote reconditioning, they could focus on developing long-lasting, high-quality reconditioning batteries, provide education to workshops about reconditioned parts, and, most importantly, utilize reconditioned spare batteries for warranty cases. While the longevity of batteries primarily addresses consumers' concerns regarding the quality of reconditioned spare batteries, educating workshops aims to reduce resistance against reconditioned and remanufactured parts (Huster et al., 2024a). Appropriate warranties could help in building up the workshops' trust in reconditioned products, thus increasing the share of workshops that offer reconditioned spare parts. It remains open whether in addition to perceived warranty issues and reduced profitability of reconditioned parts, other behavioral barriers, like status quo bias (Godefroid et al., 2023), have to be overcome. However, OEMs considering reconditioned spare batteries for warranty cases potentially has the most significant impact. Given that the simulation model only registers OEMs' demand for reconditioned batteries when the reconditioning costs are lower than the production costs for new batteries, it should be an intrinsic motivation for OEMs to utilize reconditioned batteries in such instances.

Even if OEMs do not facilitate reconditioning with the aforementioned measures, the economically viable quantities of reconditioned batteries remain significant. If approximately 850,000 EVBs are reconditioned up to 2050 (accumulated number in the base case), this equates to approximately 65 GWh in battery capacity. In the event that new spare batteries were utilized instead, approximately 5.2 million tons of CO2 equivalents more would be expended for battery production, assuming an average global warming potential of approximately 80 kg CO2 equivalents/kWh capacity for cell production, including benefits from hydrometallurgical recycling (Mohr et al., 2020). Even with the assumed CO2 intensity of reconditioning at 30%, 50%, or 70% of the new production emissions, the savings are substantial from an ecological perspective. These figures provide only a rough estimate, and future research could offer a more detailed quantification of the ecological contribution of reconditioning. While numerous LCAs of EV batteries include recycling (e.g. Feng et al., 2022; Mohr et al., 2020), repurposing is less frequently considered (e.g., Liu et al., 2023; Wrålsen and O'Born, 2023; Zhou et al., 2025), and to the authors' knowledge, no LCA includes reconditioning in detail (Husmann et al., 2024). Future research could built upon the work of Philippot et al. (2022), who explore the reuse of EV batteries in vehicles following an inspection step but without reconditioning, and extend their approach by differentiating between various current and future battery chemistries, including solid-state batteries, as Popien et al. (2023) have done for the production phase.

Furthermore, reconditioning provides consumers with cost-efficient spare parts, potentially enhancing the perceived service level. If only a limited number of batteries are reconditioned, the costs for researching and developing reconditioning processes are allocated to a small number of batteries, thereby increasing the reconditioning cost. This primarily affects destruction-free disassembly and testing technologies. However, these technologies are also beneficial for repurposing activities, and they are essential in cases where single modules or even cells should be replaced under warranty, rather than replacing the entire battery system. Therefore, further research into technologies that enable reconditioning supports other EoL strategies, and vice versa. This research can be promoted by policymakers through the provision of research grants, by companies through investments in this area of development, and by universities and other research institutions.

Policymakers have recognized the importance of EoL battery management through circular economy legislation, with one prominent example being the EU Battery Regulation. As outlined in Section C.3.1, this regulation assigns responsibility for proper EV battery EoL treatment to the economic operator who places the battery on the market, typically the OEM, through an EPR scheme. However, it does not grant this operator ownership of the EoL batteries. For remanufactured or repurposed batteries, the EPR is transferred to the operator who places the second-life battery on the market (European Parliament and European Council, 2023a). Additionally, the proposed new End-of-Life Vehicle Directive mandates that EV batteries must be removable from the vehicle, making them replaceable, potentially with reconditioned batteries (European Parliament and European Council, 2023b). On one hand, these regulations could promote reconditioning and repurposing by leveling the playing field for various stakeholders, setting uniform rules, and providing valuable information about battery chemistry and disassembly procedures via the Battery Passport. On the other hand, these regulations might also pose challenges, as the requirements could be too stringent for some stakeholders. Furthermore, there are still grey areas within the legislation that may be addressed once delegated acts, which have yet to be implemented, are executed. Given the conflicting interests of different stakeholders, finding a solution that ensures safety for end customers, fairness for economic players, and environmental benefits is a significant challenge for policymakers. Despite the constraints imposed by current and proposed legislation, policymakers still have opportunities to promote specific EoL pathways. If reconditioning is a priority, various stakeholders can be targeted with tailored measures: subsidies for reconditioned spare batteries could lower their cost, thus stimulating demand, while public information campaigns could help shift consumer attitudes toward reconditioned products. OEMs and other business entities could be incentivized to invest in reconditioning technologies through subsidies or other forms of funding. Additionally, both end customers and workshops may be more inclined to adopt reconditioned batteries if warranties for reconditioned parts are clearly defined and easy to enforce.

Another recommendation for policymakers addresses planning security. Most parameters in the model reflect decisions to be made by OEMs, consumers, recyclers, reconditioners, and policymakers. It was notable that altering the quotas for minimum recycled content shifted the recycling quantities to earlier points in time. This is relevant for OEMs and recyclers with regard to building recycling capacity and manufacturing new (spare) batteries. Additionally, decisions made in the present will often only come into effect much later, due to the long lifetime of batteries and vehicles. Therefore, policymakers should acknowledge the long lifetime of batteries and provide planning security well in advance.

C.5.2 Limitations

The presented simulation model captures the complexity associated with estimating the future demand and supply of reconditioned EVBs by allowing parametrization with 49 parameters. While the spectrum of scenarios assessable with the model is extensive, there are limitations to the approach. For selected parameters, the effect of varying those on the demand and supply of reconditioned EVBs was examined. However, this does not substitute for a detailed feature importance ranking, as is common for other types of models (e.g., machine learning methods, Konig et al. 2021). Without ascertaining the importance of a parameter, it cannot be guaranteed that it has a significant influence on the model and does not merely add complexity without contributing value. Since each simulation run requires approximately ten minutes with AnyLogic 8.9.0 on workstation equipped with an Intel Core i9-14900K processor (24 cores, 32 threads, 3.2 GHz) and 192 GB RAM, it would be advantageous to reduce the complexity if a large-scale simulation study is intended. That holds especially because due to stochasticity in the model, replications of each run are recommended, which increase the time to evaluate one configuration. The long runtime and the high number of parameters also make it difficult to conduct detailed sensitivity studies, such as Monte Carlo simulations, as they would require excessive computational time. For smaller studies that evaluate selected scenarios only, reducing the complexity by decreasing the number of input factors is of minor relevance. Looking ahead, one possible approach to address these challenges is to approximate the simulation model using machine learning methods, which could facilitate more efficient sensitivity analysis and scenario evaluation.

Another limitation of the simulation model is the lack of consideration for demand for repurposed batteries. In the base case, approximately 27 GWh of repurposed EVBs are supplied in 2030. Engel et al. (2019) estimate that the supply of reconditioned batteries for stationary applications will be approximately 35 GWh per year in 2030 in the EU, while the annual demand is expected to be two-thirds higher. Considering that Germany produces about 14.4% of the electricity in Europe (IEA, 2023b), the supply estimated in this study might exceed the demand. Other studies estimate the installed capacity of large-scale energy storage systems in Germany to be 50-100 GWh in 2030 and increase to 275-375 GWh in 2050 (Frontier Economics, 2023). Therefore, the supply estimated by the simulation model may be within the boundaries for energy storage demand, but it may also exceed it. Further studies are necessary to determine demand for second-life EVBs more precisely. If the mechanisms are fully understood, they can be integrated into the simulation model.

Additionally, the simulation model could be further refined to integrate the technical feasibility of reconditioning or repurposing in greater detail. Currently, the economic balance is considered for repurposing, while both economic factors and the preferences of consumers and workshops are taken into account for reconditioning. Furthermore, to address technical limitations and defects, a proportion of batteries is deemed unsuitable for any reuse strategy and is directed straight to recycling. Another portion is considered suitable for repurposing in less demanding applications than the original, but not for reconditioning. For a more comprehensive simulation, the supply chain model could be expanded to include a chemical simulation that accounts for the aging of battery cells in each EV battery system. This would allow for more informed decisions regarding the feasibility of repurposing or reconditioning at the cell or module level. Currently, it is often assumed that EV batteries are retired when they reach 70%-80% of their original State-of-Health (SoH), with repurposing being the only reuse option thereafter (e.g. Al-Alawi et al., 2022; Wrålsen and O'Born, 2023). However, the validity of the 70%-80% threshold for retirement has been widely questioned (Etxandi-Santolaya et al., 2023). Consequently, integrating cell aging and stakeholder-specific criteria for EV battery retirement could enhance the decision-making process between repurposing and reconditioning.

The proposed case study focuses on Germany and considers it as a closed ecosystem. This limitation can partially be addressed by extending the system boundaries in other case studies by selecting the values for the 49 parameters accordingly. However, in every non-global scenario, the outflow of batteries or battery materials from the system is possible and probable in reality. For instance, in 2017, approximately 34% of the de-registered vehicles in the EU were unaccounted for (Williams et al., 2020). The 2017 figures predominantly encompass vehicles with internal combustion engines rather than electric vehicles; nevertheless, they provide insight into the potential magnitude of vehicles and batteries that could be affected by system outflow. For the simulation model, this outflow is not modeled, as it is unlikely to significantly impact the supply and demand of reconditioned EV batteries. In the model, both batteries and vehicles must meet specific criteria regarding their condition, measured, for example, in terms of remaining useful life to be eligible for reconditioning or receiving a spare battery. It is assumed that the issue of unaccounted vehicles primarily affects batteries and vehicles in poor condition.

It has been laid out that the 49 parameters allow for modeling a broad range of real-world scenarios. This is done by feeding an MS Excel file with one column per parameter and one row per scenario to the simulation model. However, there might be changes in reality that cannot be captured by the parameters. In this case, the simulation model has to be adjusted. Some changes can easily be made, for instance with regard to the cathode scenario, for which the annual market share of different cathodes from 2015-2050 is drawn from a table ("database" object in AnyLogic). Similarly, the composition of the different cathodes per kWh is stored as a table and can easily be exchanged. Other changes would require more effort and more information about the system. That holds especially with regard to stakeholders other than the ones already implemented. For example, retailers may influence the availability of reconditioned parts for workshops, local governments may affect end customers attitude towards reconditioned spare batteries through subsidy schemes, or environmental activists could shift the perception of reconditioning by awareness campaigns. However, empirical analyses on how these stakeholders interact with those already implemented would be necessary and remain a field for future studies.

