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Assessing economic uncertainty in dynamic reverse logistics networks – A stochastic modeling approach for planning circular battery treatment

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ABSTRACT

The treatment of end-of-life (EOL) electric vehicle battery systems (EVBS) according to the circular economy principle will be a challenge in the next decades. Today, a high uncertainty exists for the EOL battery market, involving the quantities, qualities, and revenues of EOL EVBS, which may influence the optimal reverse logistics network structures and technologies to apply. To cope with these uncertainties, a two-stage stochastic programming model that optimizes a multi-period, multi-technology disassembly reverse logistics network is proposed. In the conducted case study, the economic effort is reduced by at least 16% through the combination of distinct disassembly technologies with subsequently alternative options for circular EOL treatment. It is shown that cathode type and EOL quality significantly influence the technology chosen for treatment. The case study results underline that the best approach is to set up reverse logistics networks with various disassembling options, considering the unique characteristics of each battery.

Abbreviations	
BEV	Battery electric vehicle
EVBS	Electric vehicle battery system
EOL	End-of-life
LFP	Lithium–iron–phosphate
LMFP	Lithium–iron–manganese–iron–phosphate
MFA	Material flow analysis
MILP	Mixed-integer linear program
NMC	Nickel–manganese–cobalt
OEM	Original equipment manufacturer
2nd life	Second life

1. Introduction

The increasing number of battery electric vehicles (BEV) will, after a period of time, lead to an equal growth in the number of end-of-life (EOL) electric vehicle battery systems (EVBS) that should be treated according to the principles of circular economy in the near future. In the past years, research and industry have made significant efforts to find well-suited technological options for treatments as documented by several review papers (Albertsen, Richter, Peck, Dalhammar, & Plepys, 2021; D'Adamo & Rosa, 2019; Zang et al., 2024). Different recycling technologies are either industrialized or on the edge of commercialization. Processes for the disassembly of battery systems into battery modules have been investigated to identify potential ways of automation. Disassembling traction battery systems allows retrieving battery modules that could be reused for remanufacturing spare battery systems or repurposing, for instance, to battery system storage. In addition to their application in remanufacturing, battery modules can also serve as individual spare parts if the replacement of single modules is feasible. Reverse logistics networks for EOL battery system treatment do not exist on a large scale yet because the number of EOL batteries is still below economic attractiveness. So far, the few existing EOL battery systems are handled without regionally distributed networks.

The urgent need to plan potential reverse logistics networks for EOL EVBSs, considering circular business options, has been documented by scientific literature (Glöser-Chahoud et al., 2021; Steward, Mayyas, & Mann, 2019; Wrålsen et al., 2021) and industry. Several authors have proposed models to cope with EOL battery reverse logistics networks recently (Fan, Luo, Liang, & Li, 2023; He, Li, Wu and Han, 2024; He, Li, Wu and Izui, 2024; Rosenberg et al., 2023; Tadaros, Migdalas, Samuelsson, & Segerstedt, 2020; Wenzhu Liao & Luo, 2022). They attempt to find expected optimal reverse logistics network structures and deduce knowledge about costs or potential profits in different regions worldwide.

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However, to conduct the planning of not yet established EOL EVBS logistics networks as realistic as possible, optimization models must address specific challenges:

1. Modeling changing network structures, such as extending processing capacities and opening new locations, resulting from growth in EOL amounts.
2. Identifying optimal EOL circular recovery routes from multiple alternatives, thus containing technology substitution.
3. Including one or several kinds of uncertainty related to EOL EVBSs, such as EOL amounts, product characteristics, or achievable revenues from treatment.

By addressing these challenges through a combined approach for the first time, the presented multi-period, dynamic two-stage stochastic program makes a significant contribution to the planning of EOL battery system networks. Consequently, the model addresses universal industrial barriers to the implementation of circular supply chains identified by Taddei, Sassanelli, Rosa, and Terzi (2024) in a recent comprehensive literature analysis, such as economic uncertainties, technical or organizational challenges for the strategic design of circular supply chains. The following Section Two will be used to precisely distinguish the developed model from the literature and to discuss the above-specified challenges for EOL EVBS management. Section Three presents the investigated problem and the formulation of the deterministic equivalent of the stochastic program. In Section Four, the developed case study is presented, followed by the subsequent presentation of results. In the final section, the applicability of the model and its limitations to the EOL management of EVBS are discussed.

2. Literature investigation

2.1. Circular EOL processes for battery systems

The EOL treatment pathways of battery systems can involve alternative treatment options, ranked according to the EU waste hierarchy framework introduced by the European Union (European Parliament and Council of the European Union, 2008). The waste hierarchy principles for closing material and product loops have been transferred to the recently ratified European Battery Regulation, ensuring that reusing EVBS or parts of it should be favored before recycling (European Parliament and Council of the European Union, 2023).

Alternative options for EOL battery system treatment have been outlined in various studies (Glöser-Chahoud et al., 2021; Hua et al., 2021; Zhu et al., 2021). Fig. 1 illustrates as a flow chart a simplified EOL battery process. EOL EVBSs are retrieved from their corresponding BEV. After quality testing, it is decided which EVBSs or parts are reused in a second life (2nd life). 2nd life applications are, for instance, the usage as spare parts in a BEV after a remanufacturing or refurbishment process or the usage in stationary battery storage. Recycling the EOL EVBS is an alternative recovery option that can be chosen independently of the EOL quality of the EVBS. If all circular economy rules are followed, recycling should only be chosen if the EOL quality of an EVBS is unsuitable for any further energy storage option.

Disassembly marks the next processing step, and its design will depend on the chosen pathways for recycling or reuse applications. If a recycling pathway is looked at, EVBSs are deep-discharged before a manual, often destructive disassembly occurs. Destructive means that components or joints are destroyed during the disassembling so they cannot be reused. The goal of disassembly for recycling is to retrieve the battery modules and to sort the battery system's periphery, such as the EVBS cover and bottom.

For reusing battery modules, the disassembly is non-destructive and must be conducted under high-voltage-protected working conditions. Thus, only highly qualified personnel can pursue such disassembling.

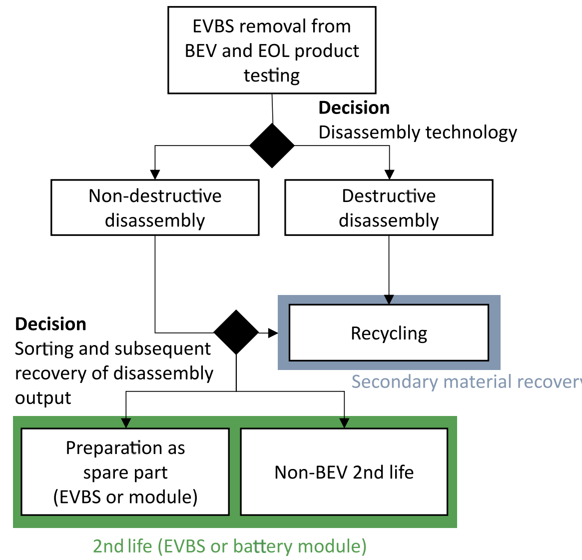

Fig. 1. Flow chart illustrating EOL processes for an EVBS.

Consequently, higher disassembly costs are expected for 2nd life applications than for recycling. Before reassembling for 2nd life purposes can occur, further battery testing and sorting take place. While techno-economic assessments have been conducted in literature for disassembling and recycling (Lander et al., 2021; Reinhart et al., 2023; Rosenberg et al., 2022), reliable information that can be generalized on the expected costs for such preparation and reassembling processes is scarce (Al-Alawi, Cugley, & Hassanin, 2022). Whereas in recent years, there has been an increased focus on analyzing recycling processes that incorporate various technologies, the scope of this paper does not extend to recycling processes or the reassembly for second-life applications.

2.2. Uncertainties in EOL battery system treatment

Uncertainties in the EOL management of battery systems are manifold, frequently stemming from the unfamiliarity associated with the novel aspect of EOL EVBSs. Xiong, Ji, and Ma (2020). The lack of information about cost data of activities along the reverse logistics network and corresponding revenues is a dominant factor. Slattery, Dunn, and Kendall (2021) analyzed transportation costs for EOL batteries in literature and found out that costs do not just vary greatly, but furthermore, they are not comparable due to a lack of traceability of assumptions. Rosenberg et al. (2022) compare available information about disassembly processes and cost estimation and discuss that although disassembly processes have been reported in the literature, cost estimates, including capital expenses and operational expenses, are not reported. Meanwhile, Lander et al. (2021) show that recycling costs vary highly among different countries, e.g., China and the United Kingdom, while the revenues obtained with recycling primarily depend on cathode material. Dong et al. (2023) summarized literature for 2nd life batteries and found that revenues for retired batteries are associated with 20%–80% of new battery prices. Mostly, the pricing of first-life retired batteries is determined by integrating battery market prices, the health status of the EOL battery, and a discount for being a second-hand product (Dong et al., 2023; Fischhaber, Regett, Schuster, Hesse, & Holger, 2016).

