RESEARCH

Remanufacturing capacity planning in new markets—effects of different forecasting assumptions on remanufacturing capacity planning for electric vehicle batteries

Sandra Huster[1] · Sonja Rosenberg[1] · Simon Glöser-Chahoud[2] · Frank Schultmann[1]

Abstract

When planning production or remanufacturing capacity, it is necessary to use forecasts. In the case of production, demand must be forecasted; in the case of remanufacturing, core supply is also uncertain. In the remanufacturing literature, there are different methods to forecast product returns in the long term, mostly material-flow analysis, system dynamics simulation, and discrete-event simulation. All methods require various assumptions to be taken. The effects of the assumptions are rarely studied, although every assumption adds a source of error. In this paper, we examine which assumptions influence long-term forecasts for remanufacturing capacity planning the most. This can help researchers and practitioners to focus on the most influencing factors and neglect those that would only add complexity without adding value. We examine assumptions concerning new product sales, product composition, product lifetime, return rate, and return quality. Our use case are electric vehicle batteries in Germany from 2022 to 2032. We find that, for the examined period, product quality and return rate have the greatest influence on capacity planning. Assumptions on an age limit for cores or a certain remaining useful life as a quality gate significantly lower the product return quantities and the resulting demand for remanufacturing capacity. The product's lifespan also influences the results, first and foremost regarding the entry point into remanufacturing activities. Sales forecasts affect the results minorly if the timeframe of the forecast and the expected product lifespan are approximately the same.

Keywords Remanufacturing · Electric vehicle batteries · Forecasting · Capacity planning

✉ Sandra Huster
   sandra.huster@kit.edu

   Sonja Rosenberg
   sonja.rosenberg@kit.edu

   Simon Glöser-Chahoud
   simon.gloeser-chahoud@bwl.tu-freiberg.de

   Frank Schultmann
   frank.schultmann@kit.edu

[1] Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), Hertzstr. 16, 76187 Karlsruhe, Germany

[2] Chair of Corporate Sustainability and Environmental Management, Technical University of Freiberg, Schlossplatz 1, 09599 Freiberg, Germany

🌀 Springer

Introduction

Opening or closing a production site and expanding or downsizing it are far-reaching, strategic decisions. They require a profound study of the market and the desired business model and have a tremendous impact on a company's financial success. These kinds of decisions are not unique to manufacturing companies. Retailers decide where to operate stores, service providers decide in which fields they want to expand, and politicians decide on locations for infrastructure. What these decisions have in common is that they have a long planning horizon and that decision-makers need reliable forecasts to achieve good, sustainable results in retrospect. With growing efforts to automate remanufacturing operations or at least parts of it, like disassembly, long-term capacity planning could become increasingly relevant in the remanufacturing industry.

Many forecast methods in supply chain management enable long-term capacity planning [9, 12, 55]. However, they are mainly intended for new product sales and established products. These methods might not be suitable for remanufactured products as they do not account for the additional uncertainties when dealing with End-of-Life (EoL) products. EoL uncertainties occur, for instance, concerning core availability, quality of cores, and collection procedures [49]. Even fewer forecast methods consider the possibility that the forecasted product is not well-established yet (e.g., [57, 74]). This means that the sales figures are uncertain too.

Long-term forecasting of EoL quantities of new products is challenging and afflicted with various sources of uncertainty, but it is highly important. For new products like electric vehicle batteries (EVBs), it is not only about *when* to build remanufacturing capacity. Remanufacturing technology must also be developed. The questions long-term forecasts answer are, therefore: How fast do we have to develop remanufacturing technologies, and how much capacity is needed at what time? Additionally, it might help to assess when remanufacturing might be an economically feasible business model since quantities are sufficient for industrial-sized remanufacturing.

Some authors have already recognized the importance of the topic and have made long-term forecasts by employing different methods (e.g., material flow analysis [11], or system dynamics simulation [70]). Since forecasts try to predict an uncertain future, it is in the nature of things that they rely on assumptions. It is also common that some assumptions are disclosed explicitly while others are made implicitly. It is not always clear why they are chosen for both methods and assumptions.

Our work aims to compare different assumptions in long-term forecasting of product returns in new markets concerning product service time, quality, and return rates. We apply the forecasts to EVBs in Germany ten years ahead (2032) as a case study. For that, we have to make some assumptions ourselves that we disclose as transparently as possible. A simple capacity optimization model is applied to make the impacts of different assumptions visible. This helps to identify which assumptions fundamentally influence the planning results and which add complexity without adding to the informative value. We contribute to the remanufacturing community by improving assumption-making in long-term forecasting for capacity planning, especially in new markets or for new products in existing markets.

The remainder of the article is as follows: The "Literature" section gives an overview of methods employed and assumptions made in the literature concerning core return forecasts. Additionally, EVB-specific assumptions taken in the literature are presented. The "Forecasting and capacity planning method" section discloses how we apply selected methods and assumptions to EVBs and describes the capacity optimization model we use

to compare the impacts of different assumptions. The "Results" section shows the outcome of the forecast application and capacity planning. The "Discussion" section debates the results regarding the strength of influence of the influencing factors and the approach's shortcomings. Subsequently, we draw "Conclusions" in the final section.

Literature

Returns forecasts

Methods employed for forecasting product returns are manifold. Some can best be described as statistical time-series analyses of past returns, e.g., exponential smoothing [24] or ARIMA [48]. Other models are based on past sales, e.g., with Distributed Lag Models (DLMs) [14, 15, 41] or stocks and flows models [11, 75]. A third class, such as neuronal network models, combines past returns, sales, and/or other indicators like gross domestic product (GDP) [22, 30, 43, 50]. Krapp, Nebel, and Sahamie [41] classify forecasting approaches by their methodology rather than their input. They differentiate between causal analysis, simulation/soft-computing, and statistical methods. Krug et al. [42] base their classification of approaches on how uncertain parameters are handled. According to them, one can assume probability distributions for uncertain parameters, use fuzzy programming, or create a set of scenarios and apply robust planning.

Besides basic methodology, input values, and degree of uncertainty incorporation, existing forecasting models for product returns can be differentiated by many other attributes. Table 1 gives an overview of selected publications concerning product returns for EoL treatment. Although Table 1 is not exhaustive, it is intended to give insights into the broad scope of return forecasting methods and assumptions. Emphasis is put on the most common methods, i.e., DLMs and DLM variations (DLMv), and Material Flow Analyses (MFA). Additionally, methods gaining popularity, like agent-based simulation (ABS) or artificial neural networks (ANN), are selected. Furthermore, classic time series methods are chosen (first order and triple exponential smoothing (1ES, 3ES)), other simulation approaches (discrete event simulation (DES) and system dynamics (SD)), and less frequently used approaches like Graphical Evaluation and Review Technique (GERT), fuzzy systems (FS), grey models (GM), scenario analysis (SA), or random sampling with a normal distribution (RN). Recent publications are preferred over older ones.

Predicting product returns is sometimes not the focus of the publications but rather a necessity for other investigations, e.g., inventory planning [13], developing purchasing strategies [14], or planning of collection and remanufacturing capacity [24]. In these cases, the entries in Table 1 only refer to the product return forecasting part.

Some of the attributes listed in Table 1 need further explanation. The variety of methods applied (column a) has already been addressed, as well as the main input the methods require (column b), i.e., past sales (PS), or past return data (PR), randomness (R), or others (O). Column c) indicates if the forecast method is mainly applicable to mature markets and products with stable demand (H), or if different product life cycle phases can be covered (A). Methods could also be intended for markets with low maturity (L), or the target market maturity can be unknown (U). Column d) shows if the paper assumes that returned products undergo a remanufacturing step and then are substitutes for new products, i.e., return to the first-hand market, or if they are instead refurbished to a quality minor to that of a brand-new product. In column e), "Compound