C.6 Conclusion

This paper presents a simulation model for estimating the demand and supply of reconditioned EVBs based on scenarios constructed from 49 parameters. These parameters encompass aspects such as BEV sales development, battery cathode evolution, expected lifetimes of batteries and vehicles, consumer preferences, and the development of costs for EoL options. The model accounts for the economic trade-offs faced by stakeholders, including OEMs' decisions to recycle, repurpose, or recondition a battery, and private consumers' decisions regarding the replacement of faulty EVBs with reconditioned or new spare batteries. Furthermore, the model incorporates the effects of the EU Battery Regulation concerning minimum recycled content requirements.

A case study focused on Germany revealed that reconditioning represents a niche EoL option for EVBs when these batteries are utilized solely as spare batteries by consumers for battery swaps after the warranty period. Consumer demand can be primarily influenced by the longevity of reconditioned batteries and the attitudes of workshops towards these batteries. The most significant factor affecting both supply and demand for reconditioned EVBs is the OEMs' decision to utilize these batteries for warranty cases. Should OEMs choose to do so, demand

and supply will increase substantially. However, due to potential temporal mismatches between returning batteries of a specific type and the demand for that type, not all warranty cases can be fulfilled with reconditioned batteries, necessitating the continued use of new spare batteries.

OEMs and policy makers have the most significant influence on the EoL option selected for EVBs. OEMs can focus on enhancing the quality of EVBs and communicate this to consumers and workshops through appropriate warranty provisions, while strategically pricing to avoid cannibalizing new spare battery sales. Additionally, they can potentially reduce warranty expenses by utilizing reconditioned batteries. Policy makers primarily influence the EoL option by establishing the regulatory framework, which should remain stable for a considerable period due to the long lifetime and consequent long-term planning requirements of EVBs.

C.7 CRediT Authorship Contribution Statement

Sandra Huster: Writing – original draft, Methodology, Conceptualization. Raphael Heck: Writing – review & editing, Methodology. Andreas Rudi: Writing – review & editing, Supervision. Sonja Rosenberg: Writing – review & editing, Conceptualization. Frank Schultmann: Writing – review & editing, Supervision.

C.8 Use of Generative Artificial Intelligence

During the preparation of this work the authors used the tool "Paperpal" in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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C.10 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

C.11 Appendix A. Supplementary Data

Supplementary data to this article can be found online at
https://doi. org/10.1016/j.jenvman.2025.125783.

C.12 Data availability

Additional data beyond that provided in the supplementary information is available from the corresponding author upon reasonable request.

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D Approximating End-of-Life Electric Vehicle Battery Flows: Surrogate Modeling of a Discrete Event and Agent-Based Simulation Model

Authors: Sandra Huster, Mona Faraji-Niri, Andreas Rudi, Frank Schultmann

Abstract

Decision support tools are essential for planning end-of-life pathways of electric vehicle (EV) batteries, including recycling, repurposing, and reconditioning. As large volumes of EV batteries reach end-of-life in the coming decades, estimating material flows under different scenarios becomes increasingly important. Detailed simulation models, such as those based on discrete event and agent-based modeling, can capture the complex dynamics of battery life cycles. However, their high computational cost limits their applicability in decision-making contexts that require extensive scenario analysis. To overcome this challenge, machine learning-based surrogate models are evaluated for approximating the outputs of a simulation model that estimates future end-of-life quantities of EV batteries. The simulation model uses static input configurations and produces time-dependent outputs, for which no historical time series exist. Two surrogate modeling strategies are compared: an all-at-once approach that predicts all time steps simultaneously, and a recursive approach that predicts them sequentially. Several machine learning algorithms are evaluated, including neural networks, Gaussian process regression, random forests, and XGBoost. Results show that neither approach consistently outperforms the other, and model performance varies strongly across key performance indicators. While surrogate models can substantially accelerate analysis, predictive accuracy is limited for outputs with sparse or highly variable data. The results underline the importance of selecting surrogate modeling approaches based on the specific characteristics of the output indicators and the analytical needs of the decision context.

Keywords: Discrete event simulation, electric vehicle batteries, remanufacturing, metamodeling, emulation, time-dependency

D.1 Introduction

The number of end-of-life (EoL) electric vehicle batteries (EVBs) that will become available for recycling, repurposing, or reconditioning in the coming years depends on numerous factors, such as the development of electric vehicle (EV) sales, technological advances in EoL pathways, and decisions by stakeholders along the value chain (Kadner et al., 2021). Recycling refers to recovering material; repurposing denotes reusing the battery in an application other than the original one, i.e., an application outside the vehicle; and reconditioning means that the battery is restored to a state suitable for usage in an EV as a spare battery (DeRousseau et al., 2017; European Commission, 2008; Potting et al., 2017). While recycling and repurposing are already practiced to some extent (Faessler, 2021; Slattery et al., 2024), reconditioning is currently only carried out on a pilot scale (e.g., Stellantis, 2023). To predict EoL quantities, material flow analyses are commonly used. These estimate EVB returns based on EV sales data and assume that a certain share of batteries is suitable for repurposing or reconditioning (Sanclemente Crespo et al., 2022; L. Yang et al., 2024). More advanced simulation models include effects of legislative measures or market dynamics such as supply-driven price effects (Pratap et al., 2024; Seika & Kubli, 2024). These models allow for more realistic and detailed representations of the EVB value chain but come with longer runtimes. One such model is a discrete event and agent-based simulation model by Huster et al. (2025), which uses 49 input parameters, including expected EV and EVB lifetimes, future EV sales, and assumptions on the profitability of EoL pathways. Based on these inputs, the model estimates quantities of returned, recycled, repurposed, reconditioned, and demanded EVBs for the period from 2025 to 2050 in five-year intervals, resulting in 30 output variables. With the large number of input factors and a runtime of about ten minutes per simulation run, extensive sensitivity studies are hardly feasible. For instance, testing only three levels per input factor would require around 817 days of computation time, not including replications to account for stochasticity.

To address such limitations, it has been proposed to approximate the input-output behavior of simulation models using simplified models, often referred to as surrogate models, response surfaces, metamodels, or emulators (McBride & Sundmacher, 2019; Pietzsch et al., 2020). These terms originate from different research communities, such as response surface methodology in statistics (Box & Wilson, 1951, as cited by Khuri & Cornell, 1987) and simulation metamodeling in operations research (Barton, 1992; Kleijnen, 1982), but they generally describe models that approximate the behavior of experiments or simulations. In this study, the term surrogate model is used as a generic term for such approximations. The basic idea of those models is that, first, sample points are generated with the original simulation model as training data, then a surrogate model is fitted, and finally, the surrogate model is evaluated (Thombre et al., 2015). Those surrogates can be created with various techniques, for example, artificial neural networks (ANNs), Gaussian process regression (GPR) or random forests (RFs) (Angione et al., 2022). The model selection depends on many factors, including the sampling size for training and the number of input factors (Williams & Cremaschi, 2021). Furthermore, the type of input and output data is crucial. While some methods are primarily used for static outputs, others, like long short-term memory (LSTM), are more suitable for time series output (Zhao et al., 2023). Surrogate modeling has been applied to different domains, from chemical process engineering to social studies (Angione et al., 2022; McBride & Sundmacher, 2019), for agent-based simulations, finite element simulations and techno-economic analyses (Hürkamp et al., 2021; ten Broeke et al., 2021; Wiesberg et al., 2021).

Typically, it is evident whether data is of a time series nature or not. Cerqueira et al. (2020) define time series as "a temporal sequence of values $Y = \{y_1, y_2, \dots, y_t\}$, where y_i is the value of Y at a time i and t is the length of Y", and time series forecasting as "the task of predicting the next value of the time series, y_{t+1} , given the previous observations of Y". Consequently, time series prediction always relies on previous time series values, potentially augmented by additional data. In emerging markets, however, predicting product sales or product return quantities must be conducted without historical precedents. Predictions must rely on static input data, such as product lifetimes and estimated consumer preferences, while the predictions are of a time series nature in that they are sequential and time-dependent. Therefore, approximating a simulation that predicts EVB recycling, repurposing, and reconditioning quantities comes with particularities:

- The input data, such as EVB lifetimes and consumer preferences, are static, but the outputs are time-related.
- The time-related outputs have no historical predecessors due to the novelty of the EV market.
- The data originate from a simulation model, allowing for repeated sampling.

It remains a gap in research which type of surrogate model and modeling technique is the most appropriate for this type of problem. While the characteristics of EoL EVB forecasting seem quite particular, the general issue of time-dependent outputs without predecessors is likely to appear in other circular economy domains. For instance, currently only 1% of used textiles in the EU are recycled, but the share is expected to rise with mandatory separate collection starting in January 2025 (EEA, 2022). Therefore, methods for approximating simulation models with time-dependent outputs but no historical time series may gain relevance beyond the EV sector.

More generally, this type of approach can be understood as part of a broader research trend that combines modeling and simulation (M&S) with data-driven techniques. In recent years, growing attention has been given to hybrid modeling approaches that integrate simulation models with machine learning methods in order to improve computational efficiency, enable faster scenario exploration, or support decision-making (Schweidtmann et al., 2024; Von Rueden et al., 2020). Such approaches combine the strengths of both paradigms: simulation models represent structural relationships and system behavior (Law, 2015), while data-driven models can approximate complex input–output relationships based on generated or observed data (Goodfellow et al., 2016).

The aim of this study is to reduce order of the EoL EVB simulation model by Huster et al. (2025), making it more agile and practically applicable. As the methodology, different machine learning techniques are evaluated for their suitability to predict the time-dependent EoL EVB output. One strategy treats the output as static and predicts all values at once. Presumably, that might lead to inaccurate results because it might omit trends in the output time series. Alternatively, a recursive approach is applied that accounts for the temporal structure by training one model per time step, using previously predicted values as additional inputs. The performance of the approaches is compared by common metrics like R^2 and (root) mean square error ((R)MSE), and the training time.

