Market Positioning of Remanufactured Products With Optimal Planning for Part Upgrades

Minjung Kwak
e-mail: kwak14@illinois.edu

Harrison Kim[1]
e-mail: hmkim@illinois.edu

Department of Industrial and Enterprise Systems Engineering,
University of Illinois at Urbana-Champaign,
Urbana, IL61801

In a market with rapid changes in technology and customer preferences, technological obsolescence of end-of-life products poses a significant challenge to product recovery. Remanufacturing with optimal part upgrades can be a promising solution for overcoming the obsolescence. This paper proposes a model for positioning a remanufactured product. By considering original product design, target market (i.e., customer preferences and competing products), and recovery economics, the model helps to find optimal specifications and the selling price of a remanufactured product at which maximum remanufacturing profit is expected. Two versions of the model are presented under different assumptions on product takeback. The first model assumes that the remanufacturer passively accepts all returns without paying any financial incentives. The second model assumes that the remanufacturer buys back end-of-life products so as to control the quality and quantity of returns. The two models are illustrated with the example of a desktop computer. [DOI: 10.1115/1.4023000]

Keywords: positioning, remanufacturing, reuse, upgrade, end-of-life recovery

1 Introduction

As awareness of sustainability grows and environmental regulations become more stringent, manufacturers are faced with the challenge of conducting green as well as profitable business. Recovering end-of-life products after customer use can be a promising solution to this challenge. In end-of-life recovery, parts and materials from end-of-life products are given a second life by means of either reuse or resale. By conducting responsible recovery of their products, manufacturers can contribute to environmental protection while also gaining social and economic benefit.

Rapid advances in technology, however, present a significant challenge to end-of-life recovery. Each year, millions of new products are released to the market, and they quickly render formerly cutting-edge products obsolete or outdated. In a market with such quick changes, refurbishing—a form of recovery which restores end-of-life products, functionally or aesthetically, to its original condition [1,2]—is hard to justify. Since refurbished products are offered with their original specifications from past years, it is difficult to attract customers who prefer more advanced technologies and performance.

Remanufacturing with part upgrades as opposed to simple refurbishing can be an effective solution to end-of-life obsolescence [3]. In remanufacturing, parts from end-of-life products are selectively reassembled with new ones to attain more advanced performance [4,5]. A problem is that the profitability of remanufacturing depends on many factors, including original product design, the quality and quantity of end-of-life products, costs of remanufacturing operations, and market demand for remanufactured products [6,7]. To make remanufacturing profitable, *the right quantity of remanufactured products must be produced with optimal part upgrades and offered to the market at a reasonable price, leading customers to choose them over competing products.*

This paper proposes a mathematical model for market positioning of remanufactured products. The model aims to maximize the profit from remanufacturing. Given a number of units of end-of-life product, the model optimizes the remanufacturing process and provides the *optimal specifications*, *selling price*, and *production quantity* for the remanufactured product. As Fig. 1 illustrates, the model considers three groups of inputs simultaneously: original product design (i.e., part combination and specifications), product end-of-life conditions (i.e., available quantity and quality of end-of-life products) and the target market (i.e., customer preferences and competing products).

The positioning model has two versions depending on the underlying takeback system. Two types of takeback systems are incorporated as categorized in Guide and Wassenhove [8]. The first version considers a "*waste-stream system*" where the remanufacturer passively accepts all returns without paying any financial incentives. The second version deals with a "*market-driven system*" where the remanufacturer buys back end-of-life products to control the quantity and quality of end-of-life products.

The proposed model is based on the following assumptions. First, the decision maker—remanufacturers, original equipment manufacturers (OEM), or designers—has no other products in the target market, so there is no risk of cannibalization. Second, the product to be remanufactured has a modular structure, and its upgrade is made through part replacement. Third, remanufacturing is instantaneous. Remanufacturing operations have a negligible lead time. Lastly, the decision maker has good knowledge of the required inputs at the time of applying the model. How to estimate input values is left out of the scope of this study.

The rest of the paper is organized as follows. Section 2 discusses the relevant literature, followed by a detailed problem description in Sec. 3. Section 4 describes two versions of the optimization model, and Sec. 5 illustrates them with the example of a desktop computer. Section 6 summarizes the paper with future research directions.

2 Relevant Literature

To compete in the market, it is critical for manufacturers to optimize their product offerings with the best specifications and

[1]Corresponding author.

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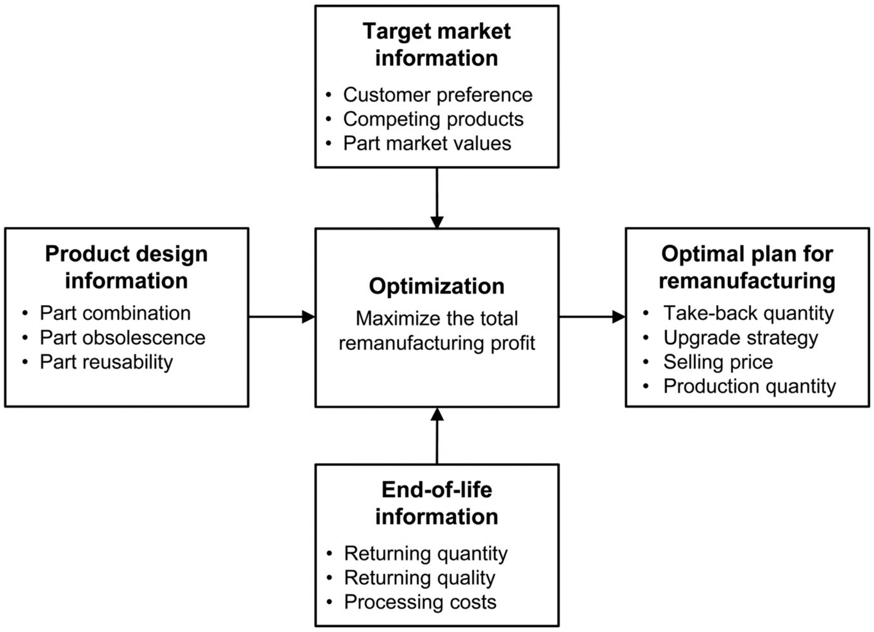

Fig. 1 Integrated model for market positioning of a remanufactured product

selling price. In the engineering design community, such optimal market positioning has been actively discussed for new product design. The decision-based design (DBD) and design for market systems (DMS) are well-known, popular approaches to this end. A variety of approaches have been proposed to optimize the design variables and the price of a new product, including Hazelrigg [9], Wassenaar et al. [10], Gu et al. [11], Kumar et al. [12], Michalek et al. [13], and Frischknecht et al. [14]. Given the rapid changes in technology and customer preferences, design upgrade and well-timed repositioning of a product have also received increasing attention, as highlighted in Wilhelm et al. [15] and Singh and Sandborn [16], to name a few.