Market prices depend primarily on the demand for raw materials and the manufacturing costs (Bajolle, Lagadic, & Louvet, 2022). Toro et al. (2023) predict technological progress for EOL treatment technologies that lead to higher process efficiencies. Besides, economy of scale effects through increasing processing capacities lead to reduced costs for EOL treatment (Lander et al., 2021; Wang, Gaustad, Babbitt, & Richa, 2014). Nevertheless, currently, it is unclear which degree of cost reduction is applicable for different market settings in the future, resulting in high uncertainties about EOL revenues.

2.3. Reverse logistics network planning models

In the introductory section, it was stated that the proposed model is the first one to address the challenges of network structure adaptability, technology substitution, and uncertainty modeling in an integrated reverse logistics network. The relevance of these model features is also underlined by the findings of several recent literature reviews:

- Govindan, Fattahi, and Keyvanshokooh (2017) review uncertainty modeling in supply chain planning, noting that multi-period modeling is used in only a third of the papers. They highlight the need to integrate multi-period location and capacity decisions with uncertainty modeling.
- Alarcon-Gerbier and Buscher (2022) confirm Govindan's et al. (2017) finding and further point out the importance of modeling product characteristics.
- Van Engeland, Beliën, de Boeck, and de Jaeger (2020) discuss that interdependencies of coexisting treatment technologies are often neglected in reverse logistics network planning. However, the economic attractiveness of each technology may be influenced by others, e.g., in the case of overcapacities.
- Karagoz, Aydin, and Simic (2020) point out that uncertainty modeling is often neglected for EOL vehicle reverse logistics networks. They can be seen as related to networks for EOL EVBSs.

Due to the importance of reverse logistics network planning for EOL EVBSs and other products, many reverse logistics models involving location and allocation decisions have been proposed in recent years. Table 1 is used to compare published models and to distinguish the model proposed in this paper.

A multi-period planning approach, which is found in about half of the investigated papers (cf. Table 1), is a first requirement to model growing EOL amounts of EVBSs. However, capacity decisions in multiple periods are only found in Alumur, Nickel, Saldanha-da Gama, and Verter (2012), Rosenberg et al. (2023) and Tari and Alumur (2014). Capacity decisions for each planning period allow for adjustment of the reverse logistics network handling capacity to the supply of EOL products that can vary over the years.

The feature of technology substitution is also found in about half of the reviewed articles. In the proposed model, the term technology substitution is used for a situation in which several alternative recovery options exist and all battery systems can be treated with either technology. But, in the vast majority of papers with multiple technologies the use of certain technologies is limited for some product groups. Thus, the technologies are not pure substitutes. Alumur et al. (2012) is the only investigated study that includes both, technology substitution and capacity decisions over a multi-period horizon. The authors propose a capacitated multi-period reverse logistics network for washing machines and tumblers in Germany. However, their developed model does not consider any kind of uncertainty.

About two-thirds of the analyzed literature in Table 1 addresses uncertainty in EOL pathways, and nearly all of them address uncertainty regarding the product quantities. Some researchers also include uncertainty about the quality of returned products (Ayvaz, Bolat, & Aydın, 2015; Fan et al., 2023; Shafiee Roudbari, Fatemi Ghomi, & Sajadieh, 2021; Wang, Feng, Woo, Wood, & Yu, 2023). Most studies with uncertainty apply stochastic programming approaches. Although five articles use fuzzy optimization or fuzzy chance-constrained modeling. These five studies apply fuzzy techniques to case studies for EOL EVBSs in different Chinese cities and areas (Fan et al., 2023; He, Li, Wu, Han, 2024; He, Li, Wu, Izui, 2024; Lin, Li, Zhao, Chen, & Wang, 2023; Wang et al., 2023).

Further Table 1 shows that the majority of published models maximize economic profit. Only Fan et al. (2023), Harijani, Mansour, and Fatemi (2023) and He, Li, Wu, Han (2024), He, Li, Wu, Izui (2024) include ecological objectives. Concerning the modeled product types, it can be stated that planning reverse logistics networks for single- or multi-products is equally common in the analyzed papers. The composition of products, in the form of a bill of material, such as the removable components, is only considered in a few papers.

Based on the literature analysis summarized in Table 1, it appears that no existing studies have developed an integrated reverse logistics model that simultaneously considers multi-period location and capacity decisions, technology substitutions, and uncertainty modeling. By setting up the model as a deterministic equivalent of a two-stage stochastic model, the model features are combined in a setting that can entail a variety of uncertain economic parameters. Furthermore, in contrast to previous models that deal with EOL EVBSs, the model contains a multi-product formulation to represent different EVBSs variants. As outlined in Section 2.2, product characteristics, such as the cathode type, are expected to influence the revenues from different EOL recovery routes. Therefore, it seems desirable to include them in reverse logistics network planning.

3. Model development

3.1. Descriptive problem formulation

Before introducing the mathematical formulation, a short descriptive problem formulation is given to further outline the modeled reverse logistics network. The reverse logistics network model includes decisions about opening, closing, and expanding disassembling facilities with different types of disassembly technologies and allocation decisions for EOL products to the locations and technologies. The technologies are perfect technology alternatives, meaning that all batteries may be treated with either technology type, while the quantity and quality of the disassembling output are distinct. In line with the reviewed literature, a profit maximization approach is used to pursue an economically optimized reverse logistics network. Because potential revenues vary among different battery cathode types due to different contained resources, multiple EOL EVBS products are modeled in the network. Additionally, product types can vary in size, representing EVBSs from EVs of different sizes and comprising varying numbers of battery modules. Furthermore, EOL battery systems may be sorted into different EOL quality groups, which also influence the amount of retrievable output of a certain quality type. A two-stage stochastic programming approach is applied and transformed into its deterministic equivalent for the mathematical formulation to model uncertainty. In the scenario-based model, it is assumed that the quantity of returned EVBS, as well as the demand for treated products, are uncertain. Moreover, the share of quality groups within the EOL products and potential revenues are uncertain, i.e., they take varying values within the scenarios.

A reverse logistics network in which potential disassembling locations are known is considered, and in each location, all disassembling technologies can be installed. The planning horizon is split into discrete periods. Changes in network structure are completed at the beginning of one period. The design of the network is constrained in certain respects, including the number of feasible modifications per period. EVBSs to be disassembled are only end-of-first-life batteries returning from their use in BEV. Thus, no return from possible second-life applications, including their application as spare parts in vehicles, is covered in the return volume.

Table 1
Classification of related reverse logistics network design models.

References	Decision			Modeling						
	Facility types	Capacity	Multi-period	Technology substitutes	Product characteristics	EOL quality classes	Uncertainty	Objective	Demand/Output limit	Case study
Alumur et al. (2012)	2	C	✓	✓	V, BOM			Max, Econ	✓	Washing machines and tumblers, Germany
Rosenberg et al. (2023)	2	C	✓		S			Min, Econ		EOL EVBSs, Germany
Harijani et al. (2023)	2	D	✓	✓	V	✓		Min, Econ, (Ecol)	✓	Appliance industry, Iran
Tari and Alumur (2014)	1	C	✓		S			Min, Econ		WEEE collection center Ankara (Turkey)
Biçe and Batun (2021)	6	D		✓	S		SC/2SP, O, P	Max, Econ	✓	Randomly generated based on previous studies for USA
Azizi, Hu, and Mokari (2020)	4		(✓)		S	✓	2SP, QT	Min, Econ	✓	Consumer goods
Simic (2016)	1		✓		S		2SP, QT	Max, Econ		Hypothetical ELV network
Jeihoonian, Kazemi Zanjani, and Gendreau (2022)	3		✓	✓	S, BOM		SP, QT	Max, Econ	✓	Washing machines, hypothetical setting
Ene and Öztürk (2015)	2		✓		S	✓	2SP, QT	Max, Econ		EOL EVBSs network, randomly generated
Shafiee Roudbari et al. (2021)	6				V, BOM	✓	2SP, QT, QL	Max, Econ		Medical equipment company
Fan et al. (2023)	5				V	✓	F, QT, QL, E, D	Min, Econ, Ecol		EOL EVBSs Tianjin, China
Ayvaz et al. (2015)	3				V	✓	2SP, QT, QL, C	Max, Econ		WEEE
Wang et al. (2023)	3				S	✓	F, QT, QL	Max, Econ	✓	EOL EVBSs Xi'an, China
John, Sridharan, and Ram Kumar (2018)	5			✓	V, BOM			Max, Econ		Mobile phones and digital cameras, India
Wenzhu Liao and Luo (2022)	4				V, BOM			Max, Econ		EOL EVs Chongqing, China
Lin et al. (2023)	2				S	✓	F, QT	Min, Econ		EOL EVBSs Chengdu, China
He, Li, Wu, Izui (2024)	4			✓	S		F, QT	Min, Econ, Ecol		EOL EVBSs in the Yangtze River Delta , China
He, Li, Wu, Han (2024)	4			✓	S		F, QT	Min, Econ, Ecol		EOL EVBSs in Nanjing Metropolitan Area
This paper	2	C	✓	✓	V, BOM	✓	2SP, QT, QL, R	Max, Econ	✓	EOL EVBSs, Germany

Explanations.
Facility types: 1, 2 etc. represents the number of echelons with location decisions.
Capacity: D: Capacity Decision once; C: Capacity changes.
Multi-period: (✓): Location decisions once for multiple periods, allocation changes over periods.
Product Characterizations: V: Various Products, S: Single/generalized product BOM: Bill-of-Material.
Uncertainty: (2)SP: (two-stage) stochastic programming, SC: scenario-based, F: fuzzy QT: quantity uncertain, QL: EOL quality uncertain;
C: costs; E: emissions; D: distances; O: output/demand, P: quality during processing/efficiency uncertain.
Objective: Min: Minimization; Max: Maximization; Econ: Economic; Ecol: Ecological; (Ecol):monetized ecological costs.
WEEE: Waste from Electrical and Electronic Equipment.