By combining a discrete event and agent-based simulation model of EV battery end-of-life flows with machine-learning-based surrogate models, the study contributes to research at the intersection of modeling and simulation and data science. In particular, it provides insights into how surrogate modeling strategies can be used to approximate simulation models that produce time-dependent outputs but lack historical time series observations.

The remainder of the study is structured as follows: First, a literature overview of methods for approximating simulation models is given in Section D.2. Subsequently, in Section D.3, the EoL EVB simulation model that shall be approximated is introduced, and the selection of the surrogate models is outlined. In Section D.4, the metrics of the selected surrogate models are presented and compared, followed by a discussion of the results in Section D.5. Finally, conclusions are drawn in Section D.6.

D.2 Literature Review

Computer simulation has long been used to represent simplified abstractions of real-world or conceptual systems in order to study their behavior under different conditions (Banks, 1998; Shannon, 1975). As systems become more complex and involve stochastic behavior, nonlinear interactions, or large numbers of components, simulation provides a means of exploring system dynamics and interactions (Banks, 1998). With the development of digital computing in the second half of the twentieth century, simulation methods became increasingly powerful and widely applied (Goldsman et al., 2009). Today, simulations are used to represent phenomena ranging from natural and physical processes, e.g., climate systems, to socio-technical systems such as manufacturing, logistics, and energy networks (Law, 2015; Obaidat & Papadimitriou, 2003).

Over time, a variety of modeling paradigms have emerged, including discrete-event simulation, system dynamics, agent-based modeling, Monte Carlo simulation, and physics-based simulation approaches such as finite element models (Cheong & Butscher, 2019; Law, 2015). The increasing availability of computational resources has enabled simulation models to represent systems in greater detail and across larger spatial and temporal scales (Pan et al., 2025). However, this increased realism has also led to growing computational demands, particularly when large parameter spaces must be explored for sensitivity analysis, scenario evaluation, or optimization (X.-S. Yang et al., 2014).

Within the simulation literature, considerable research has focused on techniques for analyzing and approximating simulation models. In particular, the concept of simulation metamodels has been developed to describe statistical or machine learning models that approximate the input–output behavior of computer experiments (Sacks et al., 1989). Such surrogates have been applied to various simulation types, including agent-based models (ABMs), discrete event simulations, finite element models, and process chains (Hürkamp et al., 2021; ten Broeke et al., 2021). For instance, Angione et al. (2022) compared eight machine learning (ML) methods, including ANN, GPR, support vector machine (SVM), and gradient-boosted trees (GBTs), to approximate the outputs of an ABM simulating social care provision. They found that ANNs performed best in terms of predictive accuracy, especially for larger datasets, while GBTs were more efficient to train. Hürkamp et al. (2021) developed surrogates for a high-dimensional finite element method and a discrete process chain simulation using RFs and decision trees (DTs). In both cases, RFs performed slightly better in terms of prediction accuracy, while maintaining relatively low training times. In groundwater management, Christelis et al. (2019) compared single and multiple surrogate models for optimization of pumping strategies. They found that while ensembles slightly outperformed single surrogates, simple models like cubic radial basis functions (RBFs) and Gaussian Kriging also delivered good solutions with minimal computational overhead. Stevanović et al. (2024) contrasted XGBoost (XGB) and AANs in the context of building energy simulations. While AANs had slightly better predictive accuracy, XGB was more efficient and required less tuning. Mukhtar et al. (2023) explored seven surrogate methods for aerospace design and found that k-nearest neighbors and RF offered high accuracy with low training costs, while GPR provided good uncertainty estimates but longer runtimes.

In the context of simulation-based optimization, Williams & Cremaschi (2021) evaluated eight surrogate modeling techniques on benchmark functions with different shapes and input dimensions. Automated learning of algebraic models (ALAMO), multivariate adaptive regression splines (MARS), and GPRs were most accurate for surface approximation, while RFs and SVMs were more reliable for identifying optimal values. The results depended on the shape of the functions, the sample size and the input dimensionality. Wang et al. (2014) similarly demonstrated that model performance depended on both sample size and problem structure, with GPR and SVMs generally outperforming ANNs on their benchmark problems. Also, Bashiri et al.'s (2022) study on surrogate model and sampling combinations on a multi-objective car front crash scenario supports that no single method consistently outperforms others.

These examples illustrate that there is no universally best surrogate modeling technique. Instead, performance depends on factors such as input and output dimensionality, the size and structure of the training data, the nature of the simulated system, and the modeling goal (e.g., prediction or optimization) (McBride & Sundmacher, 2019; Pietzsch et al., 2020; Williams & Cremaschi, 2021). This observation is reinforced by several overview studies. McBride & Sundmacher (2019) summarized surrogate modeling in chemical engineering and emphasized the importance of selecting models based on the application context. Pietzsch et al. (2020) reviewed surrogate modeling for ABMs and identified model selection, uncertainty handling, and implementation effort as key trade-offs. They concluded that GPR models perform well for prediction tasks but may require more effort than simpler ML models like RFs. Trinchero & Canavero (2021) further found that model performance varied with noise levels and output structure, with SVM and GPR showing strong performance across applications. The nature of the data, whether static or time-related, also influences model choice. While most surrogate models are trained on static input and output values, recent work has explored time series-based modeling (e.g., Dearing, 2024; Zhao et al., 2023), particularly using deep learning methods like LSTM and convolutional neural network-LSTM architectures.

The present study is related to several strands of the surrogate modeling literature. Like Hürkamp et al. (2021), it approximates an agent-based and discrete event simulation model using static inputs, and like Angione et al. (2022), it focuses on predictive performance. The present study builds on the insights from those studies but addresses two underexplored challenges in combination. First, the output of the EoL EVB simulation model consists of sequences of future quantities predicted for multiple time points. However, unlike classical time series forecasting, there are no historical values of the output variables to use as inputs. As a result, no time series-specific methods such as recurrent neural networks or autoregressive integrated moving average (ARIMA) models can sensibly be applied (Hyndman & Athanasopoulos, 2021). Instead, standard machine learning techniques are used to either predict all time steps at once or recursively: first predicting the outputs for the initial period, then feeding those predictions into the model to predict subsequent periods. To the authors' knowledge, it remains unclear how well such recursive strategies perform when no actual predecessors exist, and all temporal structure must be inferred from static input features. Second, this study addresses a multi-output prediction problem. Rather than focusing on a single key performance indicator (KPI) or using aggregated outcomes over time, multiple KPIs are predicted simultaneously, each disaggregated over five future time points. This increases the modeling complexity substantially. Angione et al. (2022) have identified multi-output prediction as a research gap in the context of surrogate modeling for ABMs. By exploring both an all-at-once and a recursive approach in this setting, this study contributes to closing this gap and offers guidance for applications where simulation outputs are time-related but not based on sequential observations.

D.3 Material and Methods

This section begins with a description of the simulation model that serves as the basis for surrogate modeling. The overall methodological procedure is then outlined (cf. Figure D.1). First, the experimental design is defined, and simulation runs are carried out accordingly. The resulting data is then preprocessed to prepare it for machine learning modeling. The final step, which is analyzing and comparing the performance of the surrogate models, is addressed in the subsequent results section.

Figure D.1: Outline of the procedure

D.3.1 Simulation Model for Approximation

The simulation model to be approximated is introduced in Huster et al. (2025) and briefly summarized in the following. It is a mixed-methods model consisting of discrete event and agent-based elements (cf. Figure D.2). The model takes a vector of 49 parameters as an input. This vector contains assumptions on EV sales numbers from 2015 to 2050, on the lifespan of EVs and EVBs, on recycling, repurposing and reconditioning costs, recycled content requirements and other aspects. As EV adoption is beyond the scope of the simulation study, external projections of EV sales are used as input parameters. Starting the simulation in the past (2015) acts as a warm-up period and ensures that the model is populated with a realistic stock of EVs at the beginning of the analyzed period. The time horizon until 2050 was chosen because EVs and their batteries have long lifetimes and circular activities such as repurposing and recycling occur with considerable delays. In addition, many policy targets and regulatory frameworks in the energy and mobility sector, including EU climate targets, are defined with a horizon up to 2050 (European Commission, n.d.). A complete table of the inputs is included in the Supplementary Material. The discrete event logic depicts the material flow of EVs and EVBs through the lifecycle stages of production, usage, rebuilding, repurposing and finally recycling. The agent-based elements account for the behavior of consumers, business entities and legislative bodies. Consumer behavior is represented through decisions regarding battery replacement in case of battery failure. Based on a survey with 837 complete responses (Huster et al., 2024b), utility functions were derived for the options of replacing the battery with a new battery, replacing it with a reconditioned battery, or replacing the entire vehicle. These utility functions depend on the vehicle and battery price, as well as the expected lifespan and environmental impact of the respective battery option. Business entities, mainly OEMs and car workshops, are modeled as decision-makers primarily driven by economic considerations, which were derived from 19 interviews and a survey with 58 participants. These considerations include, for instance, reconditioning costs and warranty periods. The legislative actor considered in the model is the EU through the EU Battery Regulation, thereby setting the regional focus to the EU. The regulation requires minimum recycled content quotas in new batteries from 2031 onwards (European Parliament and European Council, 2023), and the simulation model allows these percentages to be varied. Hence, the stakeholder behavior and key model parameters are grounded in empirical data collected through surveys and interviews, as well as in European legislation, thereby supporting the face validity and realism of the model. More detailed information about the stakeholders and their modeling can be found in Huster et al. (2025). The outputs of the model are the numbers of returning batteries, reconditioned battery supply, reconditioned battery demand, repurposed and recycled batteries, each of the KPIs for the years 2025, 2030, ..., 2050. The intermediate years can be interpolated. To further validate the model, the assumptions and simulation results were presented and discussed in an expert workshop involving 12 participants from industry, industry associations, and academia. The experts confirmed the overall plausibility of the modeled mechanisms and identified no major conceptual gaps. In addition, key trends observed in the simulation results are consistent with findings reported in related studies (e. g., Kastanaki & Giannis (2023) on the supply of reconditioned batteries; Engel et al. (2019) on the supply of repurposed batteries).