Market positioning is also a critical success factor for remanufacturing. The design of a remanufactured product must be optimized with appropriate part reuse and upgrades, and the product must be offered at reasonable prices in order for customers to choose remanufactured products over competing products. The importance of design upgrade has been emphasized by many studies, including Sand and Gu [17], Ostlin et al. [18], Lund [5], and Bras [19]. Remanufactured products must incorporate appropriate part upgrades, as the product and parts have easily become obsolete or outdated since the product was originally made. To enhance the upgradability of a product, Xing et al. [3] and Li et al. [20] presented design evaluation tools. They proposed quantitative measures for product upgradeability and developed an evaluation model that can be applied at the design stage. In addition, Umemori et al. [21] and Ishigami et al. [22] proposed a design method to enhance upgradability of a product over multiple generations. Upgrading in each generation was executed by adding to, replacing, or removing modules from a product. Given an upgrade plan, the method helped determine the product structure that is best for the plan; yet, the method for establishing the upgrade plan was not discussed.

The importance of optimal pricing in remanufacturing has been highlighted in another line of research. The imbalance between returns of end-of-life products and demand for remanufactured products is one of the major factors that complicate production planning and control in the remanufacturing business [23]. Since remanufacturing is possible only when there exists both the supply of end-of-life products and the demand for remanufactured products [7,24], remanufacturers must find a balance between returns and demand, through which the recovery profit can be maximized. Pricing of remanufactured products (i.e., at what price to sell a remanufactured product) can be an effective means to achieve this goal. Vadde et al. [25], Mitra [26], and Vorasayan and Ryan [27] presented optimal pricing models for remanufactured products. Recently, pricing models that simultaneously optimize the price of both end-of-life and remanufactured products have also been presented, as those in Guide et al. [7], Ferrer et al. [28], and Vadde et al. [29]. The previous research has shown how the optimal pricing of remanufactured products can lead to profitable remanufacturing. However, little or no attention has been paid to how product design affects customer preferences, demand, and the selling price in the remanufacturing market.

Research on market positioning for remanufactured products is still in its early stages. Positioning a remanufactured product is different from positioning a new product and requires more complicated decision-making. It involves decisions on part reuse (i.e., whether to reuse a part or upgrade it), of which the feasibility and profitability are affected by the technological obsolescence and physical deterioration of end-of-life products. Although there has been a great deal of research conducted on remanufacturing, most of the effort to date, especially in engineering design, has been focused on technical and operational issues, such as how to make the remanufacturing operation more cost effective. Most research (e.g., Refs. [2,30–34]) has assumed that a recovered product either maintains the original design without any upgrades or has a predefined design—the end-of-life product is remanufactured with part upgrades, but the upgrade levels are predefined, rather than being decided.

Concerning the content of upgrades (i.e., to what level of specifications a product must be upgraded), only a few studies have made progress. Tsubouchi and Takata [35], Rachaniotis and Pappis [4], and Chung et al. [36] presented models for determining the optimal design for a remanufactured product. However, the selling price of the remanufactured product was left out of consideration. One exception is Macdonald et al. [37], in which the authors incorporated customer preferences in making recycling decisions and determined the optimal design (i.e., the mixture of virgin and recycled material) and price of a product, considering trade-offs among the environmental impact, customer preferences, and profitability. Although the model determined both design and price, it dealt with a recycling case, and little is known about how to incorporate more complex product characteristics, such as product structure, technological obsolescence, and physical deterioration.

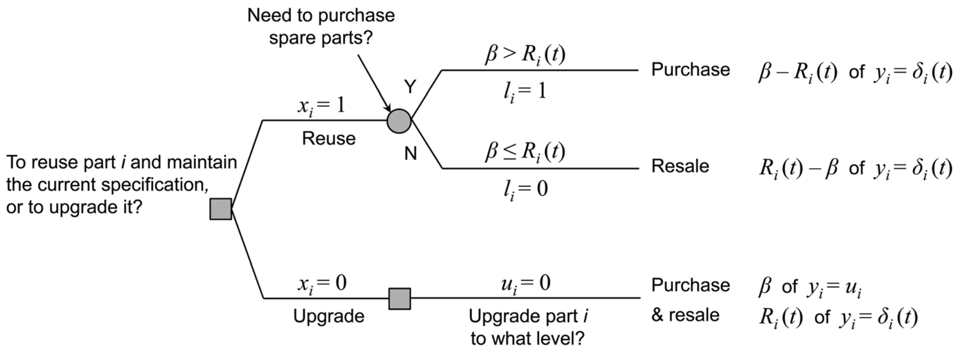

Fig. 2 Upgrade decision and its implication on parts procurement and resale

This paper presents an optimization model for market positioning of a remanufactured product. Here, the design of a remanufactured product is not a given target to achieve but rather a decision variable to optimize; the upgrade level is optimized for each part. A key contribution of the current model is its coverage of the remanufacturing process. As emphasized by Geyer and Jackson [38] and Guide and Van Wassenhove [39], remanufacturing is a problem that goes far beyond technical and operational boundaries. For the success of remanufacturing, other issues at the front end (i.e., takeback management) and the back end (i.e., remarketing for remanufactured products) must be considered simultaneously. The positioning model proposed in this paper covers the whole recovery process and suggests an advanced way of coordinating the different activities within it. The model takes into account various marketing and engineering aspects simultaneously. It considers not only the technological obsolescence and physical deterioration of end-of-life products but also customer preferences and competing products in the remanufacturing market.

3 Problem Description: Remanufacturing With Part Upgrades

As Fleishmann [40] and Guide and Van Wassenhove [39] presented, remanufacturing consists of three activities, i.e., takeback management, remanufacturing operations, and remarketing for remanufactured products. Profitable remanufacturing is only possible when the three activities are well coordinated and optimized. This section describes these three activities in remanufacturing and key decisions to maximize the remanufacturing profit.