Table 2
Ranges.

Sets	
S	Discrete scenarios with $s \in S$
B	Battery cell chemistry types with $b \in B$
G	Battery system size with $g \in G$
A	Regions of EOL battery supply with $a \in A$
I	Candidate locations of disassembly with $i \in I$
J	EOL quality class of the battery system with $j \in J$
U	Types of disassembling blocks with $u \in U$
R	Types of salvage groups $r \in R$
T	Discrete time periods $t \in T$
OC	All permitted investment time spans with $OC = \{(t_o, t_c) : (t_o, t_c \in 1..T : t_o + MinOpt - 1 \le t_c) \cup (t_o, T) : (t_o \in 1..T : t_o + MinOpt - 1 \ge T;)\}$

Table 3
Decision variables.

Decision variables	
$x_{iut_o t_c}$	Binary variable; describes if a disassembling block of technology $u \in U$ is installed at location $i \in I$ at the beginning of t_o and that ends its operation at the end of period $t_c \forall t \in (T - MinOp : t_o + MinOp - 1 \le t_c)$ or $(t \ge T - MinOpt : t_c = T)$
$t_{sbgjait}$	Transported battery systems with cell technology $b \in B$, size $g \in G$, and EOL quality category $j \in J$ from region $a \in A$ to location $i \in I$ in scenario $s \in S$ in period $t \in T$
o_{sbgjat}	Outsourced battery systems with cell technology $b \in B$, size $g \in G$ with EOL quality category $j \in J$ in region $a \in A$, in period $t \in T$
$y_{sbgjiut}$	Disassembled batteries with cell technology $b \in B$, size $g \in G$, EOL quality category $j \in J$ that is disassembled with technology block $u \in U$ in location $i \in I$ in period $t \in T$ in scenario $s \in S$
z_{sbrt}	Amount of processed and usable battery modules of salvage type $r \in R$ belonging to battery type $b \in B$ in scenario $s \in S$ in period $t \in T$
e_{sbrt}	Excess amount of battery modules that are above spare demand of salvage type $r \in R$ belonging to battery cell type $b \in B$ in scenario $s \in S$ in period $t \in T$

Table 4
Parameters.

Parameters	
$inv_{ut_ot_c}$	Discounted fixed investment depending costs for disassembling unit $u \in U$ with investment at the beginning of t_o and ending at the end of t_c
$prob_s$	Probability of the occurrence of scenario $s \in S$
rev_{sbrt}	Discounted revenue per battery module of battery type $b \in B$ if salvage group $r \in R$ is obeyed in period $t \in T$
$erev_{sbrt}$	Discounted revenue per excess battery module of battery type $b \in B$ if salvage group $r \in R$ is obeyed in period $t \in T$
oc_{ugt}	Discounted operating cost for disassembling a battery system of size $g \in G$ with disassembling block $u \in U$ in period $t \in T$
tc_{aigt}	Discounted transport cost per battery system from region $a \in A$ to location $i \in I$ in period $t \in T$
osc_{bgjt}	Discounted outsourcing costs per battery system of type $b \in B$ with size $g \in G$ and quality $j \in J$ in period $t \in T$
EOL_{sbgjat}	Supply of EOL battery systems of type $b \in B$ with quality $j \in J$ and size $g \in G$ in region $a \in A$ in scenario $s \in S$ and period $t \in T$
c_{gu}	Capacity usage of battery with size $g \in G$ if it is disassembled on disassembling block $u \in U$
cap_u	Capacity of disassembly block $u \in U$
q_{ubjgr}	Quantity of battery modules with salvage value $r \in R$ of battery type $b \in B$ if disassembled with technology block $u \in U$ in period $t \in T$
sp_{sbrgt}	Demand for spare battery modules of battery cell type $b \in B$ with salvage group $r \in R$ in period $t \in T$ and scenario $s \in S$
$UMax_t$	Maximum number of operated disassembling blocks in the reverse logistics network in period $t \in T$
$UAdd_t$	Number of disassembling blocks that can be added to the network in period $t \in T$
$MinOpt$	Calculation parameter of minimum time span for allowed investment

3.2. Mathematical model

The Tables 2, 3, and 4 introduce the nomenclature of the mathematical formulation. Objective function:

$$
\begin{aligned}
Max\ P = &-\sum_{i\in I}\sum_{u\in U}\sum_{t_o,t_c\in OC} inv_{ut_ot_c}\cdot x_{iut_ot_c} \\
&+ \sum_{s\in S} prob_s \Bigg(\sum_{b\in B}\sum_{r\in R}\sum_{t\in T}(rev_{sbrt}\cdot z_{sbrt} + erev_{sbrt}\cdot e_{sbrt}) \\
&- \sum_{a\in A}\sum_{b\in B}\sum_{g\in G}\sum_{j\in J}(osc_{bgjt}\cdot o_{sbgjat} + \sum_{i\in I} tc_{aigt}\cdot t_{sbgjait}) \\
&- \sum_{b\in B}\sum_{g\in G}\sum_{j\in J}\sum_{i\in I}\sum_{u\in U}\sum_{t\in T} oc_{ugt}\cdot y_{sbgjiut} \Bigg)
\end{aligned} \tag{1}
$$

subject to

$$
EOL_{sbgjat} - o_{sbgjat} = \sum_{i\in I} t_{sbgjait} \quad \forall s\in S, a\in A, b\in B, j\in J, g\in G, t\in T \tag{2}
$$

$$
\sum_{a\in A} t_{sbgjait} = \sum_{u\in U} y_{sbgjiut} \quad \forall s\in S, i\in I, b\in B, j\in J, g\in G, t\in T \tag{3}
$$

$$
\sum_{b\in B}\sum_{g\in G}\sum_{j\in J} c_{gu}\cdot y_{sbgjiut} \le \sum_{t_o\le t}\sum_{t\le t_c} cap_u\cdot x_{iut_ot_c} \quad \forall s\in S, i\in I, u\in U t\in T \tag{4}
$$

$$
\sum_{g\in G}\sum_{j\in J}\sum_{i\in I}\sum_{u\in U} q_{ubjgr}\cdot y_{sbgjiut} = z_{sbrt} + e_{sbrt} \quad \forall s\in S, b\in B, r\in R, t\in T \tag{5}
$$

$$
z_{srbt} \le sp_{srbt} \quad \forall s\in S, r\in R, b\in B, t\in T \tag{6}
$$

$$
\sum_{u\in U}\sum_{i\in I}\sum_{t_c\in OC} x_{iut_ot_c} \le UAdd_t \quad \forall t_o\in OC \tag{7}
$$

$$
\sum_{i\in I}\sum_{u\in U}\sum_{t_o\le t\le t_c} x_{iut_ot_c} \le UMax_t \quad \forall t\in T \tag{8}
$$

$$
x_{iut_ot_c} \in \{0,1\} \quad \forall i\in I, u\in U, t_o, t_c\in OC \tag{9}
$$

$$
t_{sbgjait}, y_{sbgjiut}, z_{srbt}, e_{srbt} \in \mathbb{R}^+ \quad \forall s\in S, a\in A, i\in I, b\in B, j\in J, g\in G, r\in R, t\in T \tag{10}
$$

The objective function (1) maximizes the economic profit and consists of the scenario-independent first-stage decisions as well as the scenario-dependent second-stage decisions. The first-stage decisions describe which capacity blocks are installed at a location i from a starting period t_o until the end of the closing period t_c. Thus, at a given point in time, multiple capacity blocks of different disassembling technologies might be installed at a location. It is noteworthy that due to the definition of the binary decision variable $x_{iut_ot_c}$ (cf. Table 3), it is ensured that the investment time span must exceed a defined number of periods or has to last until the end of the planning horizon.