Table 1 Overview of methods and assumptions in forecasting EoL product returns

Publication	a) Method	b) Main input	c) Maturity of the market	d) Reman and new perfect substitutes	e) Compound product	f) Product lifetime / return time	g) Quality	h) Return rate
[24]	1ES, SD	PR	A	Yes	No	-	F	F
[51]	ABS	PS, O	U	-	No	DC	-	AB
[22]	ANN	PS, O	H	-	No	-	-	-
[43]	ANN	PR	U	No	No	-	F	-
[48]	ARIMA, DLM	PS, PR	H	Yes	No	U	-	-
[46, 47]	DES	PS	L	Yes	Yes	DC, DD	RUL	D
[50]	DES, FS, ANN	PS, O	A	-	No	DC	-	D
[15]	DLM	PS	A	No	No	DC	-	P
[14]	DLM	PS	H	Yes	No	DC	-	-
[65]	DLM	PS	H	Yes	No	DC	-	F
[13]	DLMv	PS	U	Yes	No	DC	AL	-
[41]	DLMv	PS	A	-	No	DC, DD	AL	D
[76]	GERT	PS	U	No	Yes	DC	F	-
[30]	GM, 3ES, ANN	PR, PS	H	-	No	-	-	-
[2]	MFA	PS	L	No	No	DC	F	F
[11]	MFA	PS	L	Yes	Yes	DC-DC	F	F
[20]	MFA	PS	L	-	Yes	DD-F	-	
[57]	MFA	PS	L	-	Yes	DD-F	-	-
[73]	MFA	PS	L	-	No	DC	-	-
[74]	MFA	PS	L	-	No	DC	-	-
[75]	MFA	PS	A	-	No	DD	-	-
[5]	RN	R	H	Yes	No	-	-	-
[42]	SA	R	H	Yes	No	-	F	D
[70]	SD	PS	A	Yes	No	DC	F	F

Methods: 1ES: First Order Exponential Smoothing; 3ES: Triple Exponential Smoothing; ABS: Agent-Based Simulation; ANN: Artificial Neural Network; DES: Discrete Event Simulation; DLM(v): Distributed Lag Model (variation); FS: Fuzzy Systems; GERT: Graphical Evaluation and Review Technique; GM: Grey Model; MFA: Material Flow Analysis; RN: random by normal distribution; SA: Scenario analysis; SD: System Dynamics

Main input: O: others; PR: past returns; PS: past sales; R: randomness

Maturity of the market: A: all maturity levels; H: high; L: low; U: unclear

Product return time: DC: distributed with a continuous distribution; DD: distributed with a discrete distribution; F: fixed lag; U: unclear; x-x: different lifetimes of multiple components; -: not applicable

Quality: AL: age limit up to which products are accepted as returns for remanufacturing; F: fixed rate; RUL: based on rest-of-useful-life of the product; -: no differentiation

Return rate: AB: based on agent/customer decision; D: distributed return probability; F: fixed share; P: based on past returns; -: not considered

product", it is listed whether the forecast is made for a single product or whether it covers multiple components of a product. In the latter case, different failure rates or times to failure of the components can be considered as well as alternative reuse strategies.

How the product lifetimes or product return times are modeled is depicted in column f). It is indicated if fixed (F) or distributed lifetimes are assumed (continuous distribution: DC; discrete distribution: DD), and if compound products have separate lifetime distributions (e.g., "DD-F" for distributed lifetimes for one component and fixed lifetimes for the other component [57]). Product return times can also be unclear (U) or not applicable (-) due to the random sampling of return numbers. Columns g) and h) indicate quality and return rate considerations. They are often, if at all, included similarly, either by fixed percentages of returns/losses and high-quality returns (F), or by distributed shares (D). For quality considerations, an upper limit in product age can also function as a quality gate (AL), or for compound products, the rest-of-useful-life of a component (RUL). Losses in the return process can also be modeled by agent decision in ABSs or by time-series analysis, based on past returns (P). Mostly, quality and return rates are not considered at all (-).

Concerning the variety of methods, many methods (DLMs, Material Flow Analysis, Discrete Event Simulation) are based on the same principle: They take past sales as input and add a product lifetime to the sales. Kiesmüller and van der Laan [38] pointed out the dependency of returns on past demands, so using the same principle in different approaches seems unproblematic. In these cases, it is suspected that forecasting results are stronger influenced by assumptions than by the method itself. Exceptions are, for example, models that include customer behavior [51] or a region's GDP [22].

From Table 1, it becomes evident that often only *some* aspects that potentially influence EoL return quantities are considered in the literature. For example, Elwert et al. [20], Richa et al. [57], Wang et al. [73], and Wu et al. [74] base their returns estimation on sales forecasts, product lifetimes, and product lifetime distributions but omit quality and losses in the return process. However, it is uncertain whether these omitted factors influence the results significantly. Additionally, often only one scenario is examined, which means one sales forecast, one product lifetime, and one lifetime distribution are assumed, and no sensitivity analysis is performed [11, 20, 73, 74]. Exceptions are, for example, Ai et al. [2] and Richa et al. [57]. Richa et al. [57] create three scenarios from three sales forecasts and three product lifetime distributions. In this way, each scenario differs completely from the others, and we cannot determine the influence of the sales forecast or the lifetime distribution alone. Ai et al. [2] compare some of the assumptions they made. They find that the assumed lifetime and lifetime distribution only mildly affect the results for a short period under review [2]. Market penetration, however, influences the return quantities significantly for an extended period under review [2]. The effect of other assumptions remains open.

We summarize that it has not been studied extensively which factors affect the quantities of EoL products for remanufacturing the most, especially for unestablished products. We intend to close this gap by testing different assumptions on new product sales, product composition, product lifetime, return rate, and return quality. This can help the remanufacturing community focus on the most influencing factors and neglect those that would add complexity without adding value.

EVB-specific assumptions in the literature

In Table 1, the general assumptions made in forecasting models are presented. However, the concrete attribute values for our paper have not been addressed. As mentioned in the introduction, the use case of this paper are EVBs in Germany and their remanufacturing

potential up to the year 2032. The remainder of this paragraph summarizes the EVB-specific assumptions taken in other publications.

Sales To make long-term return forecasts, sales forecasts are needed in most of the discussed methods. EVBs are almost exclusively sold in electric vehicles (EVs). In other words, failed batteries are rarely replaced [73]. That is why we consider EVB sales to be equivalent to EV sales. EVB sales forecasts exist on different regional levels, e.g., world [6, 34, 58], continent (Europe: [17, 34, 66]), or country. Additionally, some sales forecasts contain only battery electric vehicles (BEVs). Others include (Plug-In) Hybrid Electric Vehicles and/or Fuel Cell Electric Vehicles [10, 31, 69]. For Germany, Fig. 1 gives an overview of recent BEV sales forecasts.

Remanufactured and new products as perfect substitutes To the best of our knowledge, remanufacturing of EVBs is not yet performed at an industrial scale. However, some companies investigate options for remanufacturing or have already started at least reconditioning their batteries [16, 62]. For an overview, see Albertsen et al. [3]. In all the projects we are aware of, remanufactured batteries are not seen as equivalents to new batteries but rather as spare parts for older vehicles. However, there are some publications in the literature where remanufactured batteries substitute new batteries [11, 23].

Compound product Depending on the purpose of existing papers, EVs are mainly considered as one product with a fixed time-to-failure or a single time-to-failure distribution for the whole EV [45, 73, 74]. However, some authors consider EVs and EVBs separately with separate lifetime distributions [20, 57], and others even include other components or materials [11, 47].

Product lifetime and distribution When regarding EVB lifetimes, it should be noted that battery failure does not necessarily mean that the battery does not store and release energy anymore. The literature often mentions a State-of-Health (SoH) of 70%—80% as a threshold for an EoL EVB [2, 23, 74]. EVB warranties usually cover an SoH of 70% [1], which
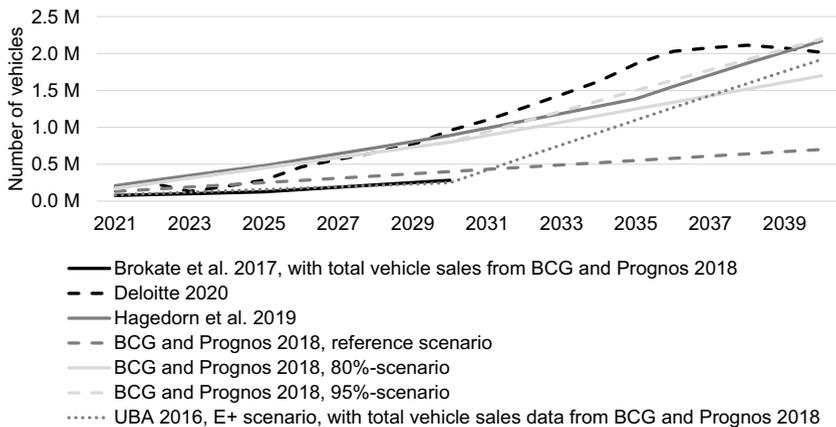
Fig. 1 BEV sales forecasts Germany (Brokate et al. 2017: [10]; BCG and Prognos 2018: [7]; Deloitte 2020: [18]; Hagedorn et al. 2019: [28]; UBA 2016: [67]

is why a threshold higher than 70% seems unrealistic. Additionally, studies have found that batteries could fulfill many customers' travel needs with an SoH of much lower than 80%-70% [59].