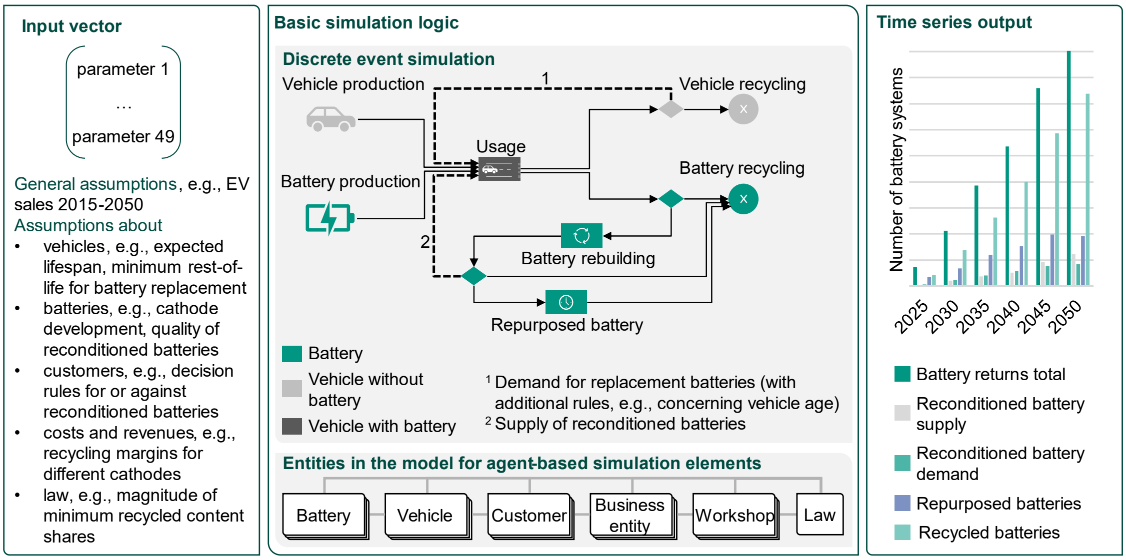

Figure D.2: General simulation logic (reprinted from Huster et al. (2025) with minor adjustments to the arrow labels, License: CC BY 4.0)

The model is implemented using the simulation software AnyLogic 8.9.3 University. The duration of each simulation run depends on the input parameters, particularly concerning the projected EV sales from 2015 to 2050. On average, a simulation run is expected to take approximately ten minutes on a workstation equipped with an Intel Core i9-14900K processor (24 cores, 32 threads, 3.2 GHz) and 192 GB of RAM. Due to the stochastic nature of the model, multiple replications are required to reduce stochastic variation in the output KPIs. In this study, three replications were conducted for each input vector, resulting in an evaluation time average of 30 minutes per vector. This choice represents a compromise between reducing stochastic variability and maintaining computational feasibility. Furthermore, each simulation run represents the lifecycle of thousands of EVs and EV batteries, meaning that stochastic elements such as battery lifetimes are sampled many times within a single run, which contributes to stabilizing the aggregated KPIs.

D.3.2 Design-of-Experiments

To generate a dataset for training and testing surrogate models, various experimental design approaches can be considered, such as (fractional) factorial designs or space-filling designs. The choice of design should take into account the specific problem, the number of input factors, and the expected structure of the data (Montgomery, 2012). For example, the objective may be to screen influential factors or to optimize inputs toward a predefined target, and factor effects may be assumed to be linear or nonlinear depending on the modeling context (Montgomery, 2012). In the case of generating training data for surrogate models based on the discrete event and agent-based simulation described in Section D.3.1, the relationships between the 49 input factors and the multiple output indicators are not known in advance, and linearity, as assumed in 2^k-factorial designs, cannot be assumed a priori. Following the recommendation by Santner et al. (2018) that *"[b]ecause one does not know the true relationship between the response and inputs, designs should allow one to fit a variety of models and should provide information about all portions of the experimental region"*, a space-filling design is chosen. This aligns with findings by Choi et al. (2021), who identify Latin Hypercube Sampling (LHS), a space-filling design, as more effective than factorial designs for metamodel construction. Among space-filling strategies such as LHS, Sobol, and Halton sampling, Williams & Cremaschi (2021) report minimal approximation performance differences across designs. Therefore, LHS was selected for this study. LHS allows comprehensive coverage of the input space and is well-suited for high-dimensional problems (Huntington & Lyrintzis, 1998; Santner et al., 2018). Specifically, a maximin LHS design was selected to maximize the minimum distance between points (Sheikholeslami & Razavi, 2017). This design was created using Matlab's "lhsdesign" function (The MathWorks, Inc., n.d.-a). For each simulation run, one value is randomly sampled from a predefined range of each input parameter. The resulting set of sampled values forms a parameter vector that is used for one simulation run. Thus, the parameter ranges are not varied within a simulation run but define the domain from which the input values are sampled across runs. The ranges of the values for the 49 parameters are detailed in the Supplementary Information. Following the guideline by Loeppky et al. (2009), which recommends using at least ten times as many experiment runs n as input dimensions d ($n = 10d$), 490 design points were generated for 49 input parameters. To account for stochasticity in the simulation model, each configuration was repeated three times, resulting in a total of 1,470 simulation runs. The computing time was approximately eleven days. KPIs of the replicated simulation runs were averaged, resulting in a dataset with 490 observations for training and testing.

D.3.3 ML Algorithm Selection

As delineated in Section D.1, various methodologies for approximating the input-output relationship of the EVB EoL simulation model are evaluated. These methodologies include:

1. Treating both input and output features as static, whereby all output features are predicted simultaneously using machine learning techniques (case name: all at once (aao)).
2. Conducting multiple one-step-ahead forecasts, in which several static models are trained, each predicting one timestep ahead, thereby incorporating the temporal component (case name: recursive (rec)).

In all methodologies, the data is preprocessed by splitting it into training and testing sets, and by scaling the input features. Splitting is done using an 80:20 ratio, with 80% of the 490 instances allocated for training and 20% for testing. This approach is widely adopted (e.g., Hürkamp et al., 2021; Nakano & Liu, 2025; Pietukhov et al., 2023). To enhance the reliability of the metrics derived from the model testing, the procedure of data splitting, model training on the 80% training subset, testing on the 20% testing subset, and metric acquisition is conducted thrice. Subsequently, the metrics from each independent train-test iteration are averaged. This approach is similar to Wang et al. (2019), who trained three models on the same train-test split to evaluate the reliability of predictions made with the approximated models. For one of the three 80:20 splits, the histograms of the training and testing data for each output parameter are depicted in the Supplementary Information. The metrics monitored include the R^2 value, MSE, RMSE, and computational time. These metrics are then averaged across the three model replications. For each split, the input and output features are scaled based on the training data to facilitate accurate model estimation. Given that no single scaling method is universally optimal (De Amorim et al., 2023; Mueller et al., 2023), various methods including the StandardScaler, the QuantileTransformer and a log transformation were evaluated. The StandardScaler produced the most favorable results concerning R^2.

D.3.3.1 All-at-once Estimations (aao)

When considering the output features as static and estimating them simultaneously (cf. Figure D.3), a variety of machine learning methods can be employed, such as ANNs, GPR or RFs (Angione et al., 2022). To obtain a preliminary assessment of the suitability of different models for the given dataset, a pre-screening was conducted using MATLAB's built-in Regression Learner (The MathWorks, Inc., n.d.-b). 28 models were estimated for each of the KPIs for a single timestep (e.g., "Battery returns total" for 2025, "Recycled batteries" for 2030, "Reconditioned batteries" for 2035, etc.). In terms of both R^2 and RMSE, various types of ANNs consistently demonstrated the best fit, followed by GPRs with different kernels and tree-based models. SVMs were found to be the least suitable models.

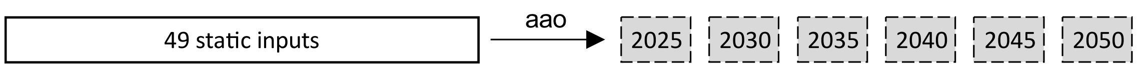

Figure D.3: Schematic representation of the aao logic

Following the preliminary screenings, ANNs, GPR, RFs and XGB were selected as the models under investigation. For comparative purposes with a simpler model, a DT model was also evaluated. Except for XGB, all estimations utilized the scikit-learn libraries (Pedregosa et al., 2011). Specifically, the MLPRegressor was employed for ANNs, the GaussianProcessRegressor for GPRs, the RandomForestRegressor for RFs, and the DecisionTreeRegressor for DTs. The XGBRegressor was used for XGBs (xgboost developers, 2022). Regarding other model parameters, the following configurations were examined:

ANN: The size of the dataset is comparably small with 490 input-output combinations. On small datasets, overly complex models can degrade model performance (Goodfellow et al., 2016). Consequently, this study evaluates simple architectures featuring two, three, and four hidden layers, initially configured with 128, 64, and 32 neurons, respectively, with the number of neurons per layer being halved in subsequent configurations. For example, in the case of a two-layer ANN, the architectures (128, 64), (64, 32) and (32, 16) are examined. The activation functions tested include all those available in the MLPRegressor library, specifically *identity*, *logistic*, *tanh* and *relu*. Similarly, all implemented solvers (*lbfgs*, *sgd* and *adam*) are used.

GPR: The primary parameter of GPR is the selection of the kernel, which defines the covariance function of the Gaussian Process (scikit-learn, n.d.). The kernels evaluated include: (1) a constant kernel combined with an RBF kernel, serving as a straightforward default configuration (abbreviation: gpr_stand); (2) a Matern kernel, suitable for high-dimensional input spaces (abbreviation: gpr_matern); (3) a rational quadratic kernel, offering flexibility in length scales (abbreviation: gpr_ratQuad); and (4) a composite kernel integrating constant, RBF, and Matern kernels to capture more complex data patterns (abbreviation: gpr_comb) (Eric P. Xing et al., 2015; Natsume, 2022).