The second-stage decisions consist of revenues generated for the disassembled battery modules and costs for transportation, operational processes, and outsourcing. Constraints (2) and (3) are used to balance the flow in the network. Constraint (2) defines that in each period, all EOL battery systems are either forwarded to disassembling or are outsourced. Constraint (3) ensures the disassembly of the transported battery systems. For the disassembling, the available capacity of different technologies cannot be exceeded (cf. constraint (4)). Constraint (5) describes the conversion of EOL EVBS into battery modules. Retrieved modules may be used for different applications associated with individual salvage values of r. The demand for battery modules may be limited, which is modeled with constraint (6). If the output of the disassembly exceeds the demand, the oversupply (e_{sbrt}) may generate a different, normally lower, salvage rate. Constraint (7) limits the number of disassembling blocks that can be added in a period $t \in T$, while constraint (8) specifies how many disassembling blocks can be operated by the complete network in each period. Lastly, the formulas (9) and (10) declare the feasible decision space.

4. Case study and results

4.1. Description of the case study

The proposed model is applied to a case study of a potential reverse logistics network in Germany. This section focuses on describing the setting of the case study and its main assumption. Detailed, quantitative data of the case study is provided within the Appendix, and additional information is given in the supplementary material.

Building upon the case study introduced by Rosenberg et al. (2023), the case study covers a potential reverse logistics network of one original equipment manufacturer (OEM) with up to eight potential locations in Germany that are illustrated in Fig. A.6. At each location, one or several disassembling blocks can be installed. Disassembling blocks have a predefined capacity per period and can offer different disassembling technologies. The planning horizon covers the years between 2035 and 2042. Each year represents one planning period.

The EOL battery amounts for different battery system types are retrieved from an adapted EOL battery forecast simulation model based on Huster, Glöser-Chahoud, Rosenberg, and Schultmann (2022), Huster, Rosenberg, Glöser-Chahoud and Schultmann (2023). The outcomes of the modified simulation model include the count of variously sized EOL battery systems, their designated battery cathode type, and their residual lifetime. Moreover, the potential demand for spare battery modules can be deduced.

For the EVBS simulation modeling, information about past registration of BEVs in Germany, electric vehicle forecasts for Germany (Deloitte, 2020), and a market share of 20% (Kraftfahrt Bundesamt, 2023b) by the modeled OEM are combined. The simulated EVBS quantities are distributed regionally among the 16 federal states of Germany (cf. Fig. A.6) according to the average stock of vehicles in the regions (Kraftfahrt Bundesamt, 2023a).

Five battery types represent different cathode specifications. In Germany and Europe, nickel–manganese–cobalt (NMC) cathodes are the dominant technology, and lithium–iron–phosphate (LFP) cathode material is primarily present for smaller vehicles (Diess & Schmall, 2021). For NMC battery systems, three generations are used (NMC622, NMC811, NMC955/NMC90505). The three generations express a shift towards nickel-rich and low-cobalt cathodes that is expected in the upcoming years (Chang et al., 2023; Maisel, Neef, Marscheider-Weidemann, & Nissen, 2023; Xu et al., 2020). For LFP, one generation change from the current LFP cathode to lithium–manganese–iron–phosphate (LMFP) is assumed.

Within the simulation, three different battery system sizes are modeled, representing large, medium, and small BEVs, which have distinct quantities of battery modules. The share between the different battery systems (20%/60%/20%) is based on the share of different BEV sizes in the current German vehicle stock (Kraftfahrt Bundesamt, 2023c). According to the simulation model, the EOL batteries are grouped into three quality groups based on their remaining lifetime.

Apart from the EOL EVBS amounts and the cost data, an unlimited demand for recycling battery modules is assumed. Because secondary materials, even if not needed for the production of batteries, could be sold to the resource market. The demand for spare battery modules per cathode type and period is declined as part of the simulation output. The model results state a potential maximum demand for spare battery systems, but not all customers will request spare batteries for various reasons (Hunka, Linder, & Habibi, 2021; Huster, Unterladstätter, Rosenberg, Rudi and Schultmann, 2023). In the case study, a spare part demand of 30% of the potential is assumed (cf. Fig. A.7b).

Two disassembling technology types, representing destructive or non-destructive disassembling, are considered. The destructive technologies retrieve the battery modules after deep-discharging. Thus, they can only be forwarded to recycling to obtain valuable materials. From non-destructive disassembly, battery modules are retrieved either with a recycling quality or for usage as battery spare parts (cf. Appendix A).

Four types of technology blocks are modeled because two different capacity blocks are available for each disassembling technology. The larger capacity classes have four times the capacity of the smaller capacity classes. The capacity usage per battery system depends on the size of the battery system and the destructive or non-destructive disassembling (cf. Table S4). Furthermore, variable discounted disassembling costs per battery system are slightly lower for the larger capacity class of each technology type (cf. Table S5). All costs and revenues are discounted values.

As the mathematical model in Section 3.2 expresses, discounted transportation costs depend on the battery sizes and the transport distance. The cost increase associated with the battery system size is assumed to be less than proportional to the increase in battery modules (cf. Table S2).

The cost data for the discounted investment-depending costs is based on the cost assessment methodology of Rosenberg et al. (2022) that was developed based on a disassembly experiment using real data. The investment-depending costs are completely incurred in the period when a new capacity block is installed. Capacity blocks have a minimum utilization time of four years. If four years exceed the planning horizon, the blocks must remain active until the end. A net present value approach that, for instance, considers the residual value is applied. Furthermore, the invest-depending costs also include costs associated with running the capacity blocks; for instance, heating costs are building side costs (cf. Table S6).

The discounted outsourcing costs (cf. Table S1) of the battery systems depend on the quality and size of the battery system. Lower costs are set for EVBS with higher quality. With a larger battery system size, outsourcing costs increase.

The remaining group of input data needed is revenue (cf. Table S7 and Table S8). For battery modules forwarded to recycling, the revenue is calculated as a share of the revenue associated with recycling.

For those modules that can be reused as spare parts, the value depends on the future battery price market (Mauler, Duffner, Zeier, & Leker, 2021), but there are differences among the battery types. An oversupply of well-functioning battery modules will be sold to the recycling market at recycling prices. Two types of revenue settings are modeled that are combined with the four return scenarios to eight scenarios in total (cf. Appendix A). Although this amount of scenarios seems relatively small for stochastic programming, it is in line with current case study applications such as Karagoz, Aydin, and Simic (2022) or Azizi and Hu (2021).

Additionally, we have the following three assumptions that are modeled with constraints:

1. The maximum allowed number of disassembling blocks in the network increases from one to six over the planning horizon.
2. A maximum of one block can be added per period
3. Location 8 must be operated in the first period (2035) and has to stay open at least until the end of 2038

The first two assumptions seem reasonable because the reverse logistics network of only one market participant is planned. Thus, from a business perspective, limits on how many network changes are manageable will exist. In practice, the budget for investment will be limited. The third assumption is made because the modeled OEM already operates a disassembling center at location eight.

The CPLEX solver in combination with CPLEX IBM Studio 22.1.1 is used to solve the model. The integrated Benders decomposition algorithm is used to solve the problem instances, as it solves the instances faster than default CPLEX settings. Mixed-integer programming warm starts are supplied to improve the solving time.

4.2. Base case results

The first-stage decisions, namely the type and number of operated disassembling blocks in the reverse logistics network over the planning horizon, can be withdrawn from Fig. 2. In the optimal solution of the case study, not more than one of each disassembling block type is operated at the same location and time. Fig. 2 displays the used candidate locations as columns, and each scenario is displayed as one row of the graphs. Because the first-stage decisions are valid for all scenarios, the installed disassembled blocks are the same over the rows, but their height might vary, representing different utilization of the installed disassembling blocks in the distinct scenarios.

Only one disassembling block can be operated in 2035, and it must be placed at location 8 due to the assumptions of the presented case study. Nevertheless, a choice between disassembling technologies exists, and a large destructive disassembling block is chosen. Once established, it is operated over the complete planning horizon. In the next year, 2036, a small non-destructive disassembling block is added at location 6, placed in the south-west of Germany. The network expands to other locations, with destructive or non-destructive disassembling technologies in the following years. In 2040, the previously established small non-destructive disassembling plant at location 6 is replaced by a large non-destructive block. One reason for the exchange to the larger capacity block is that the previously installed capacity in the network is already highly utilized in most scenarios. As the number of EOL EVBSs increases further over the years, the optimal decision in the case study is to extend the available non-destructive disassembling capacity. The previously installed small disassembling block at location 6 can be replaced by a larger one because the minimum duration for operating a block has been reached in the year 2040. The minimum duration for operating a block is included in the model formulation by defining the binary variables for installation only for selected time spans (cf. Table 3). The increase of capacity at location 6 is economically advantageous compared to opening further locations.