Product takeback is the process of collecting end-of-life products. Since product takeback determines the end-of-life products processed later in the remanufacturing operation, acquiring the right quality and quantity of products is a major concern. According to Guide and Wassenhove [8], there are two primary systems for product takeback: the waste-stream system (aimed at reducing disposal and reducing costs, driven by regulatory pressure) and the market-driven system (aimed at controlling the incoming level of quality of return and maximizing the revenue).

In the waste-stream system, the remanufacturer passively accepts all end-of-life products without paying any financial incentives to the end-user. For instance, if $S(t)$ units of an end-of-life product return at year t for recovery, all the units must be accepted and processed. In such a system, however, it is hard to obtain good-quality products. Without any incentives, consumers tend to store their products indefinitely even if they no longer use them [41]. Accordingly, the age of returned products tends to increase which implies less reusable parts inside. In the market-based system, the remanufacturer pays economic incentives for end-of-life products to acquire better quality returns [42]. How many and what quality of products to take back become key decisions to make. Although this system may increase the cost of takeback, the firm can control the quantity and quality of end-of-life products [43].

After taking back end-of-life products, the remanufacturing operation starts with disassembling all the products into parts ($i \in I$), such as subassemblies and components. The resultant parts are sorted by part type and assessed whether reusable or not based on its functional status. While nonreusable malfunctioning parts are shredded and recycled into raw materials, reusable parts are collected for further processing. Suppose that $R_i(t)$ units of reusable part i are obtained from disassembly at year t. Then, the question of interest is how to utilize the reusable parts, in other words, what and how many units of remanufactured product to produce. Key decision variables are:

- x_i: whether part i of the remanufactured product should maintain its original specification ($x_i = 1$) or upgrade its specification ($x_i = 0$)
- u_i: new specification of part i when it is to be upgraded
- β: production amount for the remanufactured product.

Figure 2 describes how the decisions affect the remanufacturing operation afterwards, more specifically, what and how many spare parts are purchased and what and how many used parts are sold to the second-hand market. If part i is determined to be upgraded ($x_i = 0$), no parts are reused in remanufacturing. All $R_i(t)$ units of reusable part i are sold to the second-hand market, while β units of a spare part with an upgraded specification u_i are newly purchased.

If part i is determined to maintain its original specification ($x_i = 1$), the next question is whether the $R_i(t)$ units of reusable part i are sufficient to meet the production amount β. If part i is insufficient in quantity for remanufacturing ($\beta > R_i(t)$), spare parts that are new but having the original specification, are purchased for as many as ($\beta - R_i(t)$). In contrast, if there are enough reusable parts ($\beta \le R_i(t)$), only β units are used in remanufacturing while the rest ($R_i(t) - \beta$) units are sold to the second-hand component market.

In this study, the specification of each part is represented using the concept of *generational difference*. The generational difference is a relative measure that indicates, in terms of the technology, how obsolete a part is compared to a current cutting-edge part. As product technology advances, cutting-edge parts of a new generation appear on the market. In this study, the newer part corresponds to the greater number of generation, and the latest cutting-edge part corresponds to the maximum generation. The generational difference of a part refers to the gap between its generation and that of the cutting-edge part (i.e., maximum generation). With this definition, each of the oldest and the latest parts (of a particular moment) corresponds to the maximum and the minimum (=0) generational differences, respectively. Also, a part's generational difference increases over time as new cutting-edge parts appear on the market. Here, $\delta_i(t)$ denotes the generational difference of original part i at year t; y_i denotes the generational difference of part i after remanufacturing and is formulated as: $y_i = x_i \cdot \delta_i(t) + u_i$.

After all remanufacturing operation, the β units of a remanufactured product are released in the target market where n competing

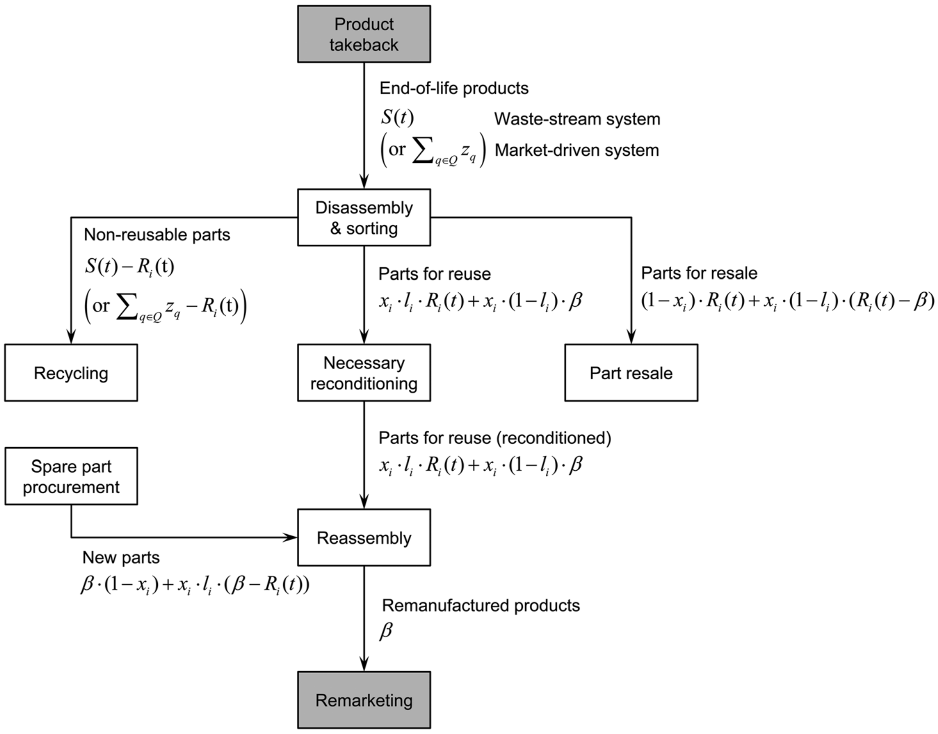

Fig. 3 Remanufacturing operation and product/part flow volumes

products exist. In this paper, the demand for a product is determined by three characteristics of the product and its competitors: part's generational differences, selling price, and product status (whether the product is new or remanufactured). Equation (1) represents the demand for the remanufactured product $D(t)$ as a function of those characteristics, where y_i and $\delta_{\text{in}}(t)$ represent the generational difference of part i of the remanufactured and the competing products, respectively; P and P_n represent the market selling price for the remanufactured and the competing products, respectively; and ρ and ρ_n represent the product status of the remanufactured and the competing products, respectively. The function can be defined through well-known demand modeling techniques, such as discrete choice analysis [10,44] and conjoint analysis [45]

$$D(t) = f(\mathbf{y}_i, P, \rho; \boldsymbol{\delta}_{in}(t), \mathbf{P}_n, \boldsymbol{\rho}_n) \tag{1}$$

With better specifications (smaller generational differences) and lower selling price, a remanufactured product can have higher market share. However, lowering generational differences requires higher costs for part replacement and upgrade, and reducing selling price decreases the revenue from selling the remanufactured product. Given the trade-off, the remanufactured product must be positioned at the optimal spot in the market, such that its generational differences and selling price can maximize the total profit from remanufacturing.

