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Remanufacturing is emerging as a promising solution for achieving green, profitable businesses. This article considers a manufacturer that produces new products and also remanufactured versions of the new products that become available at the end of their life cycle. For such a manufacturer, design decisions at the initial design stage determine both the current profit from manufacturing and future profit from remanufacturing. To maximize the total profit, design decisions must carefully consider both ends of product life cycle, *i.e.* manufacturing and end-of-life stages. This article proposes a decision-support model for the life-cycle design using mixed-integer nonlinear programming. With an aim to maximize the total life-cycle profit, the proposed model searches for an (at least locally) optimal product design (*i.e.* design specifications and the selling price) for the new and remanufactured products. It optimizes both the initial design and design upgrades at the end-of-life stage and also provides corresponding production strategies, including production quantities and take-back rate. The model is extended to a multi-objective model that maximizes both economic profit and environmental-impact saving. To illustrate, the developed model is demonstrated with an example of a desktop computer.

Keywords: remanufacturing; life-cycle design; end-of-life

1. Introduction

As environmental regulations become increasingly stringent and people are more concerned about environmental issues, manufacturers are faced with the challenge of operating both green and profitable businesses. Remanufacturing is emerging as a promising solution to meet this challenge. In remanufacturing, products with a like-new condition are produced using parts retrieved from used and discarded products (hereinafter called *end-of-life products*). By utilizing the resources and value remaining in their end-of-life products, companies can reduce the amount of waste that must be disposed of. Recently, manufacturers across a wide range of industries have turned to remanufacturing. Caterpillar, John Deere, Apple, Xerox, HP, and Sony are among the notable examples. As functional sales (such as leasing) and asset recovery services by manufacturers increase, remanufacturing is expected to become more popular and prevalent (Sundin and Bras 2005; Zhao *et al.* 2010).

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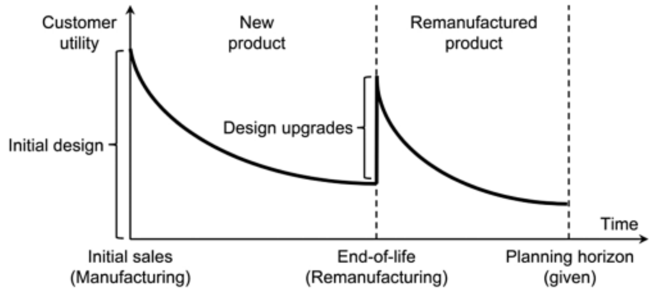

Figure 1. Two components of optimal product design for life-cycle profit: initial product design and design upgrade at the end-of-life stage.

Design is one of the most important considerations for successful remanufacturing (Lund 1984; Kerr and Ryan 2001; Kwak and Kim 2010, 2011). However, for a company which manufactures and sells both new and remanufactured products, optimizing product design is not a simple task. Design decisions made at the initial design stage affect both the profits from initial manufacturing and end-of-life remanufacturing. To maximize the total profit from the entire life cycle of a product, design decisions must be made by considering both stages together. Rapid changes in technology and customer preferences complicate the design decision even more. In a market with such rapid changes, initial product design determined at the manufacturing stage quickly becomes obsolete and outdated. To attract customers in the market, remanufactured products may need appropriate part upgrades. Therefore, product design must be optimized in a way that considers possible part upgrades at the end-of-life stage (Sand and Gu 2006; Östlin, Sundin, and Björkman 2009; Kwak and Kim 2013).

This article considers a company that makes and sells new products and also sells remanufactured versions of the new products that become available at the end of their life cycle. To help in optimal product design for the company, this article proposes a mathematical model using mixed integer programming. The proposed model identifies the optimal product design and corresponding production strategies that maximize the total life-cycle profit. Here, life-cycle profit denotes the *sum of the profits from initial manufacturing and end-of-life remanufacturing*. To be more specific, the model optimizes the following decisions (Figure 1):

- initial design (both specifications and selling price) and production quantity of the new product
- number of units of used products to take back (or buy back) at the end-of-life stage
- design upgrades and production quantity of the remanufactured product

The rest of the article is organized as follows. Section 2 discusses the relevant literature, followed by the proposed mathematical model in Section 3. Section 4 illustrates the model with the example of a desktop computer. Section 5 discusses the extension of the model to a multi-objective model that considers both life-cycle profit and environmental-impact saving. Section 6 summarizes the article with future research directions.