RF and DT: For both RF and DT estimation, the squared error is employed as the criterion for assessing quality. In the case of RF, it is also necessary to specify the number of trees within the forest. Scikit-learn's default value 100 is tested as well as the doubled quantity, i.e., 200.

XGB: Given that multi-output regression remains in an experimental phase in XGBoost 3.0 (xgboost developers, n.d.), a separate model is constructed for each KPI and period using Scikit-learn's MultiOutputRegressor. This approach remains consistent with the other models, as only the 49 input features are utilized for fitting each model.

D.3.3.2 Recursive Estimations (rec)

The recursive estimations are designed to identify patterns in the output data by training six models (rec 1 to rec 6), each tasked with predicting the KPIs for specific timesteps: 2025, 2030, 2035, 2040, 2045 and 2050. Each model for a given timestep t utilizes the 49 static input features and the *simulated* time-dependent features up to $t-1$ for training. For testing, the 49 static input features are used and the *predicted* time-dependent features up to $t-1$. The architecture is schematically illustrated in Figure D.4. Note that the same 80:20 split is used for fitting all models rec 1 to rec 6, ensuring no data leakage occurs between models for each timestep. The same ML methodologies as those used in the aao approach are evaluated.

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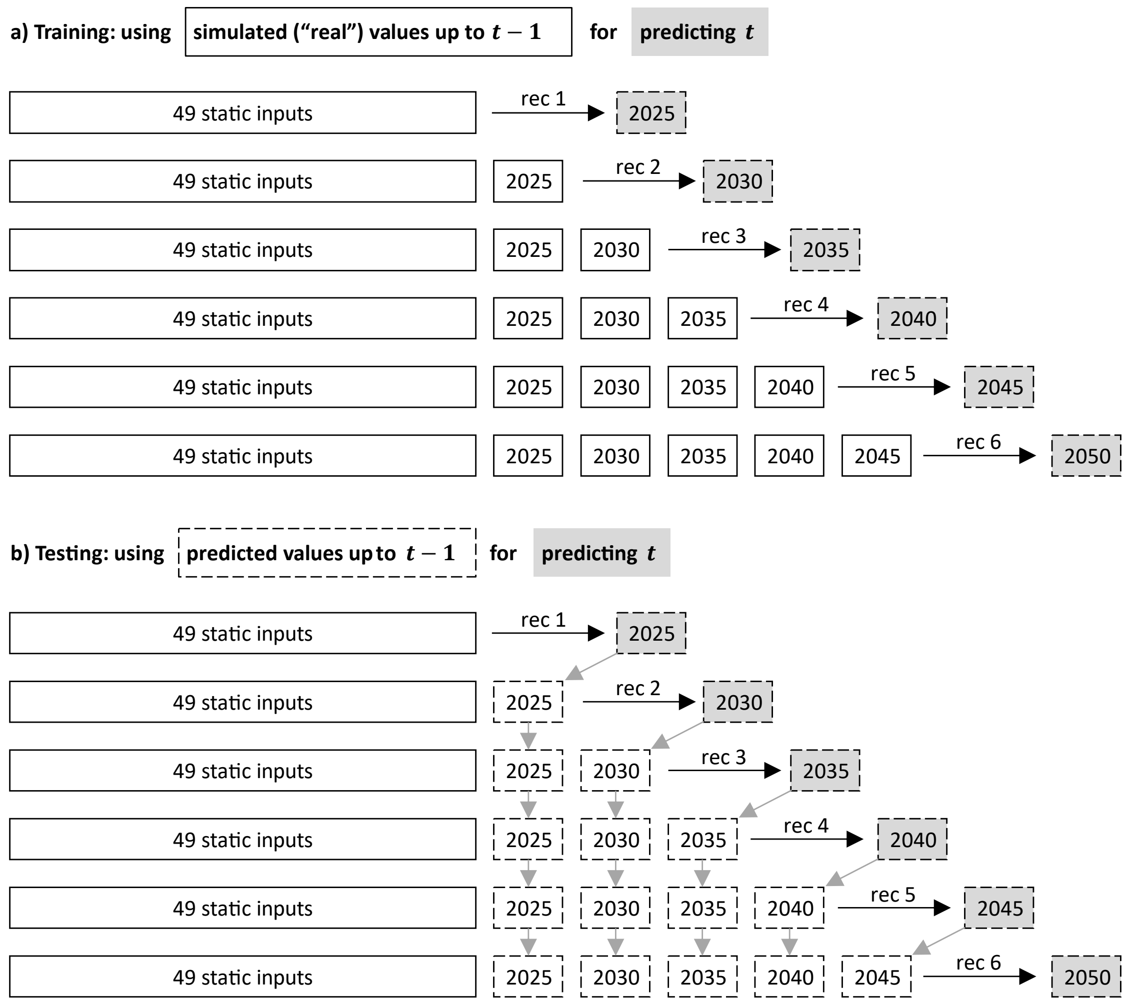

Figure D.4: Schematic representation of the rec logic

D.4 Results

This section presents a comparative analysis of the results obtained from the aao and rec approaches, evaluated at an aggregated level across all KPIs and time periods, as well as at the level of individual KPIs or periods. Subsequently, the feature importance for each KPI within each period is assessed using an XGB model. These results are then employed to estimate new surrogate models, utilizing only the ten most significant features for each KPI.

D.4.1 Comparisons and Analysis of the aao and rec Approaches

A total of 232 models were fitted, with 116 utilizing the aao approach and 116 employing the rec approach. In 50% of the instances, the aao models demonstrated higher R^2 values, while in the remaining 50%, the rec model exhibited better outcomes. On average, the aao models required 11.6 seconds to fit and achieved an R^2 of 0.34 (minimum R^2: -0.18 (DT); maximum R^2:

0.69 (XGB)). The rec models took an average of 54.9 seconds to develop, and showed an average R^2 of 0.41 (minimum R^2: -0.30 (DT); maximum R^2: 0.68 (GPR with composite kernel)). The low R^2 values indicate that among the 232 models, some produced exceedingly poor results. This is exemplified by the DT models, which even resulted in negative R^2 values, indicating outcomes inferior to using the mean as a predictor (Wall, 2022). Additionally, there were notable discrepancies in the accuracy of the ANN models. For further examination, only the four aao models with the highest average R^2 values and their rec counterparts, as well as the four rec models with the highest average R^2 values and their aao counterparts, are considered. For the aao approach, this includes the XGB model (average R^2: 0.69), an ANN with two hidden layers (128 and 64 neurons), a logistic activation function and the adam solver (average R^2: 0.68), and two GPR models, one with a Matern kernel and one with a combination of kernels, both with an average R^2 of 0.67 For the rec approach, the four most accurate models, each achieving an average R^2 of 0.68, are GPR models with the four examined kernel types (cf. Sections D.3.3.1 and D.3.3.2). Furthermore, those ANN models that deliver the best results concerning at least one KPI in a given year are included for both the aao and rec approaches (cf. Figure D.5 and Table D.1). RF models are not considered further, as their average R^2 values remain below 0.5 for both the aao and rec approaches.

Figure D.5 presents an overview of the remaining models for further analysis. It is clear that models excelling in the aao approach do not necessarily perform equally well in aao estimations. For instance, nn29 and nn32 are neural networks utilizing logistic (nn29) and relu (nn32) activation functions, both employing lbfgs as a solver and comprising two hidden layers with 128 and 64 neurons. While nn29 and nn32 rank among the top-performing neural networks for the rec approach, they exhibit relatively weak performance for the aao approach. Conversely, the aao XGB model emerges as the highest-performing model when averaged across all KPIs and periods, yet it is significantly less effective for the rec approach. The performance of the GPR models remains nearly constant across all examined kernels for both the aao and rec approaches.

The observed differences between model types can partly be explained by their modeling characteristics. In the rec approach, separate models are fitted for each period, allowing the models to adapt more easily to period-specific relationships between inputs and outputs. In contrast, the aao approach estimates all periods simultaneously with a single model and therefore learns a joint relationship across time. Tree-based ensemble methods such as XGBoost are well suited for modeling complex relationships and interactions between variables (Chen & Guestrin, 2016), which may explain their stronger performance when all periods are estimated simultaneously. GPR, in contrast, often assumes relatively smooth functional relationships between inputs and outputs (Rasmussen & Williams, 2008), which may make it well suited for modeling individual periods separately in the rec approach. Neural network models provide a flexible framework for approximating complex nonlinear functions, but their performance depends on the chosen network architecture and training procedure (Goodfellow et al., 2016), which may explain the heterogeneous results observed across models and approaches in this study.

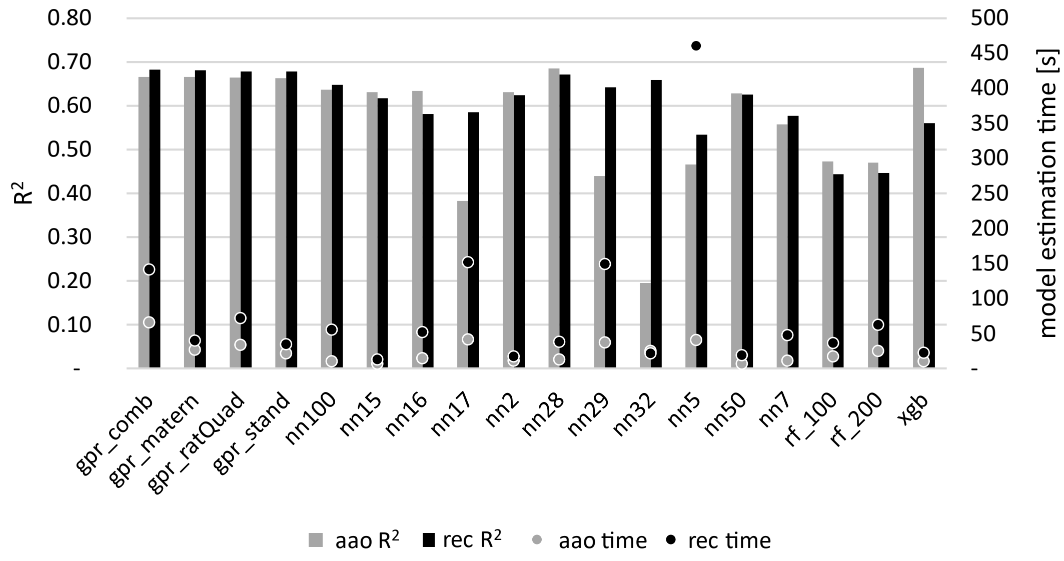

Figure D.5: R^2 of selected surrogate models, averaged over all KPIs and all periods, and fitting time of each surrogate model.