Figure 3 describes the whole remanufacturing operation and how the three activities in remanufacturing, i.e., product takeback, remanufacturing operation, and remarketing for remanufactured products, are linked with each other. As Fig. 3 illustrates, decisions made in one activity influence the feasibility and profitability of other activities. Therefore, to maximize the profit from remanufacturing, all three activities must be optimized simultaneously. Section 4 presents such an optimization model for remanufacturing. The goal is to find optimal specifications, selling price, and production quantity for a remanufactured product at which the total remanufacturing profit is maximized.

4 Mathematical Model

This section presents an optimization model for positioning a remanufactured product when the original product design and its conditions at the end-of-life stage are known. Two versions of the model are presented under different assumptions on product takeback. The first model in Sec. 4.1 assumes the waste-stream system, while the second model in Sec. 4.2 assumes the market-driven system.

4.1 Model 1: Waste-Stream System. Suppose that $S(t)$ units of an end-of-life product are returned for remanufacturing at year t, whose quality (i.e., the reusability of parts inside) is also known to be $r_i(t)$. The quality is defined as the probability of $r_i(t)$ with which a part i is to be reusable. Under the waste-stream system for the end-of-life product, the positioning model is formulated in Eqs. (2)–(8). Key decision variables are x_i (i.e., indicator of whether a part is better reused (=1) or upgraded (=0)), u_i (i.e., target generational difference of part i when it is better to upgrade), P (i.e., optimal price to sell the remanufactured product), and β (i.e., production quantity for the remanufactured product). Table 1 describes the notation used in the model

$$\begin{aligned}
&\text{maximize } V^{\text{product}} + V^{\text{part}} + V^{\text{material}} - C^{\text{spare}} - C^{\text{proc}} \\
&\quad\text{where} \quad V^{\text{product}} = \beta \cdot P \\
V^{\text{part}} &= \sum_{i\in I} [(1-x_i)\cdot R_i(t) + x_i \cdot (1-l_i)\cdot (R_i(t)-\beta)] \\
&\quad \cdot V_i^{\text{used}}(t, \delta_i(t)) \\
V^{\text{material}} &= \sum_{i\in I} (S(t) - R_i(t)) \cdot V_i^{\text{recycle}}(t, \delta_i(t)) \\
C^{\text{spare}} &= \sum_{i\in I} [\beta\cdot(1-x_i) + x_i \cdot l_i \cdot (\beta - R_i(t))] \cdot V_i^{\text{new}}(t, y_i) \\
C^{\text{proc}} &= S(t)\cdot C^{\text{proc1}} + \sum_{i\in I} [x_i \cdot l_i \cdot R_i(t) + x_i \cdot (1-l_i)\cdot\beta] \cdot C_i^{\text{proc2}} \\
&\quad + \beta \cdot C^{\text{proc3}}
\end{aligned} \tag{2}$$

Table 1 Mathematical notation for positioning model

Notation	Description
i	Index for parts; $i \in I$
n	Index for competing products; $n \in N$
t	Product end-of-life year; time when the product returns for recovery
x_i	Binary decision variable indicating whether part i maintains its original specification ($x_i = 1$) or upgrades its specification ($x_i = 0$)
y_i	Generational difference of part i of the remanufactured product
u_i	Generational difference of part i being newly decided when the part i is to be upgraded
β	Production amount for the remanufactured product
l_i	Binary variable; $l_i = 1$ when $\beta > R_i(t)$, else $l_i = 0$
P	Selling price for the remanufactured product
V^{product}	Revenue from selling a remanufactured product
V^{part}	Revenue from selling the leftover parts not being used in remanufacturing
V^{material}	Revenue from selling the nonreusable parts for material recovery
C^{spare}	Cost of purchasing new spare parts for remanufacturing
C^{proc}	Cost of entire remanufacturing operations
C^{proc1}	Cost of common operations for a unit of the end-of-life product
C_i^{proc2}	Cost of reconditioning operations for a unit of reusable part i
C^{proc3}	Cost of remarketing operations for a unit of the remanufactured product
$V_i^{\text{new}}(t, y_i)$	Market value of a new part i with generational difference y_i at year t
$V_i^{\text{used}}(t, \delta_i(t))$	Market value of a used part i with generational difference $\delta_i(t)$ at year t
$V_i^{\text{recycle}}(t, \delta_i(t))$	Market value of a nonreusable part i with generational difference $\delta_i(t)$ at year t
$D(t)$	Demand for the remanufactured product at year t
$S(t)$	Supply of the end-of-life product at year t
$R_i(t)$	Number of units of reusable part i at year t
$r_i(t)$	Reusability of part i of the end-of-life product at year t
$\delta_i(t)$	Generational difference of part i of the end-of-life product at year t
ρ	Binary variable indicating the product status of the remanufactured product ($= 1$)
$\delta_{\text{in}}(t)$	Generational difference of part i of the competing product n at year t
P_n	Selling price for the competing product n
ρ_n	Binary indicator of product status for the competing product n
$\delta_i^{\text{critical}}(t)$	Critical value for the generational difference of part i at year t
P^{critical}	Critical value for the price of the remanufactured product at year t
M	Big M; a very large positive number

$$y_i = x_i \cdot \delta_i(t) + u_i \quad \forall i$$
$$\sum_{i \in I} x_i \cdot u_i = 0 \tag{3}$$

$$D(t) = f(\mathbf{y}_i, P, \rho; \boldsymbol{\delta}_{\text{in}}(t), \mathbf{P}_n, \boldsymbol{\rho}_n)$$
$$y_i \le \delta_i^{\text{critical}}(t); \quad P \le P^{\text{critical}} \quad \forall i \tag{4}$$

$$\beta \le S(t); \quad \beta \le D(t) \tag{5}$$

$$\beta - R_i(t) \le M \cdot l_i \quad \forall i$$
$$\beta - R_i(t) \ge M \cdot (l_i - 1) \quad \forall i \tag{6}$$

$$R_i(t) = r_i(t) \cdot S(t) \quad \forall i \tag{7}$$

$$x_i, l_i \in \{0, 1\} \quad \forall i$$
$$u_i \ge 0 \text{ and integer} \quad \forall i \tag{8}$$
$$P \ge 0; \quad \beta \ge 0 \text{ and integer}$$