2. Literature review

Given the rapid changes in technology and customer preferences, optimal design is a critical success factor for manufacturers. To compete in the market, manufacturers need to identify optimal specifications and selling prices for their products. In the engineering design community, such optimal design has been discussed focusing on new product sales. Design for market systems

(DMS) and decision-based design (DBD) are well-known streams of research to this end. Various approaches have been proposed to optimize new product sales, including by Hazelrigg (1998), Wassenaar and Chen (2003), Gu *et al.* (2002), Kumar, Chen, and Kim (2006), and Frischknecht, Whitefoot, and Papalambros (2010).

When remanufacturing is involved, design optimization encompasses additional decisions on part reuse and upgrades at the end-of-life stage. The decisions include: (1) whether to reuse a part or upgrade; and (2) the new specification of a part when it is to be upgraded. Despite growing interest in remanufacturing, only a few studies have made progress concerning an optimal design of this sort that also considers upgrades. Tsubouchi and Takata (2007) presented a model for determining the optimal timing and content of module-based design upgrades. The model attempted to satisfy customers' requirements, while minimizing the environmental load from production. Rachaniotis and Pappis (2008) proposed a decision-making model for remanufacturing a set of systems, in which the parts deteriorated at different rates and had different levels of importance for the system. The model determined which parts should be reused, replaced, upgraded or disposed of in order to maximize the performance of the overall systems. Chung, Okudan, and Wysk (2010) presented a dynamic programming model for determining the optimal upgrade plan for an existing product. Assuming product users as the decision maker, the proposed model identified the timing and content of upgrades that meet future performance requirements with a minimum cost. Kwak and Kim (2013) proposed a model for market positioning of a remanufactured product. When the design of a new product is given, the model optimizes the design and selling price of the remanufactured product, considering possible upgrades of constituent parts.

One limitation of the previous methods is that design influences on the initial manufacturing and end-of-life remanufacturing have been considered separately. Product design not only determines the initial profit from the manufacturing stage, but also affects the future profit at the end-of-life stage (*i.e.* remanufacturing). Previous approaches, however, have focused on improving one only of the stages, but not the stages together. Exceptions can be found in Zhao and Thurston (2010) and Ma, Kwak, and Kim (2012). They developed a mathematical model to determine an optimal product design that maximizes the profits from both initial sales and end-of-life recovery. They showed that the total profit can be maximized when both ends of the product life cycle are considered at the same time. However, they did not incorporate part upgrades at the end-of-life stage.

The current design model presented in the next section provides a simultaneous consideration of profits from both initial manufacturing and end-of-life remanufacturing with optimal part upgrade decisions. The model can identify optimal designs for two different sets of products—new and remanufactured—while the identity of the product is maintained. For example, two sets of the same type of consumer electronics products are designed, in which the details of product specifications are different for new and remanufactured. The details of the model follow in the next section.

3. Optimal product design for life-cycle profit

This section proposes a mathematical model for optimal product design. Mathematical notations used in the model are shown in the Nomenclature. Using mixed integer programming, the proposed model identifies optimal specifications, selling prices, and the corresponding production strategies for both new and remanufactured products. The goal of the model is to maximize the total life-cycle profit, *i.e.* the sum of the profits from initial manufacturing and end-of-life remanufacturing.

The proposed model is based on the following assumptions. First, the decision maker has no other products in the target market, so there is no risk of cannibalization. Secondly, the product to be remanufactured has a modular structure, and upgrades are made through part replacement.

Thirdly, remanufacturing is instantaneous. Remanufacturing operations have a negligible lead time. Fourthly, all non-reusable and leftover parts are transferred to third party recyclers for material recovery. Lastly, the decision maker has good knowledge of the required inputs at the time of applying the model. How to estimate input values is outside the scope of this study.

3.1. *Part obsolescence and upgrade decisions*

To represent product specifications and technological obsolescence, this study uses the concept of *generational difference* (Kwak and Kim 2013). As product technology advances, cutting-edge parts of a new generation start to appear in the market. In this study, the newer part corresponds to the greater number of generations, and the cutting-edge part corresponds to the maximum generation (the latest). Then, the generational difference of a part is the gap between its generation and the current maximum generation of the cutting-edge part. (For example, a product consisting of cutting-edge parts only has zero generational differences for each and every part.) Therefore, the generational difference indicates, in terms of the technology, how old an existing part is compared with the cutting-edge part.