gpr_comb: GPR with a combination of constant, RBF and matern kernels; gpr_matern: GPR with matern kernel; gpr_ratQuad: GPR with rational quadratic kernel; gpr_stand: GPR with constant kernel with a radial basis function kernel (RBF); nn100: neural network with two layers (64, 32 neurons), activation: logistic, solver: adam; nn15: neural network with two layers (64, 32 neurons), activation: identity, solver: sgd; nn16: neural network with three layers (128, 64, 32 neurons), activation: logistic, solver: adam; nn17: neural network with three layers (128, 64, 32 neurons), activation: logistic, solver: lbfgs; nn2: neural network with four layers (128, 64, 32, 16 neurons), activation: identity, solver: lbfgs; nn28: neural network with two layers (128, 64 neurons), activation: logistic, solver: adam; nn29: neural network with two layers (128, 64 neurons), activation: logistic, solver: lbfgs; nn32: neural network with two layers (128, 64 neurons), activation: relu, solver: adam; nn5: neural network with four layers (128, 64, 32, 16 neurons), activation: logistic, solver: lbfgs; nn50: neural network with three layers (32, 16, 8 neurons), activation: identity, solver: lbfgs; nn7: neural network with four layers (128, 64, 32, 16 neurons), activation: relu, solver: adam; xgb: XGBoost.

The estimation times vary considerably between the models. While estimations using a matern and a standard kernel configuration (cf. Section D.3.3.1) require approximately 27 and 22 seconds in the aao case and 40 and 35 seconds in the rec case, the rec estimation with a combination of kernels takes approximately 140 seconds, representing an increase by a factor of 3.5-4 compared to the aforementioned kernels. Overall, it is noteworthy that rec model estimations are more time-intensive than aao model estimations. On average, among the models depicted in Figure D.5, it took 21 seconds to construct the aao models, and 51 seconds for the rec models. This 140% increase in model building time resulted in an average R^2 increase of 5% and an RMSE reduction of 3%. In the following, results are reported using R^2. corresponding figures and tables for MSE and RMSE are provided in the Supplementary Information.

Even the best-performing models exhibit relatively low R^2 values when averaged across all KPIs and years. Figure D.6 a-c provides an overview of the R^2 values for three of the KPIs across the six examined periods, averaged over all models. On average, the models predict the total number of battery returns (Figure D.6 a, d) with significantly greater accuracy than the demand for reconditioned batteries (Figure D.6 c, f). Specifically, the total number of battery returns is predicted with an R^2 of approximately 0.8 for the years 2025 and 2030 for rec models, and an R^2 of 0.7 for aao models (c.f. Figure D.6 a).

The average R^2 of the KPI "Total number of returning batteries" decreases over the years to $R^2 \approx 0.67$ for rec models and 0.62 for aao models. Figure D.6 d illustrates the corresponding simulated-versus-predicted graph for the 2035 period and the gpr_stand model, showing that the ML predicted values fall within an acceptable range compared to the simulated values. The decline in prediction accuracy over time can be attributed to the structure of the simulation model being approximated. This model takes 49 parameters as input, which remain constant throughout the simulation runtime (cf. Section D.3.1). However, certain parameters only become relevant at later points in time. For instance, recycling quotas are introduced in 2031 and 2036, in accordance with the EU Battery regulation. Consequently, the surrogate models may disregard some information in earlier periods but must account for their influence and the noise they introduce in later periods. Also, as the simulated EV fleet grows and more lifecycle pathways become possible, the output variability increases, which makes the approximation task more challenging for the surrogate models.

Figure D.6 c illustrates that the ML models possess limited predictive power regarding the KPI "Demand for reconditioned batteries." The average R^2 values exhibit a modest increase from approximately 0.3 in 2025 to 0.45 by 2050, yet they remain insufficient. Figure D.6 f complements this by displaying the simulated-versus-predicted plot for 2035 using the gpr_stand model. Interestingly, the predictive capability improves over time rather than diminishes. This trend is likely due to the fact that reconditioning is considered viable only from 2030 onwards in some training and testing datasets, leading to a weaker non-zero data foundation in earlier years. Various combinations of input features can result in minimal or no reconditioning. For example, OEMs may choose not to use reconditioned batteries for warranty purposes, repurposing or recycling might be more lucrative, or the average battery lifespan could surpass that of vehicles. These scenarios are realistic and should be included in the training and testing datasets. However, this inclusion results in numerous zero or near-zero values (cf. Supplementary Information for the histograms of the KPI values), and given the high number of input features, it is challenging for surrogate models to extract meaningful insights from the remaining data during training. The authors opted not to enhance the dataset with additional non-zero values for reconditioning KPIs through adaptive sampling, as the data scarcity also highlights the limitations of sampling for multiple KPIs (cf. Section D.3.2), which should not be concealed.

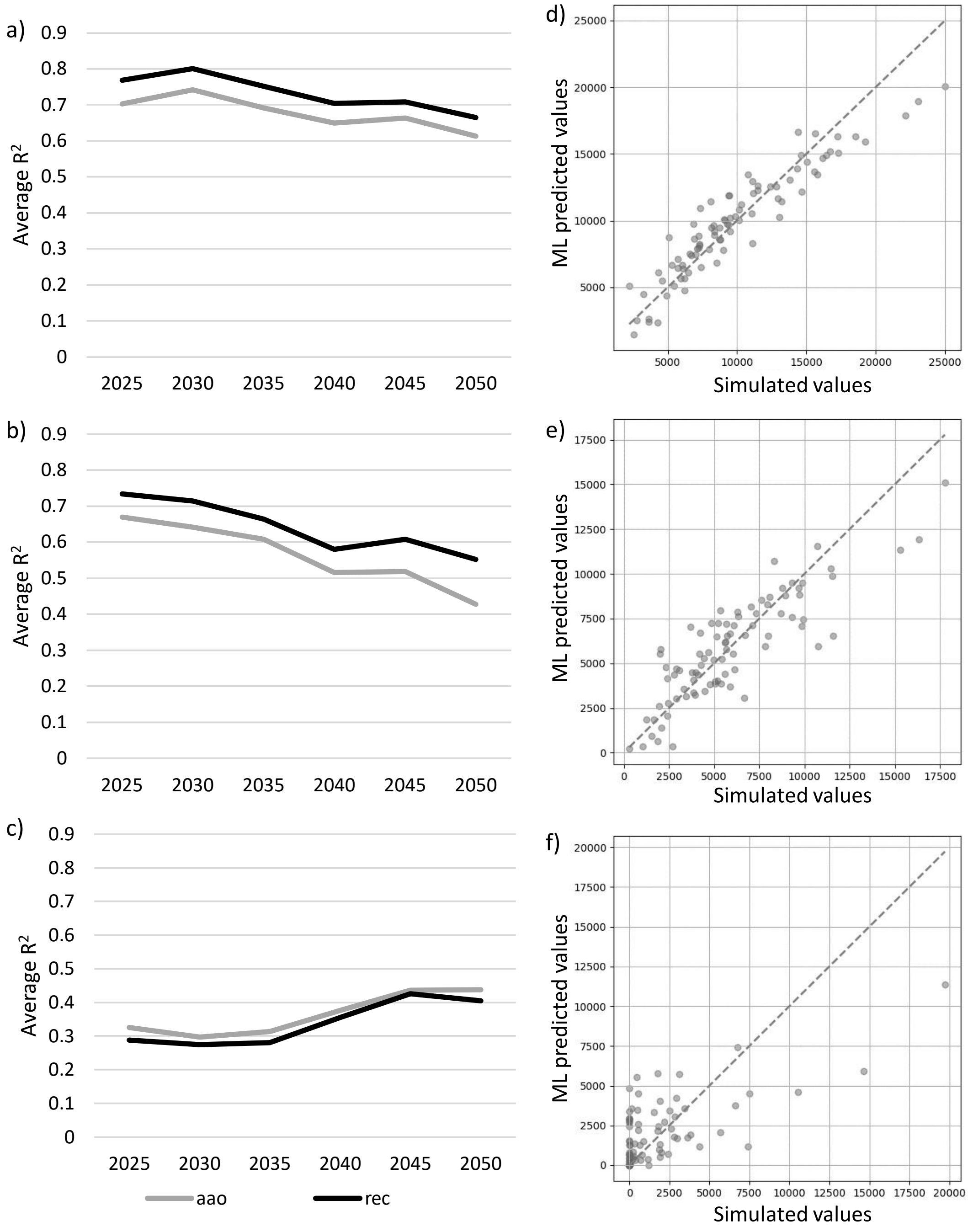

Figure D.6: a-c: Average R^2 over time of all models for a) total number of returning batteries, b) number of recycled batteries, c) demand for reconditioned batteries. d-e: simulated-vs-predicted plots for period 2035, determined with the rec gpr_stand model, for d) total number of returning batteries, e) number of recycled batteries, f) demand for reconditioned batteries. aao: all-at-once approach; rec: recursive approach.

The prediction accuracy of the number of recycled batteries (Figure D.6 b and e) is intermediate between that of the total battery return numbers and the demand for reconditioned batteries. The moderate decline in R^2 over time can similarly be explained by increasing variability in recycling flows with a growing EV fleet and with additional lifecycle pathways becoming available. As more combinations of input parameters influence recycling outcomes in later years, the surrogate models face a more complex mapping between inputs and outputs. Thus, the underlying simulation dynamics help explain the patterns observed in Figure D.6. Not shown are the figures for the KPIs "Repurposed batteries", which have accuracy measures similar to those of recycled batteries, and "Supply of reconditioned batteries", which perform similarly to "Demand for reconditioned batteries".