Vehicle and battery lifetimes are often modeled as normal or Weibull distributions [32, 45, 54, 57, 73, 74]. For example, Li et al. [45] assume a normal distribution for EVBs with a mean of 8 years and a standard deviation of 0.5, and Richa et al. [57] vary the mean in normal distributions from 8–10 years with an estimated standard deviation of 2. Wu et al. [74] and Ai et al. [2] employ Weibull distributions with shape parameters of 3.5, which results in a shape similar to a normal distribution. The assumptions concerning the mean of battery lifetimes vary significantly. Estimations of 5.5–12.5 years [2], 8 years [19], 8.5–13 years [27], or 25 years [60] can be found. Similarly, assumed mean vehicle lifespans range from 10 to 23 years [29, 52–54, 64]. These vehicle lifespans refer to Internal Combustion Engine Vehicle (ICEVs), but EVs are potentially more durable than ICEVs [33], so the stated vehicle lifetimes can be seen as lower bounds for EV lifetimes. Exceptions of vehicle lifetimes being modeled as distributions can be found, for example, in Richa et al. [57] and Elwert et al. [20]. In their EoL EVB forecasts, battery lifetimes are distributed, while EV lifetimes are fixed.

Return rate When investigating product returns, it can be problematic that customers are not driven to return their EoL products immediately or at all after failure [51]. This seems less relevant for EVBs since, presumably, only very few people keep a non-functioning EV, let alone an EVB without the vehicle. For EoL vehicles, German law obliges customers to return their cars to certified facilities [4]. Still, it is conceivable that not all EVBs return since EV(B)s can leave the system boundaries, e.g., be exported to other countries. Currently, only about 15% of the vehicles (mainly ICEVs) first registered in Germany are scrapped in Germany [68]. However, many of the exported vehicles are exported within Europe and not out of reach for the market. In the literature, little information can be found on the assumed return rate of EVBs. Ai et al. [2] provide sensitivity analyses with collection rates of 50%, 75%, and 100%. This is in line with the opinions some experts shared with the authors, where most experts estimated an EVB return rate of more than 50% in the future.

Quality The quality of returning EVBs is often neglected in EVB return forecasts since many forecasts assume the batteries to be recycled after return [20, 57, 72, 74]. When it is considered, it is in the form of a fixed share of remanufacturable cells (68%, [51]) or reusable share of remaining capacity (100%, 90%, 80%, [2]), or in the form of remaining useful life [47]. The remaining useful life of the battery or its components can only be determined if multiple components with different lifetimes are regarded separately.

Forecasting and capacity planning method

The methods employed in this paper are twofold. First, we want to estimate quantities of EVBs available for remanufacturing when assumptions are varied. Therefore, we need a model that takes attribute assumptions as input, and delivers EVB quantities for remanufacturing. Such a model is presented in the following, including an overview of the assumptions we take as model input. Second, we aim to estimate the economic effects of the return quantities resulting from different assumptions about the future. To do so, we develop a

capacity expansion model that maximizes profit. This way, we can evaluate whether uncertain return quantities affect remanufacturing capacity planning.

Application of various assumptions in forecasting

As pointed out in the literature section, the basic principle of most of the methods used in long-term forecasting is the same. Sales data or forecasts are used as input, and a lifetime distribution is added. Additionally, some other parameters diminish the resulting numbers of returns. Therefore, the focus below is on the assumptions rather than the method.

Appropriate methods to test the assumptions of the influential aspects laid out in the literature section could be Material Flow Analysis, System Dynamics, or Discrete Event Simulation. DES seems best suitable to enable assumptions that require tracking of single entities' characteristics. Entities would be batteries and vehicles, and a characteristic could be the "remaining useful life," which could be a quality criterion (cf. Table 1). The general process scheme and the points where the assumptions come into effect are illustrated in Fig. 2.

The DES is implemented in the multi-method simulation software AnyLogic 8.7.9 University. For all non-deterministic model configurations, i.e., when probability distributions are included, 30 replications are performed to receive statistically comparable results of the simulation.

The model starts with producing batteries and vehicles according to predefined, assumed sales data. The simulated timeframe is 2015–2032. Afterward, the EVs are in
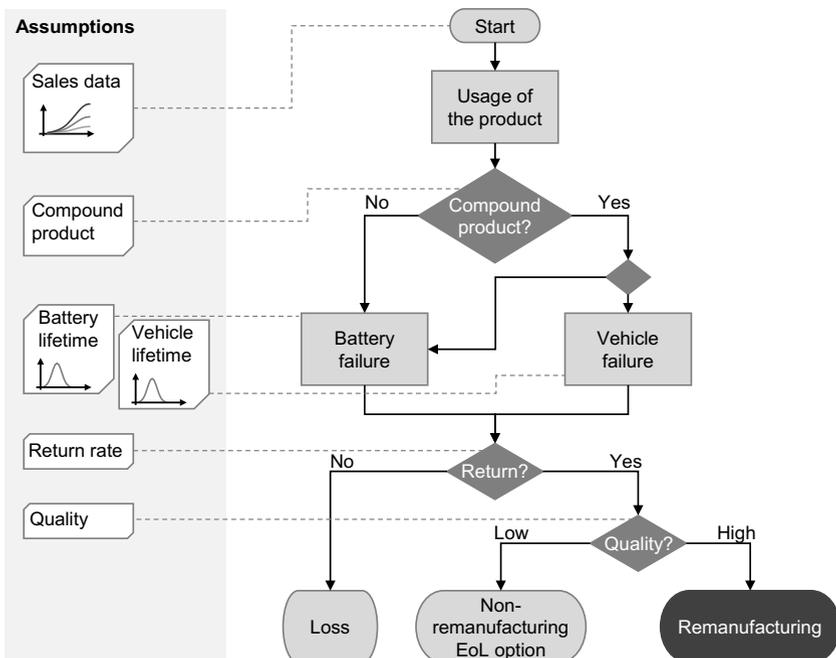

Fig. 2 Process scheme of the DES used to test the assumptions

use. If an EV is regarded as a unit that fails as a whole (non-compound product), the use phase of an EV ends when the battery life expires. If EVs are regarded as a compound of a vehicle and a battery with separate lifetimes, the use phase ends when either the battery or the vehicle life expires. After the end of the use phase, return losses can occur when an EV is not returned within the system boundaries. A quality gate then grades the returning battery as suitable or non-suitable for remanufacturing. The non-suitable batteries are assumed to undergo a recycling treatment or be repurposed. The return flows graded as suitable for remanufacturing are the main output of the model. They are aggregated on an annual level. When multiple replications of the model are performed due to non-deterministic characteristics of the model parameters, the return numbers of the same year are averaged. The averaging is done after the model execution in a data processing program and is not part of the simulation.

The tested assumptions derive from the literature section:

Main input As most methods listed in Table 1 use sales data as inputs, we also use sales as input data. We consider 20% of the German BEV market up to the year 2032, representing Volkswagen's (VW) market share [40]. This amount was chosen to represent one potential market player for remanufacturing better, namely, an OEM. We will test two sales forecasts: the forecast with the highest BEV sales in 2032 [18] and the one with the lowest BEV sales [7] in Fig. 1. In the following these sales assumptions are denoted as follows:

- SH: Sales high
- SL: Sales low

Compound product Some publications regard an EV and an EVB as a unit with a single failure probability, and others regard an EV and an EVB as separate components (cf. section "EVB-specific assumptions in the literature"). Therefore, both cases will be tested. The notation will be as follows:

- 1P: EV and EVB are a unit with a shared time-to-failure.
- 2P: EV and EVB have separate lifetimes.

Product lifetime Since product lifetimes are highly uncertain and many different assumptions have been taken (cf. section "EVB-specific assumptions in the literature"), some variation is necessary. We have to differentiate between the 1P and 2P cases since only one product lifetime has to be assigned in the former, while in the latter, two are required. For battery lifetimes, mean values of 10 years and 12 years are chosen [2, 57], while for EVs only a mean of 12 years is considered [39]. This allows us to compare the case where vehicles, on average, outlast batteries with the case where batteries and vehicles have the same life expectancy. Different combinations of fixed and distributed values are created:

- 1P:
  - BF10 (BF12): The EVB lifetimes are fixed at 10 (12) years. In this way, there is a reference value for cases incorporating distributed lifetimes.
  - BD10: EVB lifetimes follow a normal distribution with a mean of 10 years and a standard deviation of 2 years (cf. [57]). This case can easily be compared to BF10.