In the current model, x_{Ni} denotes the specification of part i of a new product. It is represented in terms of the part's generational difference at the manufacturing stage. As the specification becomes obsolete over time, the generational difference of part i increases with an annual average rate of μ_i; t years later (when the product reaches the end-of-life stage), the generational difference becomes $\delta_i(t)$, which is equal to floor($x_{Ni} + \mu_i \cdot t$), *i.e.* the greatest integer less than or equal to $x_{Ni} + \mu_i \cdot t$. Given $\delta_i(t)$, the specification of the remanufactured product x_{Ri} is defined as a function of $\delta_i(t)$, *i.e.* $x_{Ri} = \delta_i(t) \cdot y_i + u_i$, where y_i is the binary decision variable indicating whether part i of the remanufactured product maintains its original specification ($y_i = 1$) or upgrades its specification ($y_i = 0$), and u_i represents the decision on part upgrading, *i.e.* the generational difference of part i when a decision is made to upgrade the part.

Figure 2 describes how decisions on part reuse and upgrading affect the remanufacturing operation. More specifically, the figure shows which and how many used parts and spare parts are necessary in remanufacturing, when S_R units of end-of-life products are returned for recovery, and the target production quantity for the remanufactured product is given as β_R units. If part i is determined to be upgraded ($y_i = 0$), no parts are reused in remanufacturing. All S_R units of reusable part i are sold to third party recyclers for material recovery, while β_R units of a spare part with an upgraded specification u_i are newly purchased. If part i is determined to maintain its original specification ($y_i = 1$), the next question is whether the $R_i(t)$ units of reusable part i are sufficient to meet the production quantity β_R. If part i is insufficient in quantity for remanufacturing (*i.e.* $\beta_R > R_i(t)$; $l_i = 1$), spare parts that are new but having the original specification are purchased for as many as $(\beta_R - R_i(t))$; in the meantime, all non-reusable parts (*i.e.* $(S_R - R_i(t))$ units) are sent to third party recyclers. In contrast, if there are enough reusable parts (*i.e.* $\beta_R \le R_i(t)$; $l_i = 0$), only β_R units are used in remanufacturing. The rest $(S_R - \beta_R)$ units, including both the non-reusable and left-over parts, are processed for material recovery.

3.2. *Remanufacturing process*

The primary goal of remanufacturing is to retrieve valuable parts from end-of-life products and use them to produce marketable products. Remanufacturing typically involves two sequential activities: product take-back and a reprocessing operation. Figure 3 depicts the remanufacturing process considered in this article and how the process is linked with new product sales.

Product take-back is the process of collecting (buying back) end-of-life products. Since product take-back determines the quality and quantity of feedstock processed later in the reprocessing operation, a key aspect of this activity is to determine how many products should be acquired. The current model assumes that S_R units of end-of-life products, or an α fraction of the total new product sales β_N, are taken back for remanufacturing at the end-of-life stage. Here, the take-back rate α is one of the decision variables to optimize.

After product take-back, the collected products pass through a reprocessing operation. In the first stage of reprocessing, products are disassembled into a set of parts, and the resultant parts start their recovery as independent units. Two recovery options are considered for each part, *i.e.* reuse for product remanufacturing or material recycling. An important point is that not all resulting parts are reusable, and only reusable parts are qualified for reuse. In addition, as discussed in Section 3.1, upgrading decisions affect which and how many parts are reused. For the parts to be reused, reconditioning (*e.g.* cleaning, lubricating) is conducted as needed. In the last stage, parts from the end-of-life products are reassembled into β_R units of remanufactured products. Again, upgrade decisions affect the type and number of new parts to purchase, as shown in Figure 3. When there is a shortage of parts, new spare parts can be externally procured.

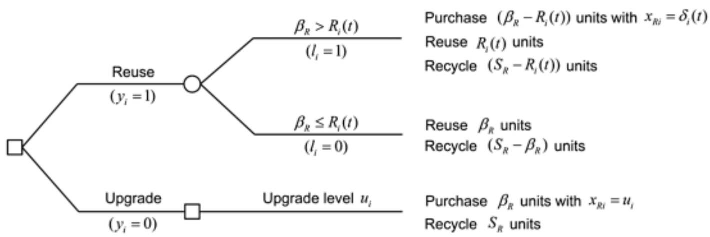

Figure 2. Possible decisions on part upgrades and their implications in remanufacturing.