The objective function in Eq. (2) represents the total profit from remanufacturing. It consists of three revenue and two cost components: the revenue from selling β units of the remanufactured product V^{product}, the revenue from selling the leftover parts not being used in remanufacturing V^{part}, the revenue from selling the nonreusable parts for material recovery V^{material}, the cost of purchasing spare parts for remanufacturing C^{spare}, and the cost of processing remanufacturing operation C^{proc}. The processing cost C^{proc} considers three types of operation: the common operation conducted for all end-of-life products (e.g., disassembly, inspection, and sorting), the part-specific operation for reconditioning reusable parts prior to reassembly, and the final operation for reassembling and distributing remanufactured products.

Equation (3) formulates decisions for part upgrades. The variable y_i denotes the generational difference of part i which is to be included in the remanufactured product. It is determined by two decision variables x_i and u_i. When x_i is 1, part i is reused, and at the same time, u_i becomes 0. Thus, y_i equals $\delta_i(t)$ which is the generational difference of original part i. In contrast, when x_i is 0, a part upgrade is conducted, and the current part with $\delta_i(t)$ is replaced by an upgraded part with u_i.

Equation (4) calculates the demand for the remanufactured product. Part generational differences, selling price, and product status (i.e., new or remanufactured) determines the size of the demand. This model also assumes that each part and the selling price have critical levels (i.e., $\delta_i^{\text{critical}}(t)$, P^{critical}) for their values. In general, customers prefer lower generational differences and price. The critical levels represent the maximum generational differences and price that customers are willing to consider for purchasing the product. For example, if any part of a product has a generational difference greater than its critical value, then customers will not choose the product at all. Equation (4) prevents the generational differences and selling price from exceeding their critical values.

Unlike new production, remanufacturing is possible only when there exist both a supply of end-of-life products and the demand for remanufactured products [7,24]. Thus, Eq. (5) constrains the production quantity β not to exceed $S(t)$ or $D(t)$. Equation (6) considers if reusable parts are sufficient in quantity to produce β units of the remanufactured product, where the number of units of reusable part i is given by Eq. (7). If part i is insufficient in quantity (i.e., $\beta > R_i(t)$), the indicator variable l_i becomes 1; as shown in Eq. (2), this implies that new parts as many as $(\beta - R_i(t))$ are purchased. Otherwise, l_i becomes 0, which represents β units of reusable part i are used in remanufacturing while the rest of the $R_i(t) - \beta$ units are sold to the second-hand market. Finally, Eq. (8) represents variable conditions.

Table 2 Mathematical notation for positioning model

Notation	Description
q	Index for product quality; $q \in Q$
z_q	Number of units of the end-of-life product with quality level q to take back
C^{takeback}	Cost of product takeback
C_q^{buyback}	Cost of buying back a unit of the end-of-life product with quality level q
$A_q(t)$	Number of units of the end-of-life product with quality level q that are available for takeback
$r_{iq}(t)$	Reusability of part i of the end-of-life product with quality level q at year t

4.2 Model 2: Market-Driven System. In the market-driven system, how many and what quality of end-of-life products should be acquired for remanufacturing becomes another key decision for a remanufacturer. Suppose that, for each quality level q ($q \in Q$), $A_q(t)$ units of an end-of-life product are available for takeback. Then, a decision must be made on the actual takeback amount for quality level q, which is denoted by z_q. The cost of takeback is a major factor that affects the takeback decision. Depending on the quality level, a different takeback cost C_q^{buyback} is required; high-quality products provide higher disassembly yield rates of reusable parts, but are usually more expensive to take back.

The positioning model under the market-driven system is formulated in Eqs. (9)–(16). The positioning model maximizes the total remanufacturing profit with respect to the product takeback amount z_q, upgrade plan x_i and u_i, and the price P and production quantity β for the remanufactured product. Table 2 describes the additional notation used in the model.

Similar to Eq. (2), the objective function in Eq. (9) represents the total profit from remanufacturing. In addition to the five components in Eq. (2), Eq. (9) includes the cost of product takeback denoted by C^{takeback}.

Equation (10) shows the constraint for the product takeback decision. The takeback amount z_q is bounded by 0 and $A_q(t)$, where $A_q(t)$ denotes the number of units of the end-of-life product that are available for takeback at year t. Equations (11) and (12) represent the part upgrade decision for part i and the corresponding demand for the remanufactured product, respectively. Equation (13) poses the upper bounds for the production quantity β, while Eq. (14) checks if the available units of reusable part i are enough in quantity to fulfill β. The number of available units for reusable part i is given by Eq. (15). Finally, Eq. (16) shows variable conditions

$$\begin{aligned} &\text{maximize } V^{\text{product}} + V^{\text{part}} + V^{\text{material}} - C^{\text{buyback}} \\ &\quad - C^{\text{spare}} - C^{\text{proc}} \\ &\text{where} \quad V^{\text{product}} = \beta \cdot P \\ V^{\text{part}} &= \sum_{i \in I} [(1 - x_i) \cdot R_i(t) + x_i \cdot (1 - l_i) \cdot (R_i(t) - \beta)] \\ &\quad \cdot V_i^{\text{used}}(t, \delta_i(t)) \\ V^{\text{material}} &= \sum_{i \in I} \left(\sum_{q \in Q} z_q - R_i(t) \right) \cdot V_i^{\text{recycle}}(t, \delta_i(t)) \\ C^{\text{takeback}} &= \sum_{q \in Q} z_q \cdot C_q^{\text{buyback}} \\ C^{\text{spare}} &= \sum_{i \in I} [\beta \cdot (1 - x_i) + x_i \cdot l_i \cdot (\beta - R_i(t))] \cdot V_i^{\text{new}}(t, y_i) \\ C^{\text{proc}} &= \sum_{q \in Q} z_q \cdot C^{\text{proc1}} + \sum_{i \in I} [x_i \cdot l_i \cdot R_i(t) + x_i \cdot (1 - l_i) \cdot \beta] \\ &\quad \cdot C_i^{\text{proc2}} + \beta \cdot C^{\text{proc3}} \end{aligned} \tag{9}$$