- 2P:
  - BD10/VF12: EVB lifetimes follow a normal distribution with a mean of 10 years and a standard deviation of 2 years (cf. [57]). Vehicle lifetimes are fixed at 12 years.
  - BD10/VD12: EVB lifetimes follow a normal distribution with a mean of 10 years and a standard deviation of 2 years (cf. [57]). Vehicle lifetimes follow a normal distribution, too, with a mean of 12 years and the same standard deviation of 2 years.

Quality From Table 1, it seems as if there was no standard for quality incorporation into forecasting yet. Therefore, different ways to include it are tested:

- QF70, QF100: Fixed shares of remanufacturability are tested (70%, 100%). Approx. 70% are in line with Kampker et al. [37], and 100% are assumed in almost all other publications.
- QD70: A uniformly distributed quality rate is assumed with a mean of 70% (U(60%, 80%)). This loosely refers to distributed qualities listed in Table 1.
- QR0: The remaining useful life of the battery is used as a quality criterion here, as did Liang et al. [46]. For simplicity, all batteries with a remaining useful life of more than zero years are considered suitable for remanufacturing; that includes all cases in which the vehicle failed first.
- QA8: Additionally, the age of the EVB at failure is chosen as a quality criterion, as it is sometimes done in other approaches listed in Table 1. The standard warranty time of 8 years is selected as an upper age limit.

Return rate Return rates are expected to influence the amount of returned EVBs significantly. For lack of other information, the fixed collection rates of Ai et al. [2] are chosen for assumption testing. Additionally, a distributed return rate is tested, as it has been applied in some of the publications listed in Table 1:

- RF50, RF75, RF100: Fixed return rates of 50%, 75% and 100%
- RD75: A uniformly distributed return rate is assumed with a mean of 75% (U(65%, 85%)).

The tested assumptions are summarized in Fig. 3 and add up to 200 combinations.

Capacity Planning

A generic capacity optimization model is applied to monetarily evaluate the resulting return numbers. It does not claim to mirror reality precisely. Instead, we intend to give a general impression of the consequences of different return numbers resulting from various assumptions. The parameters of the capacity planning module are fixed so that uncertain estimates like the cost for expanding remanufacturing capacity have the same effect in all return forecast scenarios. The mathematical formulation of the capacity optimization is as follows:

$$Max \sum_{t}^{T} \sum_{i}^{I} (Rev_t x_{it} - VC_{it} x_{it} - FC_{it} y_{it}) \tag{1}$$

$$\text{s.t. } s_t \geq \sum_{i}^{I} x_{it} \quad \forall t \in T \tag{2}$$

$$x_{it} \leq C_i y_{it} \ \forall t \in T, i \in I \tag{3}$$

$$y_{it-1} \leq y_{it} \ \forall t \in T : t > 1, i \in I \tag{4}$$

$$x_{it} \geq 0 \ \forall t \in T, i \in I \tag{5}$$

$$y_{it} \in \mathbb{Z}^{\geq 0} \tag{6}$$

Sets

T	Set of discrete time periods with t = 1,2,…T
I	Set of different remanufacturing capacity modules i = 1,2
Parameters	
Rev_t	Revenue per remanufactured EVB in period t
VC_{it}	Variable cost of remanufacturing one EVB with remanufacturing capacity module i in period t
FC_{it}	Fixed cost per period per utilized remanufacturing capacity module i in period t
s_t	Supply of EoL EVBs in period t
C_i	Maximum capacity limit of a remanufacturing capacity module size i
Decision Variables	
x_{it}	Amount of remanufactured EVBs with capacity module of type i in period t
y_{it}	Number of installed capacity modules of type i in period t

Our capacity planning module aims to maximize profit over all periods *t*, representing the years 2022–2032. We include revenues and fixed and variable costs in the objective function (1). Every remanufactured unit is assumed to generate revenue, or, in other words, there is always demand. This assumption is in line with, e.g., Foster et al. [23]. The main output of the optimization model is the number and capacity of remanufacturing facilities to achieve the goal of maximum profit. For the sake of simplicity, we introduce two capacity modules *I*, small and large, of which whole multiples y_{it} can be opened to fulfill remanufacturing tasks (6). There is no capacity contraction, which means that a capacity module cannot be built back (4). Additionally, the number of batteries to be remanufactured per period, x_{it}, is a decision variable. That means there is no obligation to remanufacture a part if it is not economically viable. This assumption is chosen because otherwise, overcapacity would be built into the model by default. As Fleischmann 2001 (as cited in [25]) pointed out, overcapacity is a common remanufacturing problem. There is no storage between periods, so the maximum number of batteries to be remanufactured per period is limited by the battery supply (2) and the installed capacity in that period (3).

The main input parameters of the optimization model are the supply quantities of EoL battery systems per period s_t. They are the results of the return forecasts described in the previous section. We use literature values and the VW ID.3 battery specifications as a guideline for estimating the other parameter values.

Sales data (S)	SH: high sales numbers	SL: low sales numbers
Compound product (P)	1P: vehicle and battery as a single entity	2P: compound of vehicle and battery
Battery lifetime (B)	BF10: fixed lifetime of 10 years BF12: fixed lifetime of 12 years	BD10: normally distributed lifetime with mean of 10 years, standard deviation of 2 years
Vehicle lifetime (V)	VF12: fixed lifetime of 12 years	VD12: normally distributed lifetime with mean of 12 years, standard deviation of 2 years
Quality (Q)	QF70: a core is remanufacturable with probability 70% QF100: a core is remanufacturable with probability 100% QA8: a core is remanufacturable if it is younger than 8 years	QD70: a core is remanufacturable with probability U(60%, 80%) QR0: a core is remanufacturable if remaining useful life >0 years
Return rate (R)	RF50: a core returns with probability 50% RF75: a core returns with probability 75%	RF100: a core returns with probability 100% RD75: a core is remanufacturable with probability U(65%, 85%)

Further notation: "sales-compound product-battery lifetime/vehicle lifetime-quality-return rate",
e.g. "SH-2P-BF10/VF12-QF70-RD75".
Variation of one aspect is denoted by an "x", e.g., "[…]-QF70-x"

Fig. 3 Summary of assumptions with abbreviations

The size of the large and the small capacity units should reflect that we intend to regard industrial-sized remanufacturing (cf. Introduction). Sommerville et al. find recycling companies in Europe to be beyond the pilot stage starting from 2000 t/year and more [61]. If the same capacity threshold is applied to remanufacturing, and the weight of a 77 kWh ID.3 battery of 514 kg is assumed [35], a small capacity unit C_1 of approx. 4,000 EVBs/year results. The large capacity unit C_2 is set to double the value, i.e., 8,000 EVBs/year.

Revenues and costs are estimated at today's level and discounted with a moderate discount rate of 3%. For revenues, 50% of the new sales price is assumed [56]. With 118 $/kWh for new BEV batteries today [8], 77 kWh per battery [71], and 0.89 €/$ [21], that makes a non-discounted revenue of approx. 4,000 € per remanufactured battery. Fixed cost comprises annualized capacity unit costs. Li et al. [45] assume opening costs of 650,000 $ per 1,500 EVBs capacity, Standridge et al. [63] 25 million $ per 30,000 EVBs capacity. With a 20-year payback-period, fixed cost per year before discounting (FC_{11}) of 100,000 € per small capacity unit (4000 EVBs/year) is between the abovementioned studies. With moderate economies of scale [44], the fixed cost of the large capacity unit is 160,000 €/year (FC_{21}). Variable cost is assumed to be equal for both capacity modules and takes on the value of 3000 €/battery (VC_{i1}) [36, 45].