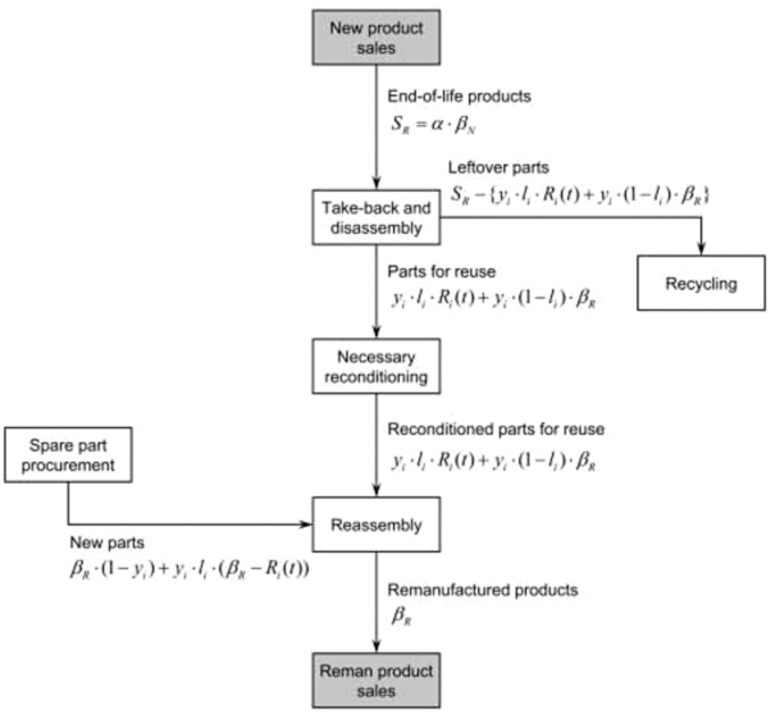

Figure 3. Remanufacturing process and product/part flow volumes.

3.3. *Mathematical model*

The optimization model is formulated in Equations (1)–(6). The objective of this model (Equation 1) is to maximize the total life-cycle profit, where the life-cycle profit is the sum of two components: the profit from selling new products, Π_N, and the profit from selling remanufactured products, Π_R. The profit from remanufacturing is discounted with an annual interest rate of θ.

$$
\begin{aligned}
&\text{maximize } \Pi_N + (1+\theta)^{-t} \cdot \Pi_R \\
&\text{with respect to } x_{Ni},\ p_N,\ \beta_N,\ x_{Ri},\ p_R,\ \beta_R,\ \alpha,\ y_i,\ l_i,\ u_i,\ \delta_i(t) \\
&\text{where} \\
&\Pi_N = p_N \cdot \beta_N - (C_N^{\text{part}} + C_N^{\text{market}}) \\
&\Pi_R = p_R \cdot \beta_R + M_R^{\text{recycle}} - (C_R^{\text{takeback}} + C_R^{\text{part}} + C_R^{\text{recond}} + C_R^{\text{market}}) \\
&C_N^{\text{part}} = \beta_N \cdot \sum_{i \in I} V_i^{\text{new}}(x_{Ni}) \\
&C_N^{\text{market}} = c^{\text{market}} \cdot \beta_N \\
&C_R^{\text{takeback}} = c^{\text{takeback}} \cdot S_R \\
&C_R^{\text{part}} = \sum_{i \in I} [(1-y_i) \cdot \beta_R + y_i \cdot l_i \cdot (\beta_R - R_t(t))] \cdot V_i^{\text{new}}(x_{Ri}) \\
&C_R^{\text{recond}} = \sum_{i \in I} [y_i \cdot l_i \cdot R_i(t) + y_i \cdot (1-l_i) \cdot \beta_R] \cdot c_i^{\text{recond}} \\
&C_R^{\text{market}} = c^{\text{market}} \cdot \beta_R \\
&M_R^{\text{recycle}} = \sum_{i \in I} [S_R - y_i \cdot l_i \cdot R_i(t) - y_i \cdot (1-l_i) \cdot \beta_R] \cdot V_i^{\text{matl}}(x_{Ri}) \\
&S_R = \alpha \cdot \beta_N
\end{aligned}
\tag{1}
$$

The profit from new product sales consists of three parts: the revenue from selling β_N units of new products (*i.e.* $p_N \cdot \beta_N$), the cost of purchasing (or manufacturing) parts for making β_N products (*i.e.* C_N^{part}), and the cost of assembling and distributing β_N products (*i.e.* C_N^{market}). The profit from remanufacturing consists of six components: the revenue from selling β_R units of remanufactured products (*i.e.* $p_R \cdot \beta_R$), the revenue from selling non-reusable or left-over parts to third party recyclers (*i.e.* M_R^{recycle}), the cost of taking back S_R units of end-of-life products (*i.e.* C_R^{takeback}), the cost of acquiring parts for making β_R products (*i.e.* C_R^{part}), the cost of reconditioning reusable parts (*i.e.* C_R^{recond}), and the cost of assembling and distributing β_R products (*i.e.* C_R^{market}). As described in Section 3.2, the supply of end-of-life products S_R is determined by the initial sales β_N and the take-back rate α.