$$0 \le z_q \le A_q(t) \quad \forall q \tag{10}$$

$$\begin{aligned} y_i &= x_i \cdot \delta_i(t) + u_i \quad \forall i \\ &\sum_{i \in I} x_i \cdot u_i = 0 \end{aligned} \tag{11}$$

$$\begin{aligned} D(t) &= f(\mathbf{y}_i, P, \rho; \boldsymbol{\delta}_{\text{in}}(t), \mathbf{P}_n, \boldsymbol{\rho}_n) \\ y_i &\le \delta_i^{\text{critical}}(t); \quad P \le P^{\text{critical}} \quad \forall i \end{aligned} \tag{12}$$

$$\beta \le \sum_{q \in Q} z_q; \quad \beta \le D(t) \tag{13}$$

$$\begin{aligned} \beta - R_i(t) &\le M \cdot l_i \quad \forall i \\ \beta - R_i(t) &\ge M \cdot (l_i - 1) \quad \forall i \end{aligned} \tag{14}$$

$$R_i(t) = \sum_{q \in Q} r_{iq}(t) \cdot z_q \quad \forall i \tag{15}$$

$$\begin{aligned} x_i, l_i &\in \{0, 1\} \quad \forall i \\ u_i &\ge 0 \text{ and integer} \quad \forall i \\ z_q &\ge 0 \text{ and integer} \quad \forall q \\ P \ge 0; \quad \beta &\ge 0 \text{ and integer} \end{aligned} \tag{16}$$

5 Case Study: Desktop Computer

5.1 Case Illustration. Suppose that a manufacturer is planning to offer a high-end desktop model, called *Desktop X*, which consists of the newest, most up-to-date parts (i.e., $\delta_i(0) = 0$ for all part i). The desktop comprises seven parts, including a CPU (central processing unit), RAM (random-access memory), and a chassis (case, fan, and power supply). It is assumed that 5000 units of *Desktop X* will reach the end of their lives after 4 yr ($t = 4$). It is also expected that each end-of-life *Desktop X* is assigned to one of the three levels of quality, i.e., good, normal, and poor, with the probability of 20, 50, and 30%, respectively. Given the estimate of the quality and available quantity of end-of-life *Desktop X* (Table 3), the manufacturer aims to assess the potential profitability of remanufacturing *Desktop X* at year 4.

Table 3 shows the generational differences of *Desktop X* and the reusability of its constituent parts for each quality level. Due to technological obsolescence, each part of *Desktop X* will have an increased generational difference $\delta_i(t)$ at year 4. Each part also experiences physical deterioration, which in turn decreases the part's reusability. Since each part deteriorates physically or functionally at its own speed and degree, the generational differences and part reusability differ greatly by part.

Depending on the product quality level, different part reusability is expected, as shown in Table 3. The better the quality of a product, the more reusable parts it provides. To acquire *Desktop X* of the good or normal quality, however, it is assumed that \$50 or \$30 must be paid for each end-of-life product. If the waste-stream system is assumed for takeback, no economic incentive is given for any product. Consequently, only poor-quality products with no buyback price are expected to return.

Table 3 Assumptions on the end-of-life *Desktop X* ($t = 4$)

Part i	$\delta_i(t)$	$r_{i,\text{good}}(t)$	$r_{i,\text{normal}}(t)$	$r_{i,\text{poor}}(t)$
CPU	2	0.9974	0.8801	0.7745
RAM	2	0.9974	0.8801	0.7745
Motherboard	2	0.9748	0.7745	0.5999
Hard drive	4	0.8801	0.7745	0.2787
Graphic card	4	0.9974	0.7745	0.4646
Optical drive	1	0.9748	0.5999	0.0466
Chassis	0	0.8801	0.7745	0.4646
$A_q(t)$(unit)	—	1000	2500	1500
C_q^{buyback}(\$)	—	50	30	0

Table 4 Assumptions on the target market: competing products

Attribute	High-spec	Midspec	Low-spec
Generational difference			
CPU	0	1	2
RAM	0	1	2
Motherboard	0	1	2
Hard drive	0	1	2
Graphic card	0	1	2
Optical drive	0	1	1
Chassis	0	0	0
Price ($)	1200	800	400
Market share (status quo)	0.1	0.2	0.7

Once remanufactured, the remanufactured *Desktop X* (hereinafter referred to as *Reman X*) is supposed to be released in another market where the company is offering no other products. Table 4 describes the target market under consideration. There are three competing products on the market (i.e., high-spec, midspec, and low-spec), and they differ from each other in terms of part specifications and selling price. For instance, the low-spec desktop is the cheapest product in the market ($400), but includes relatively obsolete parts—the parts are mostly two-generation old except for the optical drive and chassis. The market share of the status quo (before *Reman X* enters the market) implies that the target customers consider the cheap price most important. Despite the obsolete specification, the low-spec model is taking 70% of the target market.

The expected demand $D(t)$ for *Reman X* is given by Eq. (17), where $Q(t)$ denotes the total market size, and N refers to the three competing products. The market share of *Reman X* (or the probability that customers choose *Reman X* over the competing products) is defined using a conditional multinomial logit choice model, where the customer utility for a product is defined as Eq. (18). Here, k is a scaling parameter; as $k \to 0$, all choices have the same demand [46]. In this study, k was calibrated on the status-quo market share and defined as 36.09. The target market size $Q(t)$ is assumed to be 10,000 units

$$D(t) = \frac{\exp\left[kV(\mathbf{y}_i, P, \rho)\right]}{\exp\left[kV(\mathbf{y}_i, P, \rho)\right] + \sum_{n\in N} \exp\left[kV(\boldsymbol{\delta}_{in}(t), P_n, \rho_n)\right]} \cdot Q(t) \tag{17}$$

$$\begin{aligned} U(\boldsymbol{\delta}_{ij}(t), P_j, \rho_j) &= V(\boldsymbol{\delta}_{ij}(t), P_j, \rho_j) + \varepsilon_j \\ V(\boldsymbol{\delta}_{ij}(t), P_j, \rho_j) &= (1 - \alpha\rho_j) \cdot \left(\sum_{i\in I} (w_i \delta'_{ij}(t)) + w_{\text{price}} P'_j \right) \\ \delta'_{ij}(t) &= \frac{\delta_i^{\text{critical}}(t) - \delta_{ij}(t)}{\delta_i^{\text{critical}}(t)}; \quad P'_j(t) = \frac{P^{\text{critical}}(t) - P_j(t)}{P^{\text{critical}}(t)} \end{aligned} \tag{18}$$