The utilization rates of the operated disassembling blocks show several differences among the scenarios. As explained in the case study, four different return scenarios are mixed with two alternative revenue scenarios. Thus, by comparing scenario 1 with scenario 5 (cf. Figure S7-S9 for other scenarios), one can deduce how the scenario revenue settings influence the allocation of batteries.

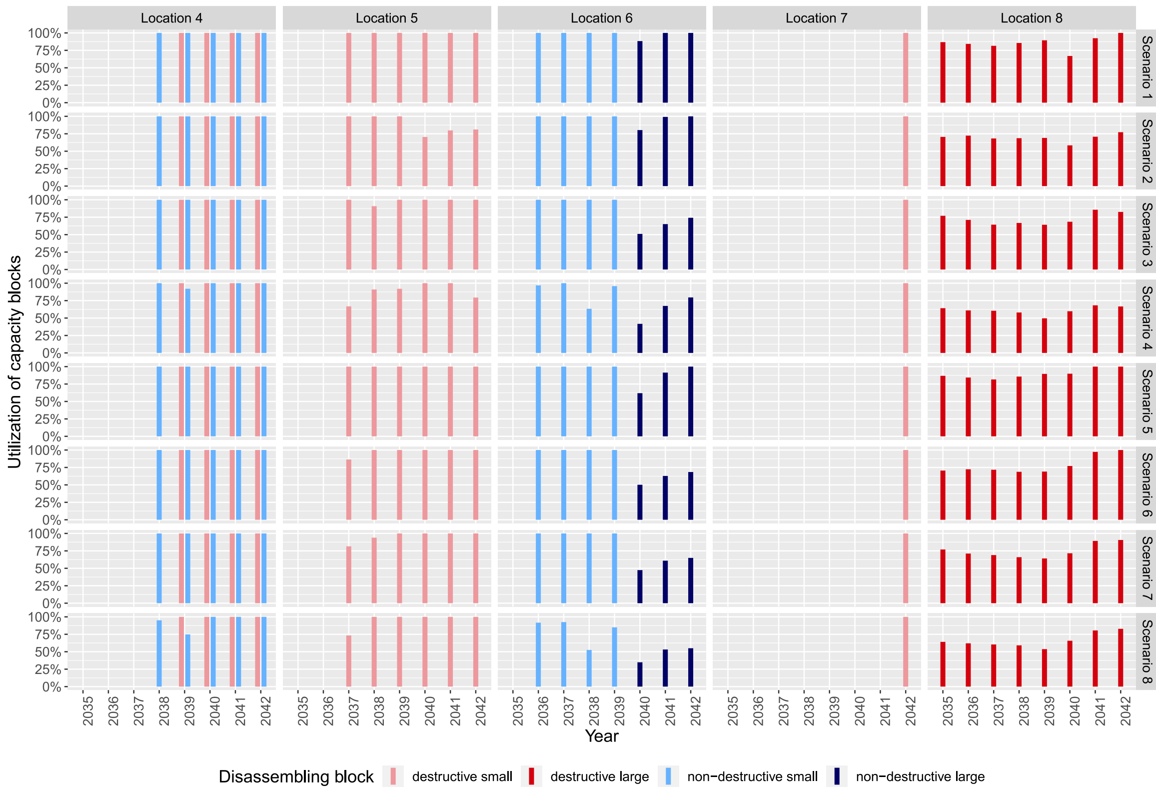

Fig. 2. Utilization of installed capacity in each scenario in the base case over all locations.

Fig. 3 depicts differences between scenarios 1 and 5. Fig. 3a shows that for LFP and LFMP, destructive disassembly is preferred in both scenarios, although in scenario 5, the share of EVBS with LFP and LFMP that are treated non-destructive is a bit higher. Thus, it is concluded that due to lower revenues for LFP and LMFP compared to the NMC generations, their disassembling and preparation as spare parts is not economically preferable if disassembling for recycling is the alternative. For the different NMC cathode generations, it can be reasoned with Fig. A.7b in mind that the usage of the non-destructive disassembling blocks is aligned to the demand for the NMC cathode type that changes over the planning horizon.

Fig. 3b displays the assignment of EVBS with their EOL quality and size to the different disassembling block types. In scenario 1, which is more spare part-supportive than scenario 5, battery systems with a medium quality make up a larger percentage of the non-destructive disassembled battery systems than in scenario 5. One can observe that about 10% of disassembled EVBS at the large destructive disassembling block are of medium or high quality. This quality share stays nearly constant over all planning periods. This includes periods, such as 2040 and 2041, in which the non-destructive disassembling capacities are not fully utilized (cf. Fig. 2).

The overall analysis of the fulfilled demand for spare modules shows that apart from the first period, in which non-destructive disassembling is not performed, the demand satisfaction varies between the scenarios and periods from about 47% to 100%. On average, over all scenarios and years, 66% of the demand for spare modules is fulfilled. Because the utilization for non-destructive disassembly is below 100% in many scenarios and years, it is concluded that destructive disassembly is economically more attractive for some EVBS.

The solution values of the case study reveal that, in total, the costs are higher than the revenues. Thus, no profit can be attained by operating the disassembling network, and losses are made. We, therefore, report on the costs that are associated with the optimal network structure. Discounted costs per EVBS are used to describe the cost structure to have a more tangible monetary size. Costs and losses per EVBS treatment are derived by using the average number of EOL EVBS over all scenarios for each year (cf. Table S10).

The resulting average discounted total cost per EVBS is about 144 EUR. About 40% of the total costs are operating costs, followed by 35% investment-depending costs and 25% transportation costs. Outsourcing costs are below 1%. If the discounted turnover is considered, the average loss per EVBS is about 86 EUR.

To quantify the influence of technology substitution on the base case, the results of the base case can be compared with reverse logistics networks in which either only non-destructive or destructive technology is available. It is found out that, as expected, in the case of only destructive disassembly, the average discounted costs are lower at about 129 EUR, but the average losses are higher at 100 EUR. In the case of only non-destructive disassembly technology, the average discounted costs are 181 EUR, and the average losses sum up to 121 EUR. Thus, it is summed up that in the reverse logistics network, the average losses are about 16% or 30% lower than in the cases of only one available disassembling technology (cf. Table S9).

4.3. Non-destructive demand stimulation

In the base case, it is assumed that non-destructively retrieved battery modules that exceed the spare demand in a year are sold with recycling revenues. This setting reflects an OEM that applies non-destructive disassembly primarily to retrieve modules for spare part production.

In this subsection, two altered case studies are investigated. In the first alteration compared to the case study in Section 4.2, functioning retrieved battery modules that exceed the spare demand are assumed to be sold to a third-party player that may use them for other second-life options. The revenues for those second-life modules are set to 60% of the internally used spare modules. This revenue setting reflects that external market participants request price discounts for bearing risks of