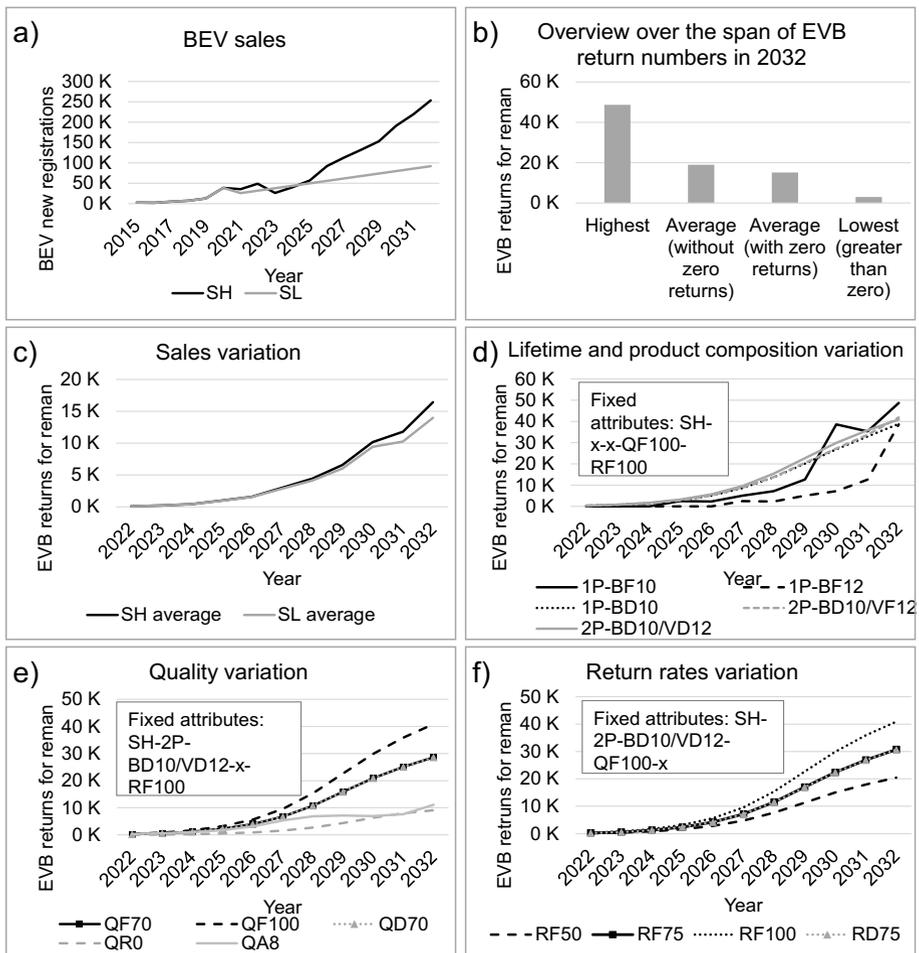# Results

We first present the results concerning the expected EVB quantities for remanufacturing when varying the assumptions. In the following section, we show the results of the capacity optimization tool when inputting the EVB return amounts.

Battery returns for remanufacturing

In Fig. 4a, the EV sales data are depicted for comparison with our EoL battery forecasts. The sales scenarios overlap until about 2025 and then diverge into high and low sales numbers.

Figure 4b-f summarizes the results of forecasting EVB returns with our forecast model and different assumptions. Figure 4b gives an overview of the span of results concerning

Fig. 4 Results of BEV return forecasts for remanufacturing up to 2032 under different attribute assumptions

EVB returns for remanufacturing in 2032. The highest return number of about 48,500 EVBs results from assuming high sales numbers, fixed battery lifetimes of 10 years, no separate vehicle lifetimes, 100% of cores are suitable for reman, and 100% return rate (SH-1P-BF10-QF100-RF100). The lowest reman numbers are zero and result from assumption combinations that inevitably lead to no cores, e.g., combining the one-product case 1P with the quality criterion QR0, i.e., remaining life greater than zero. Other than that, the lowest return number in 2032 is approx. 3000 EVBs (SL-2P-BD10/VF12-QR0-RF50). On average, approx. 15,000 cores, including cases with zero returns, and 19,000 cores, excluding cases with zero returns, can be expected in 2032 for our modeled market player.

Figure 4c shows the average annual EVB returns for all cases that incorporate high and low sales (SH and SL). As expected, the SH cases, on average, lead to more EVB returns. However, the difference in 2032 is only 18% of the lower case. Depending on the assumptions, the difference can increase to approx. 53% (1P-BF10) or even lower to approx. 0% (1P-BF12). This can be explained by the shape of the sales Figs. 4a. In the 1P-BF10 cases, the returns in 2032 equal the sales in 2022 (=2032–10 years) minus reductions for quality and return losses; In 2022 the sales numbers of BEVs were higher in the SH scenario than in the SL scenario, which reflects in the return quantities. In the 1P-BF12 cases, however, basically the sales of 2020 (=2032–12 years) are depicted, and up to 2020 real-world sales data were used; That means, in 2020 the SL and the SH scenario are the sameand no difference between the scenarios can be detected. In general, it becomes evident that for long-living products and a planning horizon of approximately the lifespan of a product, the sales forecasts are probably less important since future returns mainly depend on present sales.

Figure 4d also shows that the 1P-BF10 and 1P-BF12 cases mirror the sales of 2022 and 2020. While the fixed lifetime cases follow the sales figures sharply, the distributed cases smooth out extreme values. The 1P-B*D*10 case, therefore, leads to fewer returns in 2032 than the 1P-B*F*10 case, although they have the same mean value for battery lifetimes. If vehicles can also lead to a system failure and, therefore, to battery returns, EVBs return slightly earlier. The only *slight* difference is probably due to the distribution parameters, where most batteries will fail before the vehicles do. There are a few more (i.e., earlier) battery returns when vehicle lifetimes are also distributed.

Quality and return rate, as shown in Figs. 4e and f, seem to influence EVB returns the most. Naturally, from QF100 to QF70 (RF100 to RF75 and RF50), there is a 30% (25% and 50%) decline. Notably, the uniform quality and return rate distributions do not affect the return quantities (QF70≈QD70; RF75≈RD75). The mean seems to be the determining value here. For quality, however, two unusual criteria were tested as well, namely QR0 (remaining useful life greater than zero) and QA8 (failure age less or equal to 8 years). These reduce the number of cores for remanufacturing significantly; still, they are seldom used in literature (cf. section "EVB-specific assumptions in the literature"). Here, the thresholds of zero and eight, respectively, are chosen more or less randomly (cf. section "Application of various assumptions in forecasting"). It seems as if these criteria should gain more attention in remanufacturing forecasting, especially since they include information that intuitively might be more relevant than fixed shares. Whether that holds remains to be examined.

Remanufacturing capacity

As described in the "Capacity Planning" section, capacity planning based on a linear optimization model is performed with the return numbers resulting from the simulation. As a result, we obtain the installed capacity per period with small and large capacity units and

the potential cost and revenues. Figure 5 illustrates the results for (a) the scenarios with the highest and the lowest return numbers in 2032 (cf. Fig. 4b) and (b) for the altered assumptions concerning the quality determination. The different return numbers lead to substantially different optimal capacity expansions and different associated costs. While return forecasts like those that lead to the highest return numbers in 2032 (Fig. 5a) indicate that EVB remanufacturing capacity is needed only from 2025 onwards and on a larger scale only from 2030 onwards ("Highest" case), others indicate that investing in remanufacturing capacity much earlier would be beneficial (Fig. 5b). For the SH-2P-BD10/VD12-QR0-RF100 case (denoted as QR0), investment in a large capacity unit of 8000 EVBs/year would be beneficial from 2022 onwards. All other quality metrics with the otherwise same assumptions suggest little EVB remanufacturing capacity from 2023 onwards.

Similar results concerning expansion timings can be obtained from the lifetime and product composition variation (Fig. 5c). Here, the slowest capacity expansion is suggested for the 1-product, fixed lifetime at 12 years case (1P-BF12), following the low return numbers of that case (Fig. 4d). The higher the number of early failures due to distributed lifetimes of one or both components, the earlier capacity expansion would be beneficial. However, at the end of the period under examination, in 2032, the total installed capacity is almost identical for all lifetime distributions.

Discussion

We showed that applying common assumptions in EVB returns forecasting leads to a wide range of core quantities. We then used the core quantities as inputs for a model that optimizes remanufacturing capacity costs. The resulting capacity expansion plans differed majorly regarding the time when capacity should be first built and the final size. All of the attributes under examination seem to affect return quantities and optimal remanufacturing capacity. However, the effects are not equally severe. Sales numbers, for example, are not as influential as we expected. This is probably because the planning horizon of 10 years ahead is equal to or less than the assumed product lifetime, and, therefore, most EVBs returning in 2032 are registered today. Concerning product lifetime, the battery life turned out to be more important than the vehicle lifetime. Quality and return rates also significantly influence the number of cores for remanufacturing and the necessary capacity. However, they are probably most uncertain in new markets.