Although the rec and aao approaches are expected to yield similar results for the first period, small but systematic differences can still occur. One reason is that the training processes differ slightly between the two approaches: in the rec approach, models are fitted separately for each period, while in the all-at-once approach, a single model is trained to predict all periods simultaneously. Moreover, even slight variations in the treatment of training data, such as the independent standardization of input features and target variables for each period compared to a collective standardization across all periods, can result in moderate differences in model performance.

Table D.1 presents the models with the highest performance, as determined by the R^2 values averaged across all periods, for each of the evaluated KPIs.

Table D.1: Best models per KPI, averaged over all periods

KPI	aao/rec	model name	R^2	estimation time
all	aao	xgb	0.6870	10.31
	rec	gpr_comb	0.6820	140.71
Battery returns total	aao	nn28	0.8070	12.83
	rec	gpr_comb	0.8105	140.71
Recycled batteries	aao	nn28	0.7266	12.83
	rec	gpr_comb	0.7026	140.71
Repurposed batteries	aao	nn28	0.6891	12.83
	rec	nn29	0.6861	37.80
Demand for reconditioned batteries	aao	xgb	0.6157	10.31
	rec	nn32	0.5021	21.53
Supply of reconditioned batteries	aao	nn28	0.4820	12.83
	rec	nn100	0.4857	54.99

aao: all-at-once approach; gpr_comb: Gaussian process regression with a combination of constant, radial basis function and matern kernels; nn28: neural network with two layers (128, 64 neurons), activation: logistic, solver: adam; nn29: neural network with two layers (128, 64 neurons), activation: logistic, solver: lbfgs; nn32: neural network with two layers (128, 64 neurons), activation: relu, solver: adam; nn100: neural network with two layers (64, 32 neurons), activation: logistic, solver: adam; rec: recursive approach; xgb: XGBoost

The data indicate that the models with the best overall performance (XGB for the aao approach and gpr_comb for the rec approach) also demonstrate superior accuracy for certain, though not all, KPIs. Notably, neural networks in various configurations are among those achieving the highest R^2 values. These networks consistently feature only two dense layers, either (128, 64) or (64, 32), supporting the literature's findings that excessively complex models may compromise accuracy due to overfitting (Goodfellow et al., 2016). Of the AANs, three utilize a logistic activation function, while one employs a relu activation. Additionally, two networks use the adam solver, and two utilize lbfgs.

Evaluating KPIs individually across periods shows that certain models consistently perform better than others. Figure D.7 presents the maximum R^2 values achievable for each KPI and year. The xgb model, fitted through the aao approach, emerges as the most effective model when averaged across all KPIs and is also the leading model for nine out of the 30 targets. Equally frequently, the aao nn28 model, a neural network with two layers (128 and 64 neurons), activated by a logistic function and utilizing the adam solver, is identified as the top performer. The rec GPR model, which employs a combination of kernels (cf. Section D.3.3.1), ranks as the next most successful model. Additional neural networks using a rec approach are recognized as the most effective for the remaining targets.

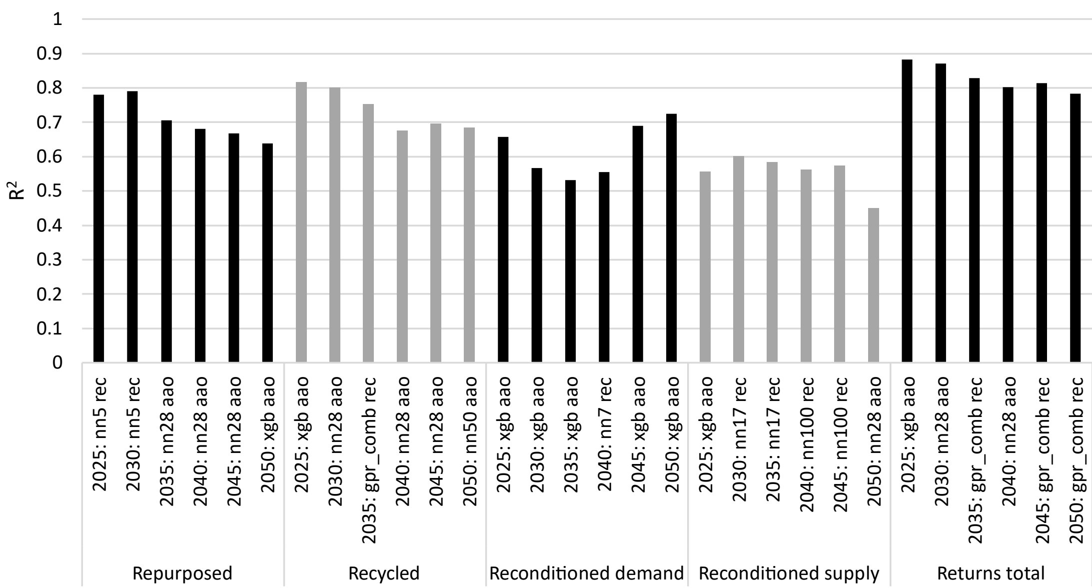

Figure D.7: R^2 of the best performing surrogate model per KPI and year. aao: all-at-once approach; gpr_comb: Gaussian process regression with a combination of constant, radial basis function and matern kernels; nn5: neural network with four layers (128, 64, 32, 16 neurons), activation: logistic, solver: lbfgs; nn7: neural network with four layers (128, 64, 32, 16 neurons), activation: relu, solver: adam; nn17: neural network with three layers (128, 64, 32 neurons), activation: logistic, solver: lbfgs; nn28: neural network with two layers (128, 64 neurons), activation: logistic, solver: adam; nn50: neural network with three layers (32, 16, 8 neurons), activation: identity, solver: lbfgs; nn100: neural network with two layers (64, 32 neurons), activation: logistic, solver: adam; rec: recursive approach; xgb: XGBoost

D.4.2 Feature Engineering

While conducting a comprehensive examination of the significance of features for the original simulation model (cf. Section D.3.1) through extensive sensitivity analysis would be exceedingly time-consuming, certain surrogate models offer inherent feature importance rankings. For instance, XGB models assess importance as the "fractional contribution of each feature to the model based on the total gain of this feature's splits" (Chen et al., n.d.). To extract the feature importance for each of the five KPIs across six periods, an XGB model was estimated for each KPI and period using the aao approach, resulting in 30 models. Subsequently, the feature importance for each model was determined. This analysis revealed that among the 49 features, 16 never appear among the top ten most important, whereas the remaining 33 do at least once. The feature most frequently appearing in the top ten list (29 out of 30 instances) is the life expectancy of NCx batteries, referring to batteries with Nickel-Manganese-Cobalt (NMC) or Nickel-Cobalt-Oxide (NCO) cell chemistry. Additionally, the decisions by OEMs regarding the use of reconditioned batteries for warranty cases and the proportion of batteries damaged beyond repair are also significant, appearing 23 and 20 times, respectively, in the top ten for various KPIs and periods. Furthermore, EV sales data from 2020 to 2035 and the average vehicle lifetime are mentioned in the top ten at least ten times. The relevance of these KPIs appears justified. The simulation encompasses a timeframe extending to the year 2050. In the initial years, NCx batteries are among the most frequently sold EVBs, making their average lifespan critical for the period when these batteries are returned and potentially repurposed for a second-life application. The average battery lifespan varies across the experiments, ranging from 6 to 20 years. Consequently, EV sales data from years immediately preceding the end of the examined timeframe are less important than those from earlier years.

To mitigate noise potentially introduced by an excessive number of features, each period of each KPI is approximated using an XGB surrogate model that incorporates only the ten most significant features for that specific KPI and period. The outcomes are depicted in Figure D.8 and are compared with the results derived from estimations utilizing all 49 features. On average, the models employing ten features exhibited a 6.6% decrease in performance compared to the 49-feature models. However, this overall average does not accurately represent performance at the KPI level. The differences are relatively minor for repurposed batteries (-2.9%), recycled batteries (-3.0%), the supply of reconditioned batteries (-3.6%), and the total number of returning batteries (-1.8%). In contrast, the performance for the demand for reconditioned batteries declines significantly (-22.6%). This indicates that for most KPIs, a reduced number of features suffices without substantial information loss, whereas for reconditioned battery demand, a greater number of features is necessary. The reduced-feature approach necessitates the determination of feature importance, which involves fitting models with all features. Therefore, it would only be considered beneficial if the additional estimation step enhances accuracy rather than diminishes it.

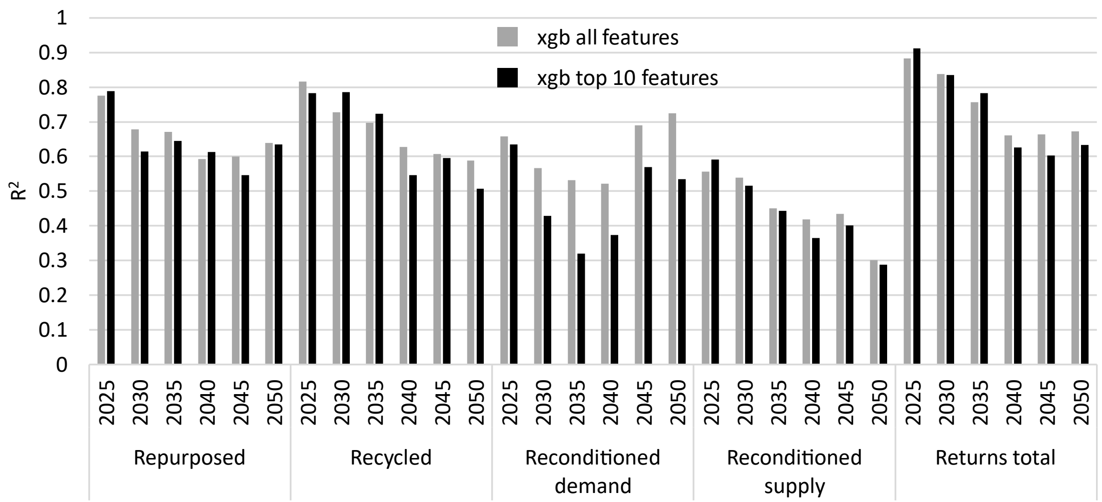

Figure D.8: R^2 of the xgb surrogate model estimated with all 49 features and with the 10 most important features of each KPI and year. xgb: XGBoost

D.5 Discussion

The results of this study highlight both the opportunities and limitations of using ML techniques to approximate a simulation model for predicting EoL EVB quantities. While the overall performance of the surrogate models varied considerably across KPIs and periods, several consistent insights emerged and suggest avenues for further research.