Table 5 Assumptions on the target market: customer preference

Attribute	Part-worth	Critical
Generational difference		
CPU	0.125	3
RAM	0.125	3
Motherboard	0.100	3
Hard drive	0.050	5
Graphic card	0.025	5
Optical drive	0.050	3
Chassis	0.025	2
Price ($)	0.500	1200

Table 6 Assumptions on part market values ($) ($t = 4$)

Part i	$V_i^{\text{used}}(t, \delta_i(t))$	$V_i^{\text{recycle}}(t, \delta_i(t))$	$V_i^{\text{new}}(t, 0)$	ϕ_i
CPU	23	1	175	0.6733
RAM	5	0.75	50	0.8378
Motherboard	20	1	150	0.6733
Hard drive	13	0.5	120	0.1717
Graphic card	16	0.75	100	0.2883
Optical drive	8	0.75	80	0.8088
Chassis	0	0	75	0.1500

In Eq. (18), the utility for product j is defined as a linear weighted sum of its generational differences $\delta_{ij}(t)$ and the selling price P_j. The $\delta_{ij}(t)$ and P_j are rescaled to lie between 0 and 1, and ε_j is an error term. The condition of a product ρ_j involves a utility discount. A discounting factor α is applied when the product is remanufactured ($\rho_j = 1$). Here, $\alpha = 0.25$ is assumed. Table 5 shows the weight (or part-worth utility) assumed for each rescaled $\delta_{ij}(t)$ and P_j. The 'critical' column in Table 5 provides $\delta_i^{\text{critical}}(t)$ and P^{critical} that are used for the scaling. As described in Sec. 4, the critical values are the maximum generational differences and selling price that customers are willing to consider for purchasing a product. If any part has a generational difference greater than the critical one, then customers will not choose the product. For example, the customers will not buy a product if its CPU is more than three generations old.

Tables 6 and 7 provide assumptions on the remanufacturing cost and revenue. In Table 6, $V_i^{\text{used}}(t,\ \delta_i(t))$ and $V_i^{\text{recycle}}(t,\ \delta_i(t))$ show the per-unit revenue from reselling and recycling part i, respectively. The cost of purchasing a new part is given by Eq. (19). It assumes that a part's market value depreciates exponentially by its generational difference [47]. A constant parameter ϕ_i in Table 6 is applied to each part i to reflect the part's own speed of value depreciation. The market value of the newest cutting-edge part $V_i^{\text{new}}(t,\ 0)$ is also given in Table 6. Finally, Table 7 shows the assumptions for other processing costs. They are assumed based on Refs. [48,49]

$$V_i^{\text{new}}(t, y_i) = V_i^{\text{new}}(t, 0) \cdot e^{-\phi_i \cdot y_i} \tag{19}$$

5.2 Result: Optimal Market Position. To identify the optimal market position for *Reman X*, the positioning model described in Sec. 4 was applied to the case illustrated. Two scenarios were considered: Scenario 1 assumes the waste-steam takeback system (i.e., $S(t) = 1500$; all the returned products have poor quality), whereas Scenario 2 assumes the market-driven system. In this study, *Risk Solver Platform* 11.0 was used for the optimization. The Standard Evolutionary Engine was used alongside the Standard LSGRG Nonlinear Engine to find the optimal or at least a reasonably good solution.

Table 8 presents the optimization results. It shows the optimal generational differences, production quantity, and selling price for *Reman X* at which the maximum profit is expected. The first part of the table (takeback amount) shows the optimal takeback plan for *Desktop X*. In Scenario 1, the takeback amount is an uncontrollable given parameter. In Scenario 2, on the contrary, the takeback

Table 7 Assumptions on processing costs ($)

Type	Remanufacturing operation	Per-unit cost
C^{proc1}	Sorting and disassembly	4.5
	Sanitizing hard drive	24
C_i^{proc2}	Cleansing and testing a part	5
C^{proc3}	Reloading software	8
	Testing a PC	12
	Packaging and shipping	15

Table 8 Optimal market position for *Reman X* ($t=4$)

	Scenario 1 (Waste-stream system)	Scenario 2 (Market-driven system)
Takeback amount		
Good quality	0 units	1000 units
Normal quality	0 units	2500 units
Poor quality	1500 units	1500 units
Generational difference		
CPU	0 (upgrade)	0 (upgrade)
RAM	0 (upgrade)	0 (upgrade)
Motherboard	0 (upgrade)	0 (upgrade)
Hard drive	0 (upgrade)	4 (reuse)
Graphic card	4 (reuse)	4 (reuse)
Optical drive	1 (reuse)	1 (reuse)
Chassis	0 (reuse)	0 (reuse)
Price	$739.47	$570.74
Production quantity (β)	697 units	1454 units
Cost (average per unit)		
Takeback	$0 ($0)	$125,000 ($86)
Spare part purchase	$367,363($527)	$545,250 ($375)
Processing	$74,464 ($107)	$222,470 ($153)
Revenue (average per unit)		
Remanufacturing	$515,408 ($739)	$829,863 ($571)
Part resale	$55,962 ($80)	$264,980 ($182)
Material recovery	$3,408 ($5)	$6,061 ($4)
Total profit	$132,951	$208,184
Profit per unit	$191	$143
Profit margin (%)	23	19
ROI	0.30	0.23

amount becomes a decision variable, and the optimization result indicates that the optimal plan is to take back all available units at every quality level, despite the cost of takeback (=$125,000 in total).

The second part (generational difference) shows the optimal part reuse and upgrade decision for each part i. The number in a cell represents the optimal generational difference y_i $(=x_i \delta_i(t)+u_i)$ for *Reman X*. When part i is reused ($x_i=1$), y_i is identical to $\delta_i(t)$ in Table 3. In Scenario 1, the optimal market position indicates that the graphic card, optical drive, and chassis are better utilized through reuse in *Reman X*. In Scenario 2, reusing the hard drive is also recommended, as a result of the improved quality of incoming end-of-life products. In both scenarios, the CPU, RAM and motherboard are recommended for upgrading to the newest cutting-edge parts ($x_i=0$; $u_i=0$). All reusable CPUs, RAM and motherboards from *Desktop X* are sent to the second-hand market for part resale.