For the research community, several implications can be drawn. First, for long-living products, it is less relevant which sales forecast is used for core forecasting since the return numbers in the foreseeable future mainly depend on past sales. That means return estimates in the literature that only used one sales projection as an input rightfully did so (e.g., [11, 20]). Ai et al. [2] come to a different conclusion. In their study, the EV market penetration influences product returns significantly. However, their study covers a broader time frame (2000 – 2040) and uses estimates from 2017 onwards. That means they cover a time frame which is far broader than the average product lifespan. Our study does not allow statements about such an extended period. One exemption from the unimportance of sales forecasts occurs when fixed product lifespans are assumed because the return forecast then shadows the sales projection precisely. Only a minority of researchers made this assumption (cf. Table 1), and we do not recommend it. Other than in the fixed lifespan cases, the lifespan and the distribution do not seem to have a large effect. This is in line with the literature [2].
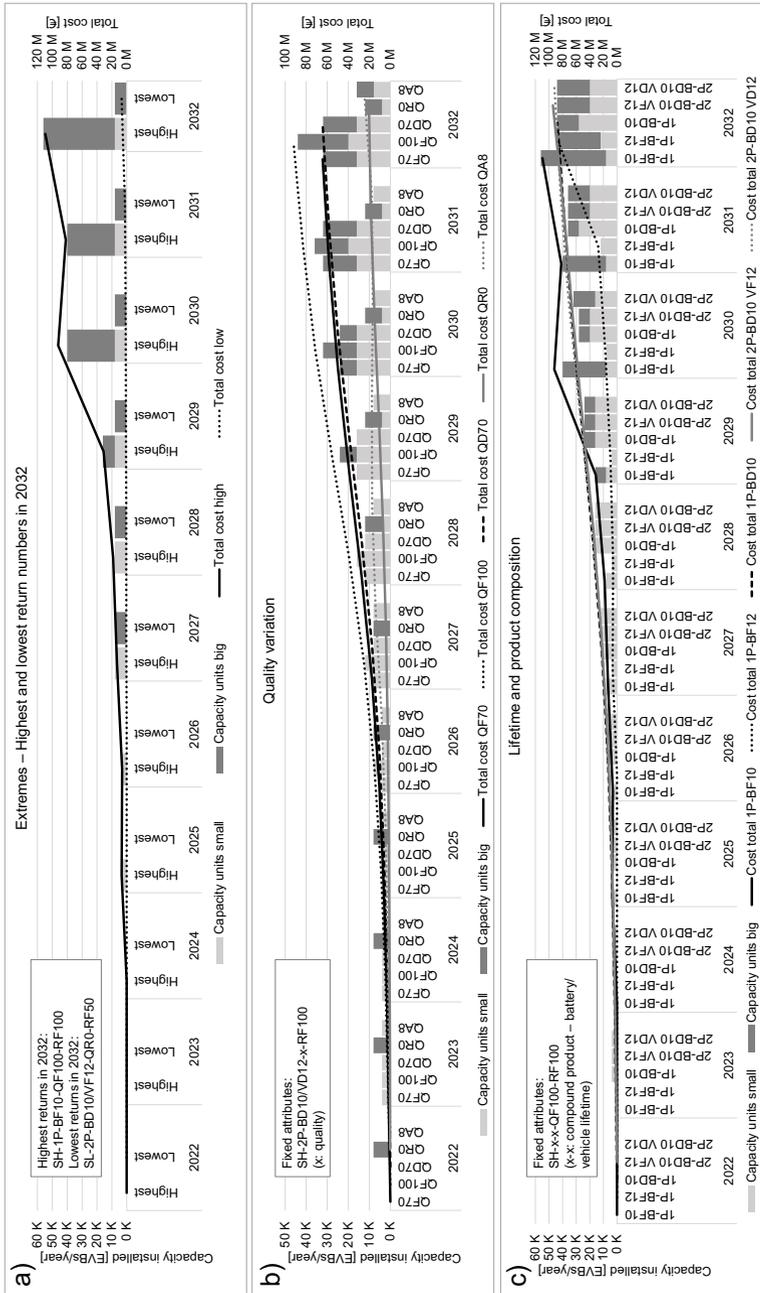
Fig. 5 Capacity to be installed and associated cost (fixed and variable) in **a**) the highest and the lowest return scenarios, **b**) different quality determination scenarios, and **c**) different lifetime and product composition scenarios

Another research implication comes from the multi-component cases. Multi-component products with individual failure times are interesting for several reasons. E.g., they enable more elaborate quality criteria and single entity tracking. Nonetheless, if the only research goal is to quantify core numbers for remanufacturing, early failures of a second component only slightly influence the overall results. This holds for the lifespan values we tested. That means putting effort into detailed component modeling should be evaluated based on the use case.

Most attention should be paid to the modeling and parameterization of return rate and quality criteria. We showed that these have a significant effect on the results. However, they are seldomly incorporated into forecasting models (cf. Table 1). Making no assumption about these criteria means assuming a return and quality rate of 100%. We recommend that quality and return rate assumptions are evaluated and justified more carefully in the future. Additionally, we suggest collaboration with practitioners to gain more knowledge about good quality criteria that can be beneficially incorporated into long-term forecasts.

We already mentioned that our statements are only valid for a limited timeframe compared to the product's lifespan. Besides that, we are also bound by the other parameter values we chose. We tried to justify these values in the methods section. However, we cannot guarantee that the results would have been the same with other values. This holds not only for the assumed parameter values but also for the method. We argued that with a discrete event simulation, we could include all relevant assumption categories and that it would include the main elements of a DLM or a MFA. However, verifying that claim remains open. Additionally, we performed the forecasting and the capacity planning with static input values. Future research could test the effect of dynamic parameters on forecasting and capacity optimization.

For the industry, the broad results span is problematic since trusting one forecast that indicates a large number of early returns might lead to malinvestments in remanufacturing capacity. If another forecast turns out to be accurate, this capacity might not be needed so soon and, therefore, only causes cost but little revenue. Similarly, late investments indicated by other forecasts might lead to lost profit if EVBs return earlier than anticipated. Of course, a capacity expansion plan ten years ahead is not static for the whole planning period but is constantly adjusted to reality and newly available information. Nevertheless, early decisions on if and when to open a remanufacturing facility, in combination with the decision if and when to engage in remanufacturing R&D activities of a new product, can affect future success. Therefore, the applied generic optimization model might be altered and could potentially be used as a stochastic model.

Our approach compared different assumptions in remanufacturing quantity forecasting found in the literature. Forecasting in business, however, might differ from that. During our research, informal communication with remanufacturers has disclosed that personal experience and internal planning tools support the planning process. However, it was also confirmed that there are still many unknown parameters for forecasting core quantities and understanding the interrelations between the influencing factors and stakeholders. Future research could, therefore, extend the sales- and lifespan-based approach by including more perspectives that might influence return rates and qualities, e.g.:

- Politics/legislation: Legislation can support remanufacturing by implementing reman-friendly regulation or even force remanufacturing, or hinder it by, e.g., setting high market entrance barriers or favoring other EoL options.

- Remanufacturers' characteristics: Core accessibility and quality of these cores might differ if the forecast is done for an OEM in contrast to an independent remanufacturer. An OEM has access to contract workshops as sources for cores and potential selling points of remanufactured products. Therefore, the recipient of the forecast should be considered more closely.
- Further stakeholders, like workshops, scrapyards, and core brokers: It could be examined which contract models favor a core return and how deposits and buyback prices influence return rates.

Furthermore, the demand side should not be neglected. Some approaches already include demand, e.g., by assuming a demand distribution [5], by linking it to new product demand by "net demand" forecasting [26], or by assuming known and stationary demand [70]. However, when assuming that demand for remanufactured products mainly comes from the aftermarket, more research should be done on aftermarket customers, e.g., concerning their intentions to replace faulty components and their acceptance of remanufactured spare parts. We, therefore, suggest extending research concerning agent behavior and external conditions to improve forecasting in remanufacturing.

Conclusions

In this article, we examined how different assumptions in product return forecasting for remanufacturing affect long-term remanufacturing capacity planning for the case of electric vehicle batteries. Grounded in literature, we assumed two different sales forecasts, a single and a compound product case, five lifetime combinations for the single or compound product, five ways to determine the quality of returning products, and four return rates. Afterward, we applied an optimization model to determine remanufacturing capacity expansion plans. We found that battery lifetime, quality determination, and return rate had the greatest influence on product return quantities and, therefore, on capacity planning for the chosen assumptions. We also found that the assumptions led to substantially differing optimal entry points into remanufacturing activities and unequal expectations about the total market size for EVB remanufacturing in the coming decade. All in all, it seems as if not all factors influencing product returns for remanufacturing are known, or they are known in business but have not reached the scientific community yet. Because of the importance of this knowledge concerning R&D activities and profitability of potential businesses, we suggest investigating the influential factors more closely, e.g., examining the stakeholders' behavior.