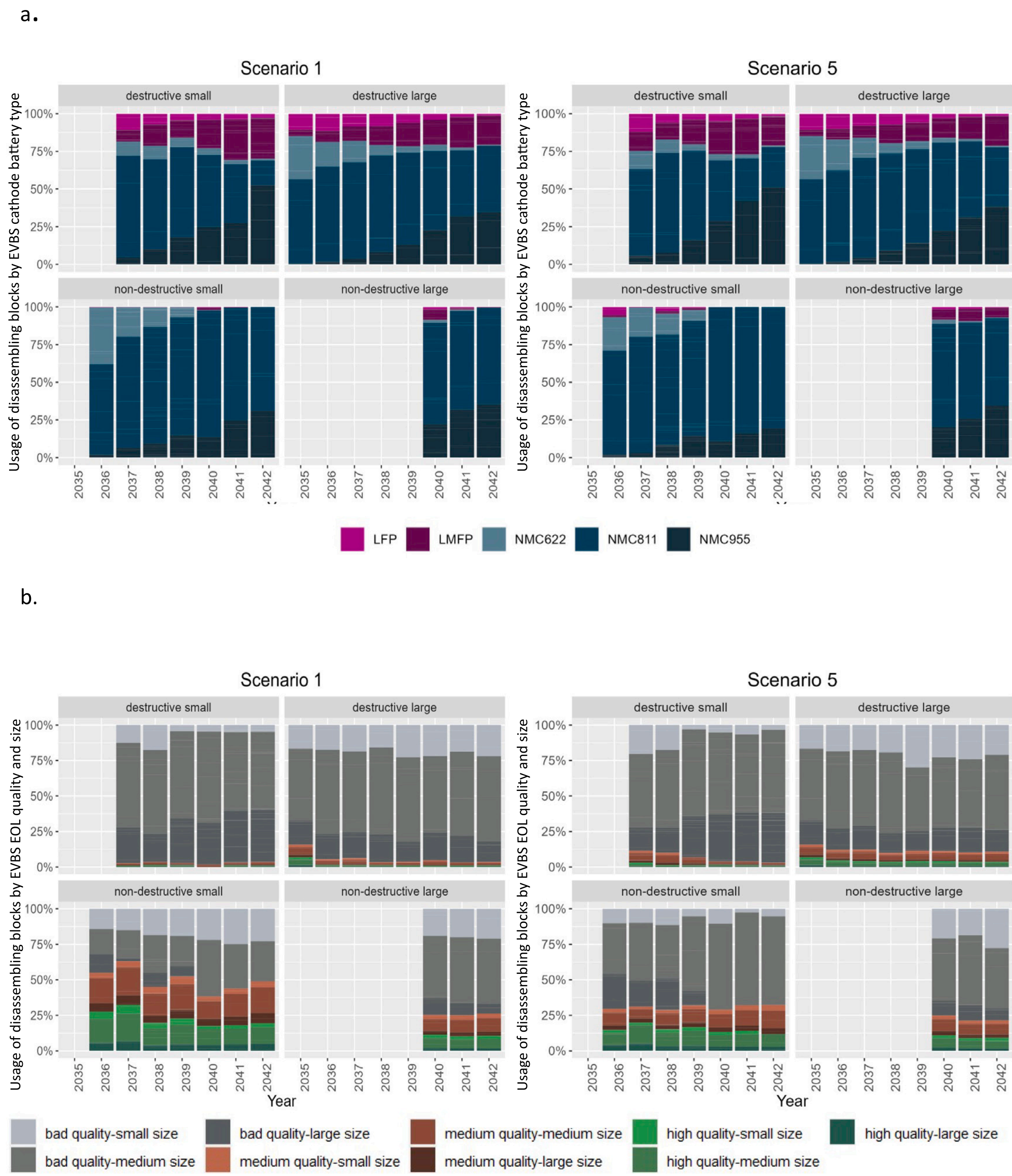

Fig. 3. Analysis of disassembling block usage and product characteristics Fig. 3a: Battery cathode type of electric battery systems Fig. 3b: Electric vehicle battery systems with EOL quality and size indication.

used products. Furthermore, the third-party market participant has to make its product match the battery module. Thus, they have additional financial burdens to cover and are not willing to pay the full price.

The second altered case study keeps the revenue values of the base case but includes an increase in demand for spare modules by 10 percent points. Thus, more vehicle owners are requesting spare battery systems, which leads to an increase in the demand for used battery modules. Both altered cases should potentially lead to an increase in the investment of non-destructive disassembly technology.

Fig. 4 displays the utilization of the installed disassembling blocks of the first altered case study. In contrast to the base case, a non-destructive plant is chosen for location 8 in the first period. In the following years, multiple small destructive disassembling blocks are added at different locations, forming a widespread reverse logistics network. A second small non-destructive disassembling block is added at location 5 in 2039. In contrast to the base case, there is a larger variation in utilization over the scenarios and years. One can observe decreases in utilization in some periods when new locations are added.

In Fig. 5, the utilization of the second case study alteration is displayed, in which the demand for spare modules has been increased. Similar to the first alteration, a large non-destructive block will be installed in 2035 at location 8 and will be kept open until the end of the planning horizon. In location 4, the first installed small destructive disassembly block is only utilized for three periods. In the fourth period, 2040, it is still open, but instead, the newly installed large destructive block is used. Because the small block is not utilized at all, it does not appear in Fig. 5. In contrast to the first alteration, small non-destructive disassembling blocks are added in 2039 and 2041.

It is noteworthy that the same locations, as in the first altered case study, are chosen. In most years and locations, the same type of disassembling blocks are operated. Consequently, similar costs per EVBS are reached with about 161 EUR (alteration 2nd life) and 162

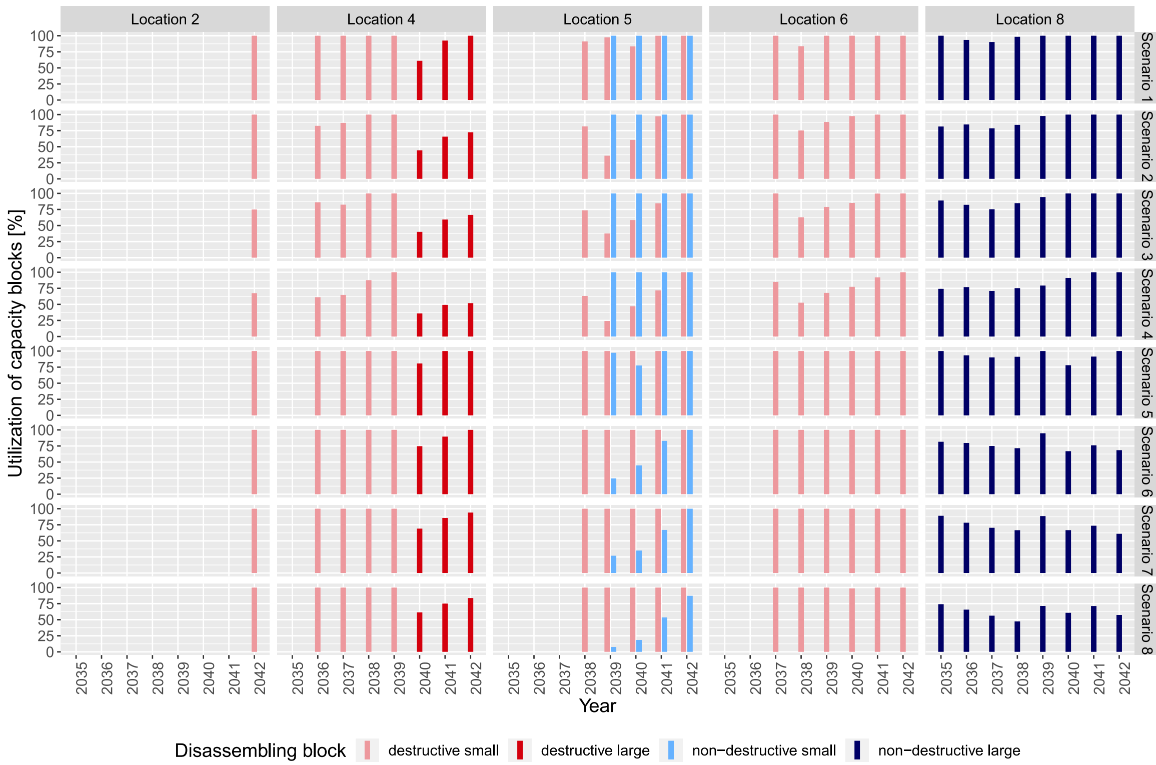

Fig. 4. Utilization of installed capacity in each scenario in the case of the first altered case study, i.e., considering an external market for 2nd life modules.

EUR (increase of spare demand). The losses per EVBS are reduced to 79 EUR and 81 EUR, respectively. Lastly, the spare module demand fulfillment rate can be compared to the base case. The 2nd life revenue case (altered case study one) has a fulfillment rate of 93% over all periods and scenarios, which is 27 percent points higher than in the base case. Meanwhile, for the increased spare demand case study, a demand fulfillment rate of 88% is documented. It is noted that the non-destructive disassembling technology is not fully utilized in the scenarios in which the demand is not fulfilled.

5. Discussion and limitation

5.1. Abstraction level of the model

In contrast to the reviewed models that cover EOL EVBS networks, the model proposed in this paper entails more details about product characteristics such as quality, battery system size, and cathode type. In the model, the quality attribute is assigned to the EOL quantities at the point and time of becoming an EOL product. This is in contrast to common practice in other models where quality classes are introduced during the first treatment step, normally as a percentage share. In this model, the quality assignment is introduced at an earlier network stage because battery diagnostics will enable quality grading at the point of collection of EOL battery systems. The EU battery regulation contains rules to ensure that EOL economic operators can access battery quality information (European Parliament and Council of the European Union, 2023). Furthermore, from a technical perspective, the development of testing software that allows quick quality tests has made progress in the last years (D'hoore, Ernst, & Kolb, 2021). The EU battery regulation also establishes the obligatory introduction of digital passports for EVBSs in the coming years. The digital passports will contain valuable information for EOL treatment decisions, such as the battery cathode materials. This EOL information is often missing today and is an obstacle to determining the best circular treatment pathway. Meanwhile, real-time data is a prerequisite for potentially benefiting from digital solutions that can improve overall circular supply chain efficiency (Taddei, Sassanelli, Rosa, & Terzi, 2022; Toth-Peter, Torres De Oliveira, Mathews, Barner, & Figueira, 2023).

The assignment of battery systems to three different quality classes is a simplification because it is assumed that depending on the size and quality class, a predefined number of EVBS modules can be used as spare parts if non-destructive disassembly is conducted. All retrieved modules as spare parts come with the same quality, and they are interchangeable as long as the cathode material (battery type) is the same. From a technological perspective, little information is available that describes to what extent battery modules can be combined to form new spare battery systems, but standardization of battery systems increases the possibility of interchangeable parts. Standardizing battery systems by reducing the number of different battery module types used by an OEM is an ongoing challenge, but also a way to reduce the production cost of new electric vehicles (Diess & Schmall, 2021). This is one of the reasons why a concentration on a few interchangeable battery modules seems likely in the future. Furthermore, technological advances in the software development of battery management controllers can help to improve the usage of spare battery modules and battery systems (Rufino Júnior et al., 2023).