The third and fourth parts of the table present the optimal price and production quantity for *Reman X*. In the waste-stream system in Scenario 1, the optimal price for *Reman X* is given as $740, and the corresponding market share is estimated as 6.97%. As *Reman X* is newly offered to the market, the market shares of the three competing products, i.e., high-spec, midspec, and low-spec, are expected to be changed from 10%, 20%, and 70% to 9.50%, 18.41%, and 65.12%, respectively. Compared to Scenario 1, the market-driven system in Scenario 2 can start the remanufacturing operation with more reusable parts. Accordingly, the market-driven system requires a lower amount of spare parts to remanufacture the same amount of *Reman X*. With the advantage, the market-driven system can offer *Reman X* at a cheaper price ($571), which leads to a greater market share of 14.54%. The market shares of the competing products are estimated as 8.73 (high-spec), 16.91 (midspec), and 59.82% (low-spec).

The next part of Table 8 shows the cost and revenue implications of the optimal market position. Both the total and the average cost (or revenue) per unit are shown. As Scenario 2 takes back more end-of-life products and reuses more parts from them, the processing amounts are also increased for the common process

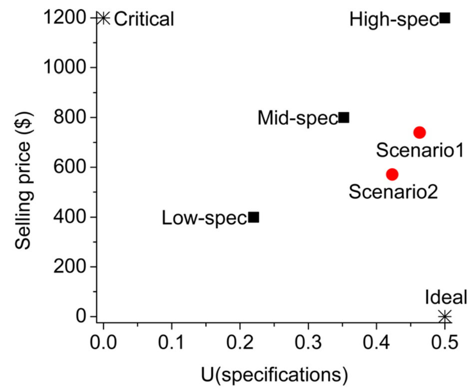

Fig. 4 Optimal market position for *Reman X* ($t=4$)

and the part-specific refurbishing process. This leads to an increase in the per-unit processing cost in Scenario 2, compared to Scenario 1.

The rest of the table shows the profit implications of the optimal market position. In terms of the total maximum profit, the market-driven system generates 57% more profit than the waste-stream system. The waste-stream system, however, gives a higher profit per unit ($191 versus $143). The profit margin (i.e., total profit/total revenue $\times$ 100) and return on investment (i.e., ROI; total profit/total cost) are also higher than those of the market-driven system.

Figure 4 depicts the optimization results on a two-dimensional map. The three competing products (i.e., high-spec, midspec, and low-spec) and the ideal and the critical products from the customer's perspective (i.e., the most- and the least-preferred products, respectively, which customers are willing to consider for purchasing a product) are also marked on their market position. The y-axis of the graph represents the selling price of a unit of product. The x-axis represents the total sum of part-worth utilities from product specifications (i.e., $\sum_i w_i y_i'(t)$); in the ideal case (i.e., all parts are up-to-date), it reaches 0.5. Thus, the ideal and critical products are located in the lower right [0.5, $0] and the upper left corners [0, $1200], respectively. With respect to product specifications, *Reman X* is positioned between two competing products, i.e., midspec and high-spec desktops. However, *Reman X* has a competitive price advantage; it is positioned between the low-spec and midspec desktops. Considering the price of the midspec desktop (i.e., $800), *Reman X* gives a price discount of 10–30% over new products. If the price of the high-spec desktop is considered (i.e., $1200), the price discount becomes 40–50%. These results are in accordance with actual discounts reported in the market [50–52].

As shown in the case study, the positioning model can find the optimal specifications and selling price of the remanufactured product to maximize total profit from remanufacturing. With this capability, the model can help remanufacturers plan and manage their production process. The model can also support design for remanufacturing, combined with appropriate prediction at the design stage for estimating necessary inputs (e.g., available end-of-life products and their quality, the evolution of generational differences, part market values). The model can help evaluate a product's remanufacturability from an economic perspective. It provides quantitative measures for remanufacturability, such as the total remanufacturing profit, profit margin, and ROI. More importantly, the model reveals which parts are better reused and which parts are better resold separately at the end-of-life. Since parts for in-house reuse and parts for resale have different design concerns, the optimization results can provide valuable insight into design for remanufacturing. To be more specific, since parts for reuse are likely to be reassembled with more advanced parts in the future, their compatibility with the other parts must be considered at the initial design stage. Parts for resale, however, would need different approaches. Standardization of the parts across product family can be considered to increase demand for the used parts. Also, security and liability issues become more important to the parts, since they are likely to be used outside the company's territory.

6 Discussion and Conclusion

Remanufacturing with part upgrades can be a promising solution for overcoming the challenge of technological obsolescence in end-of-life recovery. One difficulty, however, is that remanufacturing is a complex problem involving various engineering and marketing aspects that must be taken into account together. To make remanufacturing profitable, an end-of-life product must be remanufactured with appropriate part upgrading and be offered to the market at a reasonable price, leading customers to choose the remanufactured product over competing products.

The model proposed in this paper addresses positioning of a remanufactured product with the aim to assist in remanufacturing with part upgrades. By optimizing product take-back, remanufacturing operations, and remarketing for remanufactured products simultaneously, the developed model provides the optimal design specifications and selling price for the remanufactured product. The model and its potential applications are illustrated with an example of a desktop computer.

The integrated model proposed in this study has two potential uses. First, the models can help remanufacturing planning at the end-of-life stage. Second, the models can support design for remanufacturing at the original design stage. The model helps assess the original design from a recovery perspective and provides an estimate for the total remanufacturing profit which can be used for design evaluation and selection. Moreover, the model provides essential information for design improvements, such as what parts should be reused or upgraded at the end-of-life stage. Since parts for in-house reuse and parts for resale have different design concerns (e.g., part compatibility, security and liability), product design can be improved based on the proposed model. It should be noted, however, that the inputs needed for the models may bring additional challenges of prediction, especially for the use at the design stage. Although such future prediction is beyond the scope of this study, a prediction model needs to be developed in the future. Predictive-data mining and time-series analyses (e.g., Refs. [53,54]) would provide a promising solution to this challenge.

In the future, the model can be improved for multi-objective decision making by incorporating an environmental perspective. Another potentially productive line of research would be to incorporate the positioning of new product into the model. Although the current model considers the positioning of only a remanufactured product, future research can incorporate the positioning of new products into the model as well to see the impact of remanufacturing on market cannibalization.

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