First, the generally low R^2 values across models and KPIs point to the inherent difficulty of the problem at hand. The input data is static, while the outputs are sequential but lack temporal predecessors. This creates a setting that cannot be fully addressed by conventional static regression or standard time series forecasting techniques. Moreover, the dataset size (490 samples) represents a limitation of this study and may have constrained model performance. Preliminary experiments with additional preprocessing steps, such as logarithmic transformations, did not lead to consistent improvements in predictive performance. This suggests that the main limitation lies less in the preprocessing of the dataset and more in the limited number of simulation samples and the complexity of the underlying input-output relationships. Although the number of samples is in line with surrogate modeling literature (e.g., Loeppky et al., 2009), this size may be insufficient for capturing complex, nonlinear relationships, especially when outputs interact strongly or are dominated by zero values, as seen in the reconditioning-related KPIs, which represents an additional challenge and limitation for surrogate modeling in this setting. Several contributions in the literature emphasize the value of adaptive sampling, where training points are iteratively added in regions of high model uncertainty or near optima. For example, Wang et al. (2014) showed that adaptive sampling significantly improved model performance for both surface approximation and optimization tasks. Similarly, ten Broeke et al. (2021) employed adaptive sampling in ABM analysis to efficiently explore tipping points. Future work could explore whether larger simulation datasets, adaptive sampling strategies, more extensive data preprocessing, or alternative machine learning approaches enhance surrogate performance in settings like ours. The presented approach can serve as a basis for further developments in data-driven circular economy modeling.

Second, although recursive models achieved slightly higher average performance than the aao approach, they required longer estimation times. However, all models in this study were trained within a few seconds to two and a half minutes, meaning time savings are not practically relevant in this setting. The benefits of faster training times become more important with larger datasets or extended feature sets.

Third, model performance varied across KPIs, and the results also reveal differences in the suitability of individual surrogate modeling techniques. Predictions for total battery returns were relatively accurate across most models, likely due to more stable relationships between inputs and outputs and the comparatively large number of non-zero observations. In contrast, demand for reconditioned batteries proved harder to model, likely because it depends on multiple interacting features, including policy assumptions, OEM decisions, and competing end-of-life pathways. These assumptions are inherited from the underlying simulation model described in Huster et al. (2025). Looking at the individual surrogate models, GPR models achieved comparatively stable results across KPIs and years and were frequently among the better-performing models, particularly within the recursive approach. For the aao approach, the XGBoost model reached the highest average accuracy across KPIs. Neural network models with relatively simple architectures also performed well for several outputs and showed particularly good performance for KPIs related to repurposed and reconditioned batteries. These outputs depend on a larger number of interacting input factors and contain fewer informative observations than more aggregate outputs such as total battery returns or recycled batteries, which may explain why more flexible model structures achieved better results for these targets. Overall, these findings suggest that GPR models represent a robust general-purpose choice for approximating the outputs of the simulation model, while XGBoost provides a strong alternative for the aao approach. For outputs characterized by sparse observations and stronger nonlinear dependencies, such as repurposing and reconditioning demand, neural network models may offer advantages. At the same time, the unequal accuracy among the KPIs suggests that surrogate modeling is not equally effective across all types of outputs, and more specialized modeling strategies may be required for sparse or volatile targets. This also highlights that the suitability of a given surrogate model ultimately depends on the characteristics of the underlying data and the specific prediction task. The present study therefore provides a structured approach for comparing and selecting surrogate models in similar settings, rather than identifying a universally optimal method.

Fourth, feature selection results indicate that dimensionality reduction can be useful, though its benefits are KPI-specific. Using only the ten most important features preserved model accuracy for several outputs, such as recycled and repurposed batteries. However, this strategy significantly reduced performance for reconditioning demand, pointing to a need for richer input representations when modeling outputs are shaped by multiple interdependent factors.

Overall, the results highlight both the potential and the limitations of using surrogate models to approximate complex simulation outputs in this setting. The relatively small training dataset, the high dimensionality of the input space, and the sparsity of several KPIs, particularly those related to reconditioning, represent important limitations that likely constrained predictive performance. In addition, the surrogate models approximate the behavior of a single simulation model and therefore inherit the assumptions embedded in that model, including policy assumptions and behavioral rules of stakeholders. Despite these limitations, the surrogate models developed in this study can substantially accelerate simulation-based evaluations. Given that each simulation run takes approximately ten minutes, surrogate models, especially those with acceptable accuracy, can drastically reduce computation time in tasks such as optimization, sensitivity analysis, or policy testing to the fraction of a second. This opens the door for more agile planning in contexts where historical data is sparse, but future-oriented decisions are necessary, such as in early-stage circular economy strategies.

Future work should explore enhancements to model architecture and training. This includes experimenting with hybrid approaches that combine ML with system-specific knowledge, testing architectures more suited to sparse or structured outputs, and evaluating performance on larger datasets. Furthermore, applying the surrogate models within optimization frameworks or interactive scenario tools would demonstrate their practical value more fully. Expanding this research to other domains with similar data challenges, such as resource planning, critical material recovery, or other product reuse systems, would help test the robustness and generalizability of the approach.

D.6 Conclusion

This study addressed the challenge of accelerating scenario analysis in a discrete event and agent-based simulation model used to forecast end-of-life quantities of EV batteries. The simulation model estimates the availability of batteries for recycling, repurposing, and reconditioning from 2025 to 2050 based on 49 static input parameters, including EV sales projections, battery lifetimes, and economic assumptions. While this approach offers a detailed representation of second-life battery pathways, its computational demands limit the feasibility of extensive sensitivity analyses and parameter optimization. To reduce runtime and support broader scenario exploration, machine learning-based surrogate models were tested as an approximation of the simulation's input–output relationships. Two modeling strategies were compared: predicting all time steps simultaneously, and a recursive approach that forecasts time steps sequentially using prior predictions.

Results showed that neither approach was universally superior. Recursive models achieved slightly higher *average* accuracy (R^2 of 0.41 vs. 0.34) but required longer training times (on average 140% longer). Still, with training durations under three minutes for all models, this trade-off was practically irrelevant for the given dataset. Among the algorithms, XGBoost performed best in the all-at-once setup with regard to accuracy (R^2: 0.69), while Gaussian process regression was most accurate in the recursive approach (R^2: 0.68). Neural networks also performed well in both setups when kept relatively simple, whereas decision trees consistently underperformed. Prediction accuracy varied strongly across output indicators. Battery return volumes were estimated with high reliability, while reconditioning demand and supply proved more difficult due to sparse and volatile simulation outputs. Feature reduction using XGBoost importance rankings worked well for most KPIs but significantly hurt performance for reconditioning demand.

The results suggest that surrogate models are a viable tool for reducing simulation complexity in second-life battery studies. They may support early-stage planning and scenario analysis where empirical data is scarce and a wide range of possible developments must be considered. Future research should investigate adaptive sampling strategies, hybrid architectures, and optimization performance to extend these insights to more complex and dynamic circular economy applications.

D.7 Abbreviations

aao: All-at-once estimation; ABM: Agent-based modeling; ALAMO: Automated Learning of Algebraic Models; ANN: Artificial Neural Network; ARIMA: Autoregressive Integrated Moving Average; DT: Decision Tree; EoL: End-of-Life; EV: Electric vehicle; EVB: Electric vehicle battery; GBT: Gradient-Boosted Trees; GPR: Gaussian Process Regression; gpr_stand: Gaussian Process Regression with a Constant Kernel combined with a Radial Basis Function Kernel; gpr_matern: Gaussian Process Regression with a Matern Kernel; gpr_ratQuad: Gaussian Process Regression with a Rational Quadratic Kernel; gpr_comb: Gaussian Process Regression with a composite Kernel integrating Constant, RBF, and Matern kernels; KPI: Key performance indicator; LHS: Latin Hypercube Sampling; LSTM: Long Short-Term Memory; MARS: Multivariate Adaptive Regression Splines; ML: Machine Learning; M&S: Modeling and Simulation; MSE: Mean Square Error; NCO: Nickel-Cobalt-Oxide; NCx: NCO or NMC battery; NMC: Nickel-Manganese-Cobalt; OEM: Original Equipment Manufacturer; RBF: Radial Basis Function; rec: Recursive estimation; RF: Random Forest; RMSE: Root Mean Square Error; SVM: Support Vector Machine; XGB: XGBoost

D.8 Data Availability

Additional data supporting the findings of this study, beyond those provided in the Supplementary Information, are available from the corresponding author (SH) upon reasonable request.

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D.11 Author Information

Authors and Affiliations

Institute for Industrial Production, Karlsruhe Institute of Technology, Hertzstr. 16, 76187, Karlsruhe, Germany
Sandra Huster, Andreas Rudi & Frank Schultmann

Warwick Manufacturing Group, University of Warwick, Coventry, CV4 7AL, UK
Sandra Huster & Mona Faraji-Niri

The Faraday Institution, Harwell Science and Innovation Campus, Quad One, Didcot, UK
Mona Faraji-Niri

Contributions

SH: Methodology, Conceptualization, Writing—Original Draft; MFN: Conceptualization, Supervision, Writing—Review & Editing; AR: Writing—Review & Editing; FS: Writing—Review & Editing, Supervision.

Corresponding author

Correspondence to Sandra Huster.

D.12 Ethics Declarations

Conflict Interest

The authors have no relevant financial or non-financial interests to disclose.

Use of Generative Artificial Intelligence

During the preparation of this work the authors used the tool “Paperpal” in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

D.13 Supplementary Information

The Supplementary Information includes a description of the simulation model parameters (cf. Section D.3.1) and the ranges explored in the experimental design. It also presents histograms of the target variables for the training and testing datasets corresponding to one of the three data splits. In addition, further figures and tables reporting MSE and RMSE as performance measures are provided.

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