The problem formulation could also be adapted to model how retrieved battery modules can be combined. One could, for example, assume that the retrieved battery can only be combined with EOL EVBS modules from the same vehicle size or according to the quality class of the disassembled battery system.

In the case study, destructive and non-destructive disassembling technologies are distinguished, but combining these technologies in one block is not a modeled option. In industrial practice, in a building designed for non-destructive disassembly, the destructive disassembling of deep-discharged battery systems should be possible. Consequently, introducing mixed disassembling blocks might be a potential extension of the model. However, additional constraints need to be added to model the material flows. Furthermore, from an industrial perspective, integrated disassembling is not common yet.

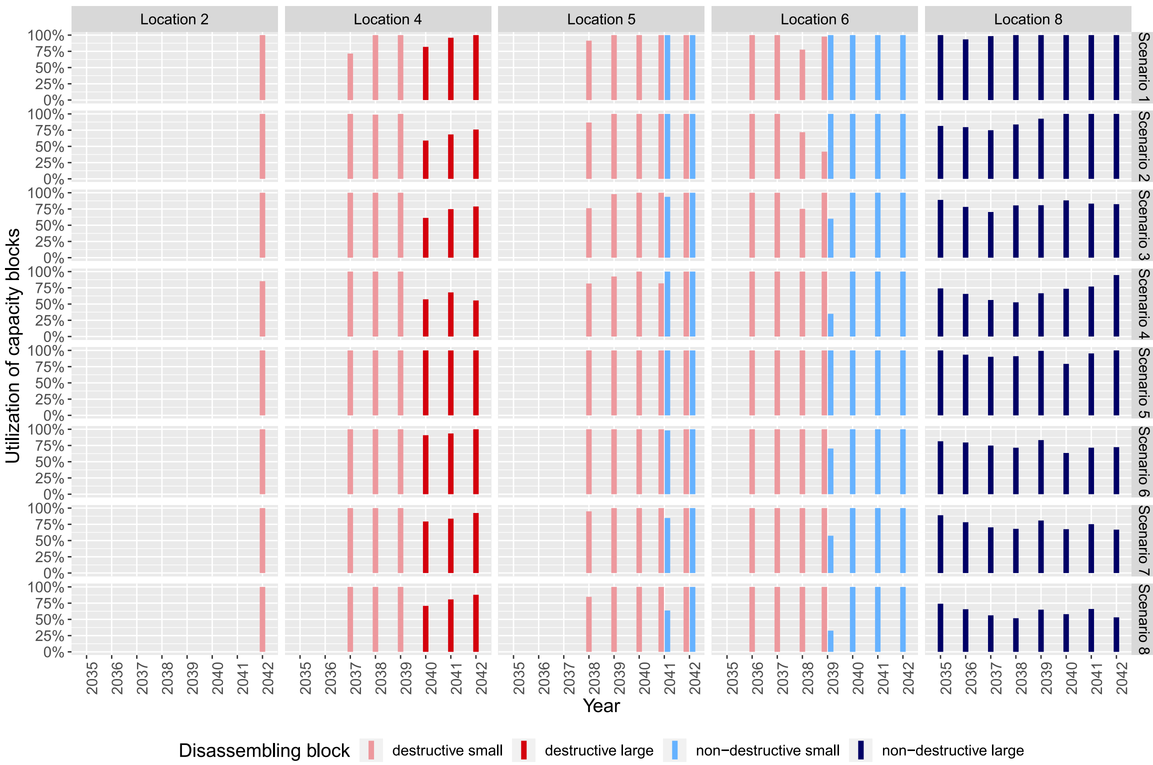

Fig. 5. Utilization of installed capacity in each scenario in the case of the second altered case study, i.e., increasing the spare demand.

Because no profit is attained in the case study, the question arises as to why an OEM should engage in the EOL management of battery systems. Once again, the answer is found in the EU Battery Regulation that establishes a producer responsibility scheme in which the OEM, who will be the producer by law in most cases, is responsible for covering the EOL treatment costs. Thus, even if losses are made with the EOL management, OEMs should try to minimize these losses. Therefore, differences in cathode material that are responsible for the second material value must be included in the planning. Consequently, a maximization problem is formulated.

Two altered case studies that both stimulate non-destructive disassembling attractiveness are introduced. Both altered case studies showed a positive impact on the overall business performance. According to circular economy principles, reusing functioning battery modules should be supported whenever possible but needs to be economically attractive. Although not profitable, both alterations of the case study come with lower costs than the base case. On the one hand, for OEMs, it might be interesting to set up strategic partnerships to increase the market for 2nd life battery modules. On the other hand, they can also develop their business models to increase demand for spare modules, e.g., by actively promoting remanufactured and tested 2nd life spare batteries.

5.2. Implication and transfer of findings

The developed case study builds upon an OEM that retrieves its own EOL EVBSs. The chosen market constellation allows for overcoming some barriers of disassembly, such as a reduction of the high number of EVBS variants and the assumption of common and generalized battery modules. However, it is also a simplification because no coordination is needed between different actors in the EOL supply chain. Nevertheless, the model could also be used to assess situations in which multiple market players offer different EOL recovery steps. The mathematical formulation involves several different technology blocks with diverse capacity levels and might be used to express the potential business offers by market participants. In a situation with multiple market participants that offer different services, it seems evident that further steps of the EOL management process should be integrated into the network model. However, attention should be given to the modeling to ensure that the goals and objectives of individual market participants are adequately represented. Due to the complexity of multiple periods and every technology substitute, solving problem instances optimally can become computationally challenging. Besides, through the introduction of outsourcing costs, market players can assess if it is more desirable to conduct certain disassembly or other recovery steps by themselves or outsource them.

From the results of the case study, it is also possible to derive some political implications. Demand limitations for second-life usages are one barrier to engaging in the circular concepts that focus on reuse instead of recycling. Potential actions to increase 2nd life demand can either focus on the consumer's perspective, which might be reluctant to use 2nd life spare parts, or can focus on minimizing business risks for second-life battery use, for instance, by developing unified (industry) standards for reassembling processes.

Although the model was developed to cope with EOL EVBSs, it can be of interest to transfer and adapt it for other EOL product flows that are expected to increase significantly within the next decades. Possible product groups could be EOL photovoltaic modules or carbon wind turbines (Delaney et al., 2023; Preet & Smith, 2024), which both require disassembly before other steps of recycling can take place.

5.3. Further research need and possible model extensions

Some potential extensions of the model have been highlighted in the previous subsections. Besides, there are related questions in reverse logistics network planning for EOL EVBSs that should be considered in the future.

Taking the market position of an OEM, closed-loop supply chain optimization seems to be of high interest. Among other topics, the European Battery Regulation provides rules concerning the obligatory use of secondary material for specific resources in the future (European

Parliament and Council of the European Union, 2023). To ensure sufficient secondary material, closed-loop models may contain constraints that ensure sufficient recycling output.

One of the main differences between the model in this paper and those in the literature is the decisions about the changes in the disassembling capacity of the network. In the proposed model, disassembling blocks with fixed capacity classes that can be added or removed are modeled. For future research, it would be of interest to determine the optimal sizes of capacity blocks under the assumption that a certain number of different blocks are possible.

Further research potential is the development of robust location and capacity models. Robust optimization can help single-market players if they seek to set up reverse logistics network structures oriented towards managing worst-case scenarios efficiently (Egri, Dávid, Kis, & Krész, 2020).

6. Conclusion

Within the study, a reverse logistics network model is developed that integrates several challenges found in the planning of EOL EVBS supply chains: the need for logistics network structure adaptability to a growing market, deciding about the best circular recovery pathway for a certain product, and considering economic uncertainty about future developments. A comprehensive literature analysis outlines the research gap in mathematical reverse logistics network modeling as well as state-of-the-art research on EOL EVBSs. The developed stochastic model is formulated and solved as a deterministic equivalent of a two-stage stochastic program.

A case study is presented that assumes a reverse logistics disassembly network from a single OEM in Germany. The results imply that the economic performance of the EOL management can be improved through the combination of non-destructive and destructive disassembly technologies, allowing recycling or 2nd life usage of battery modules. Consequently, it seems favorable to consider multiple circular pathways for EOL battery systems in the future. The analysis further shows that the cathode type, as one of multiple product characteristics, can significantly influence the allocation of battery systems to certain disassembly technologies.

There are several limitations to the model, especially due to assumptions in the case study that might oversimplify the problem, e.g., because today, decisive information for EOL product characteristics is commonly missing. Consequently, it is discussed which ongoing research on EOL EVBSs should further be strengthened to overcome technical barriers.