Declarations

Competing interests The authors declare no competing interests.

References

1. ADAC (2021) Elektroauto-Batterie: Lebensdauer. Garantie, Reparatur. https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/info/elektroauto-batterie/
2. Ai N, Zheng J, Chen W-Q (2019) U.S. end-of-life electric vehicle batteries: Dynamic inventory modeling and spatial analysis for regional solutions. Resour Conserv Recycl 145:208–219. https://doi.org/10.1016/j.resconrec.2019.01.021
3. Albertsen L, Richter JL, Peck P et al (2021) Circular business models for electric vehicle lithium-ion batteries: An analysis of current practices of vehicle manufacturers and policies in the EU. Resour Conserv Recycl 172:105658. https://doi.org/10.1016/j.resconrec.2021.105658
4. Altfahrzeug-Verordnung [End-of-life Vehicles Regulation] in the version published on June 21, 2002 (BGBl. I p. 2214), as last amended by Article 1 of the Regulation of November 18, 2020 (BGBl. I p. 2451)
5. Baki MF, Chaouch BA, Abdul-Kader W (2014) A heuristic solution procedure for the dynamic lot sizing problem with remanufacturing and product recovery. Comput Oper Res 43:225–236. https://doi.org/10.1016/j.cor.2013.10.001
6. BCG (2020) Who will drive electric cars to the tipping point? https://image-src.bcg.com/Images/BCG-Who-Will-Drive-Electric-Cars-to-the-Tipping-Point-Jan-2020-rev_tcm9-237575.pdf
7. BCG, Prognos (2018) Klimapfade für Deutschland. https://www.bcg.com/de-de/publications/2018/climate-paths-for-germany
8. BloombergNEF (2021) Battery pack prices fall to an average of $132/kWh, but rising commodity prices start to bite | BloombergNEF. https://about.bnef.com/blog/battery-pack-prices-fall-to-an-average-of-132-kwh-but-rising-commodity-prices-start-to-bite/
9. Boone T, Ganeshan R, Jain A et al (2019) Forecasting sales in the supply chain: Consumer analytics in the big data era. Int J Forecast 35:170–180. https://doi.org/10.1016/j.ijforecast.2018.09.003
10. Brokate J, Schimeczek C, Friedrich HE (2017) A disaggregated approach to model international passenger car markets and their interdependencies. In: European battery, hybrid and fuel cell electric vehicle congress, Geneva, 2017
11. Busch J, Steinberger JK, Dawson DA et al (2014) Managing critical materials with a technology-specific stocks and flows model. Environl Sci Technol 48:1298–1305. https://doi.org/10.1021/es404877u
12. Chambers JC, Mullick SK, Smith DD (1971) How to choose the right forecasting technique. Harv Bus Rev (July 1971)
13. Chou M, Sim CK, Yuan XM (2020) Policies for inventory models with product returns forecast from past demands and past sales. Ann Oper Res 288:137–180. https://doi.org/10.1007/s10479-020-03545-4
14. Clottey T (2016) Development and evaluation of a rolling horizon purchasing policy for cores. Int J Prod Res 54:2780–2790. https://doi.org/10.1080/00207543.2016.1142133
15. Clottey T, Benton W (2014) Determining core acquisition quantities when products have long return lags. IIE Transactions 46:880–893. https://doi.org/10.1080/0740817X.2014.882531
16. Daimler (2021) Patented cell replacement treatment. https://www.daimler.com/sustainability/battery-life-cycle/use-charging/remanufacturing-reportage.html
17. Deloitte (2020) Electric vehicles: Setting a course for 2030. https://www2.deloitte.com/uk/en/insights/focus/future-of-mobility/electric-vehicle-trends-2030.html

18. Deloitte (2020) Elektromobilität in Deutschland. Marktenwicklung bis 2030 und Handlungsempfehlungen. https://www2.deloitte.com/de/de/pages/consumer-industrial-products/articles/elektromobilitaet-in-deutschland.html. Accessed 10 Feb 2021

19. Drabik E, Rizos V (2018) Prospects for electric vehicle batteries in a circular economy. CEPS Research Report. https://www.ceps.eu/download/publication/?id=10660&pdf=RR%202018_05_Circular%20Impacts_batteries.pdf

20. Elwert T, Römer F, Schneider K et al (2018) Recycling of batteries from electric vehicles. In: Pistoia G, Liaw B (eds) Behaviour of lithium-ion batteries in electric vehicles. Springer International Publishing, Cham, pp 289–321

21. European Central Bank (2022) ECB euro reference exchange rate: US dollar (USD). https://www.ecb.europa.eu/stats/policy_and_exchange_rates/euro_reference_exchange_rates/html/eurofxref-graph-usd.en.html

22. Fang X, Ni SY, Li HL et al (2018) General regression neural network and artificial-bee-colony based general regression neural network approaches to the number of end-of-life vehicles in China. IEEE Access 6:19278–19286. https://doi.org/10.1109/ACCESS.2018.2814054

23. Foster M, Isely P, Standridge CR et al (2014) Feasibility assessment of remanufacturing, repurposing, and recycling of end of vehicle application lithium-ion batteries. JIEM 7. https://doi.org/10.3926/jiem.939

24. Georgiadis P, Vlachos D, Tagaras G (2006) The impact of product lifecycle on capacity planning of closed-loop supply chains with remanufacturing. Prod Oper Manag 15:514–527

25. Georgiadis P, Athanasiou E (2013) Flexible long-term capacity planning in closed-loop supply chains with remanufacturing. Eur J Oper Res 225:44–58. https://doi.org/10.1016/j.ejor.2012.09.021

26. Goltsos TE, Syntetos AA, van der Laan E (2019) Forecasting for remanufacturing: The effects of serialization. J Oper Manag 65:447–467. https://doi.org/10.1002/joom.1031

27. Guenther C, Schott B, Hennings W et al (2013) Model-based investigation of electric vehicle battery aging by means of vehicle-to-grid scenario simulations. J Power Sources 239:604–610. https://doi.org/10.1016/j.jpowsour.2013.02.041

28. Hagedorn M, Hartmann S, Heilert D et al (2019) Automobile Wertschöpfung 2030/2050. Studie im Auftraag des Bundesministeriums für Wirtschaft und Energie. https://www.bmwi.de/Redaktion/DE/Publikationen/Studien/automobile-wertschoepfung-2030-2050.pdf?__blob=publicationFile&v=16

29. Hao H, Geng Y, Sarkis J (2016) Carbon footprint of global passenger cars: Scenarios through 2050. Energy 101:121–131. https://doi.org/10.1016/j.energy.2016.01.089

30. Hao H, Zhang Q, Wang ZG et al (2018) Forecasting the number of end-of-life vehicles using a hybrid model based on grey model and artificial neural network. J Clean Prod 202:684–696. https://doi.org/10.1016/j.jclepro.2018.08.176

31. Harlow JE, Ma X, Li J et al (2019) A wide range of testing results on an excellent lithium-ion cell chemistry to be used as benchmarks for new battery technologies. J Electrochem Soc 166:A3031–A3044. https://doi.org/10.1149/2.0981913jes

32. Harris SJ, Harris DJ, Li C (2017) Failure statistics for commercial lithium ion batteries: A study of 24 pouch cells. J Power Sources 342:589–597. https://doi.org/10.1016/j.jpowsour.2016.12.083

33. Hoekstra A, Steinbuch M (2020) Comparing the lifetime green house gas emissions of electric cars with the emissions of cars using gasoline or diesel. https://static.arkku.datadesk.hs.fi/arkku/files/26649046englisch_StudieEAutoversusVerbrenner_CO2.pdf

34. IEA (2020) Global EV outlook 2020. Entering the decade of electric drive? https://www.iea.org/reports/global-ev-outlook-2020

35. Illgen Autohaus (2021) 10 Dinge die Sie vor dem Kauf eines Volkswagen ID.3 wissen sollten. https://www.autohaus-illgen.de/vw-id3-diese-10-dinge-sollten-sie-ueber-den-volkswagen-id-3-wissen/. Accessed 03 Feb 2022

36. Kampker A, Heimes H, Ordung M et al (2016) Evaluation of a remanufacturing for lithium ion batteries from electric cars. World Academy of Science, Engineering and Technology, International Journal of Mechanical and Mechatronics Engineering 3:1929–1935