Currently, the applied case study assumes that one market participant assesses its own reverse logistics network. To better represent reverse logistics networks in which several market participants cooperate, future research should focus on extending the disassembling-centered network to further recovery steps and ensure a formulation in which the individual interests of market players are considered. Such a market-oriented model could also give a chance to assess how potential political measures might influence the attractiveness of different circular pathways.

CRediT authorship contribution statement

Sonja Rosenberg: Writing – original draft, Methodology, Data curation, Conceptualization. **Sandra Huster:** Writing – review & editing, Data curation. **Andreas Rudi:** Writing – review & editing. **Frank Schultmann:** Writing – review & editing, Project administration, Funding acquisition.

AI usage disclosure statement

This article and the developed model were developed without AI tools and services.

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.

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Appendix A. Case study background information

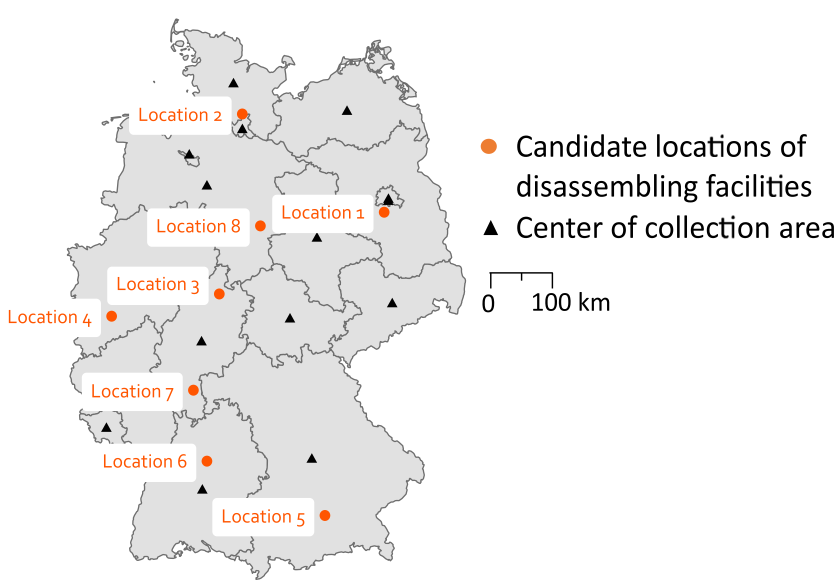

Fig. A.6. Map of Germany with candidate locations and center of collection areas. These points are used for distance calculations via an available street network.

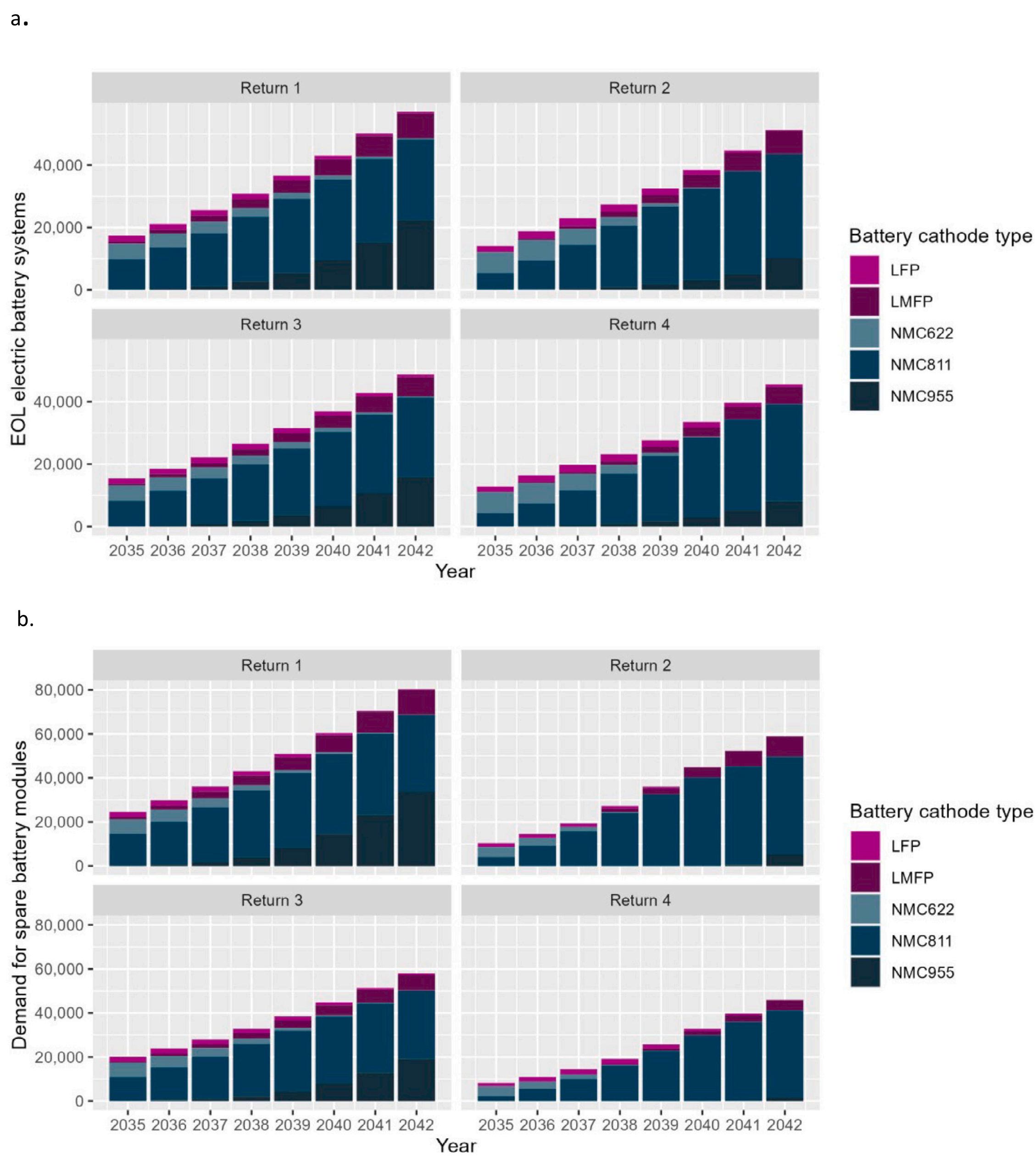

Fig. A.7. a: Return scenarios for EOL battery systems retrieved from the simulation; b: Demand for spare battery modules for each return scenario from simulation.

Reverse logistics network map

Fig. A.6 displays the used reverse logistics network for Germany, consisting of 8 potential locations. The numbers are used within the paper to refer to the different location sites.

Simulation data

The simulation model was run for four scenarios that resulted in varying amounts and quality of the EoL battery systems due to different lifetime distributions. Fig. A.7a depicts the result of the four return scenarios. All scenarios assume the same lifetime distribution for vehicles (Weibull distribution, shape parameter of 3.5, expected lifetime of 14 years) but different lifetime distributions for the batteries. Weibull or Gumbel distributions are used for the battery lifetime. The parameters of the lifetime distribution are configured in a way that the Weibull distributions (for return Scenarios 1 and 3) exhibit a symmetrical shape, while the Gumbel distribution (for return Scenarios 2 and 4) is right-skewed. This Gumbel distribution reflects a lifetime distribution where only a few early failures of battery systems occur. In return scenarios 3 and 4, we further model that the expected lifetime of the battery systems increases over time.

EOL EVBS modeling

Large battery systems contain ten modules, medium eight, and small systems six. According to the simulation model, the EOL batteries are grouped into three quality groups based on their remaining lifetime

1. Low quality: EOL EVBS with a remaining lifetime of under three years
2. Medium quality: EOL EVBS with a remaining lifetime between three and under six years
3. High quality: EOL EVBS with a remaining lifetime of at least six years.

The amount of battery modules usable as spare modules is calculated as follows:

- Two spare modules are retrieved from an EVBS with low-quality
- 50% of the modules from EVBS with medium quality are retrieved as spare modules
- All but two modules are retrieved as spare modules from EVBS with high-quality

While the number of EOL battery systems for the different vehicle segments is based on reported industry data, the assumptions about the assignment to quality classes and also the number of battery modules that can be reused cannot be underlined with industry data, as empirical data is missing due to the novelty of the EVBS market.

Scenarios

In total, eight scenarios are included in the case study. Scenarios 1 to 4 consist of return/demand scenarios 1 to 4 (cf. A.7a and b) and revenue settings that are remanufacturing or spare demand friendly. In these scenarios, revenues for recycling make up only 2%–3% of those for modules that can be used as spare parts. In contrast, scenarios 5 to 8 have a revenue setting in which the recycling revenue reaches between 14% and 30% of the spare module revenue and the same return and demand scenarios are used from Fig. A.7.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cie.2025.110900.

Data availability

Data will be made available on request.

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