37. Kampker A, Wessel S, Fiedler F et al (2020) Battery pack remanufacturing process up to cell level with sorting and repurposing of battery cells. Jnl Remanufactur. https://doi.org/10.1007/s13243-020-00088-6

38. Kiesmüller GP, van der Laan EA (2001) An inventory model with dependent product demands and returns. https://ssrn.com/abstract=370876

39. Kolli Z (2011) Car longevity : A biometric approach. In: Proceedings of YRS2011 - seminar 2011, Denmark, 24

40. Kraftfahrt-Bundesamt (2021) Neuzulassungen von Personenkraftwagen nach Marken und Modellreihen FZ 10. Monatsergebnisse Dezember 2020. https://www.kba.de/DE/Statistik/Fahrzeuge/

Neuzulassungen/MonatlicheNeuzulassungen/monatl_neuzulassungen_node.htm. Accessed 18 Feb 2021

41. Krapp M, Nebel J, Sahamie R (2013) Forecasting product returns in closed-loop supply chains. Int Jnl Phys Dist & Log Manage 43:614–637. https://doi.org/10.1108/IJPDLM-03-2012-0078

42. Krug Z, Guillaume R, Battaïa O (2021) Exploring the opportunities in establishing a closed-loop supply chain under uncertainty. Int J Prod Res 59:1606–1625. https://doi.org/10.1080/00207543.2020.1808259

43. Kumar DT, Soleimani H, Kannan G (2014) Forecasting return products in an integrated forward/reverse supply chain utilizing an ANFIS. Int J Appl Math Comput Sci 24:669–682. https://doi.org/10.2478/amcs-2014-0049

44. Kwade A, Bärwaldt G (2012) LithoRec - recycling von lithium-ionen-batterien. Abschlussbericht des Verbundvorhabens

45. Li L, Dababneh F, Zhao J (2018) Cost-effective supply chain for electric vehicle battery remanufacturing. Appl Energy 226:277–286. https://doi.org/10.1016/j.apenergy.2018.05.115

46. Liang X, Jin X, Ni J (2014) Forecasting product returns for remanufacturing systems. Jnl Remanufactur 4. https://doi.org/10.1186/s13243-014-0008-x

47. Liang X (2018) A general approach to electical vehicle battery remanufacturing system design. Dissertation. University of Michigan

48. Ma J, Kim HM (2016) Predictive model selection for forecasting product returns. J Mech Des 138. https://doi.org/10.1115/1.4033086

49. Marcos JT, Scheller C, Godina R et al (2021) Sources of uncertainty in the closed-loop supply chain of lithium-ion batteries for electric vehicles. Clean Logist Supply Chain 1:100006. https://doi.org/10.1016/j.clscn.2021.100006

50. Marx-Gómez J, Rautenstrauch C, Nürnberger A et al (2002) Neuro-fuzzy approach to forecast returns of scrapped products to recycling and remanufacturing. Knowl Based Syst 15:119–128. https://doi.org/10.1016/S0950-7051(01)00128-9

51. Mashhadi AR, Esmaeilian B, Behdad S (2016) Simulation modeling of consumers' participation in product take-back systems. J Mech Des 138. https://doi.org/10.1115/1.4032773

52. Masias A (2018) Lithium-ion battery design for transportation. In: Pistoia G, Liaw B (eds) Behaviour of lithium-ion batteries in electric vehicles. Springer International Publishing, Cham, pp 1–33

53. Mueller DB, Cao J, Kongar E et al. (2007) Service lifetimes of mineral end uses. Final report. U.S. Geological Survey (USGS) [Final Report, Minerals Resources External Research Program, Award Number: 06HQGR0174]

54. Oguchi M, Fuse M (2015) Regional and longitudinal estimation of product lifespan distribution: a case study for automobiles and a simplified estimation method. Environ Sci Technol 49:1738–1743. https://doi.org/10.1021/es505245q

55. Olhager J, Rudberg M, Wikner J (2001) Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. Int J Prod Econ 69:215–225. https://doi.org/10.1016/S0925-5273(99)00098-5

56. Persistence Market Research (2019) Global market study on automotive parts remanufacturing: 30-50% cost benefit over high-quality original products to accelerate revenue growth. https://www.persistencemarketresearch.com/market-research/automotive-parts-remanufacturing-market.asp

57. Richa K, Babbitt CW, Gaustad G et al (2014) A future perspective on lithium-ion battery waste flows from electric vehicles. Resour Conserv Recycl 83:63–76. https://doi.org/10.1016/j.resconrec.2013.11.008

58. Rietmann N, Hügler B, Lieven T (2020) Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO2 emissions. J Clean Prod 261:121038. https://doi.org/10.1016/j.jclepro.2020.121038

59. Saxena S, Le Floch C, MacDonald J et al (2015) Quantifying EV battery end-of-life through analysis of travel needs with vehicle powertrain models. J Power Sources 282:265–276. https://doi.org/10.1016/j.jpowsour.2015.01.072

60. Schoch J (2018) Battery life optimal operation of electric vehicles. Dissertation, Karlsruher Institut für Technologie

61. Sommerville R, Zhu P, Rajaeifar MA et al (2020) SWAVE for LIB recycling (1.2.0) [data set]

62. Spiers New Technologies (2022) Spiers new technologies. http://www.spiersnewtechnologies.com/#snt

63. Standridge C, Corneal L (2014) Remanufacturing, repurposing, and recycling of post-vehicle-application. Lithium-ion batteries. https://www.michigan.gov/documents/mdot/RC1604_462068_7.pdf?20140708085845

64. Thielmann A, Sauer A, Wietschel M (2015) Produkt-Roadmap Energiespeicher für die Elektromobilität:2030. http://www.isi.fraunhofer.de/isi-wAssets/docs/t/de/publikati
65. Toktay B, van der Laan EA, Brito MP de (2003) Managing product returns: The role of forecasting
66. Tsiko D, Papadimitriou CN, Psomopoulos CS et al (2019) Study and analysis on EVs penetration scenarios based in prognostic tools. In: Xiamen-Custipen workshop on the equation of state of dense neuron-rich matter in the era of gravitational wave astronomy. AIP Publishing, p 030008. https://doi.org/10.1063/1.5117039
67. UBA (2016) Erarbeitung einer fachlichen Strategie zur Energieversorgung des Verkehrs bis zum Jahr:2050 https://www.umweltbundesamt.de/publikationen/erarbeitung-einer-fachlichen-strategie-zur
68. Umweltbundesamt (2021) Altfahrzeugverwertung und Fahrzeugverbleib. https://www.umweltbundesamt.de/daten/ressourcen-abfall/verwertung-entsorgung-ausgewaehlter-abfallarten/altfahrzeugverwertung-fahrzeugverbleib#rund-eine-halbe-million-altfahrzeuge-jahrlich
69. US Energy Information Administration (2021) Annual energy outlook 2021. https://www.eia.gov/outlooks/aeo/
70. Vlachos D, Georgiadis P, Iakovou E (2007) A system dynamics model for dynamic capacity planning of remanufacturing in closed-loop supply chains. Comput Oper Res 34:367–394. https://doi.org/10.1016/j.cor.2005.03.005
71. Volkswagen (2022) Der ID.3 | Elektrofahrzeug | Modelle | Volkswagen Deutschland. https://www.volkswagen.de/de/modelle/id3.html. Accessed 03 Feb 2022
72. Wang H, Peng Q, Zhang J et al (2017) Selective disassembly planning for the end-of-life product. Procedia CIRP 60:512–517. https://doi.org/10.1016/j.procir.2017.02.003
73. Wang M, Tian Y, Liu W et al (2020) A moving urban mine: The spent batteries of electric passenger vehicles. J Clean Prod 265:121769. https://doi.org/10.1016/j.jclepro.2020.121769
74. Wu Y, Yang L, Tian X et al (2020) Temporal and spatial analysis for end-of-life power batteries from electric vehicles in China. Resour Conserv Recycl 155:104651. https://doi.org/10.1016/j.resconrec.2019.104651
75. Yu J, Williams E, Ju M et al (2010) Forecasting global generation of obsolete personal computers. Environ Sci Technol 44:3232–3237. https://doi.org/10.1021/es903350q
76. Zhou L, Xie J, Gu X et al (2016) Forecasting return of used products for remanufacturing using Graphical Evaluation and Review Technique (GERT). Int J Prod Econ 181:315–324. https://doi.org/10.1016/j.ijpe.2016.04.016