Equations (2)–(6) formulate the constraints of the model. Equation (2) calculates the demand for the new and remanufactured products, *i.e.* D_N and D_R. Product specifications, $\mathbf{x}_{Ni}$ and $\mathbf{x}_{Ri}$, and selling prices, p_N and p_R, determine the size of the demand. The demand function can be defined through well-known demand modelling techniques, such as discrete choice analysis (Ben-Akiva and Lerman 1985; Wassenaar and Chen 2003) and conjoint analysis (Green, Krieger, and Wind 2001). This model also assumes that each part and the selling price have critical levels for their values, *i.e.* $\delta_{Ni}^{\max}$, $\delta_{Ri}^{\max}$, $p_N^{\max}$, $p_R^{\max}$. 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 (2) prevents the generational differences and selling price from exceeding their critical values.

$$\begin{aligned} &D_N = f_N(\mathbf{x}_{Ni}, p_N);\ D_R = f_R(\mathbf{x}_{Ri}, p_R) \\ &\mathbf{x}_{Ni} \leq \boldsymbol{\delta}_{Ni}^{\max};\ \mathbf{x}_{Ri} \leq \boldsymbol{\delta}_{Ri}^{\max};\ p_N \leq p_N^{\max};\ p_R \leq p_R^{\max} \end{aligned} \tag{2}$$

Equation (3) constrains the production quantity (or initial sales) β_N so as not to exceed the demand size D_N. Unlike new production, remanufacturing is possible only when there exist both a supply of end-of-life products and demand for remanufactured products (Guide, Teunter, and Van Wassenhove 2003; Umeda, Kondoh, and Sugino 2006). Thus, Equation (3) also constrains the production quantity β_R so as not to exceed the supply S_R or demand D_R.

$$\beta_N \leq D_N;\ \beta_R \leq D_R;\ \beta_R \leq S_R \tag{3}$$

Equation (4) formulates decisions for part upgrades at the end-of-life stage for each and every part $i (i \in I)$. The variable x_{Ri} denotes the generational difference of part i which is to be included in the remanufactured product. It is determined by two decision variables, y_i and u_i. When y_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. When y_i is 1, part i is reused, and at the same time, u_i becomes 0. Accordingly, x_{Ri} equals $\delta_i(t)$, which is the generational difference of the original part i at the end-of-life stage, *i.e.* floor($x_{Ni} + \mu_i.t$). The floor function is linearized in Equation (4) using a positive number ε less than 1 (*e.g.* 0.1 in this study).

$$\begin{aligned} x_{Ri} &= \delta_i(t) \cdot y_i + u_i && \forall i \\ \delta_i(t) &\leq x_{Ni} + \mu_i \cdot t && \forall i \\ \delta_i(t) &\geq (x_{Ni} + \mu_i \cdot t) - 1 + \varepsilon && \forall i \\ \sum_{i \in I} y_i \cdot u_i &= 0 \end{aligned} \tag{4}$$

Equation (5) considers whether the available quantity of reusable part i (*i.e.* $R_i(t)$) is sufficient to produce β_R units of the remanufactured product. The available quantity $R_i(t)$ depends on $r_i(t)$, that is, the reusability of part i of the end-of-life product at year t. If part i is insufficient in quantity (*i.e.* $\beta_R > R_i(t)$), the indicator variable l_i becomes 1; in Equation (1), this implies that new parts as many as $(\beta_R - R_i(t))$ are purchased. Finally, Equation (6) represents variable conditions.

$$\begin{aligned} R_i(t) &= r_i(t) \cdot S_R && \forall i \\ \beta_R - R_i(t) &\leq M \cdot l_i && \forall i \\ \beta_R - R_i(t) &\geq M \cdot (l_i - 1) && \forall i \end{aligned} \tag{5}$$

$$\begin{aligned} \beta_N, \beta_R, x_{Ni}, x_{Ri}, u_i, \delta_i(t) \in \text{ non-negative integer};\ y_i, l_i \in \{0,1\} \quad & \forall i \\ 0 \leq \alpha \leq 1;\ p_N \geq 0;\ p_R \geq 0 \quad & \end{aligned} \tag{6}$$

4. Case illustration

In this section, the proposed model is illustrated through an example using desktop computers. Suppose that there is an original equipment manufacturer conducting both manufacturing and

Table 1. Target market information.

New market	Part worth	Critical value	Competitor 1	Competitor 2	Competitor 3
CPU	0.125	(2, 3)	0	0	2
RAM	0.125	(2, 3)	0	1	2
Motherboard	0.100	(2, 3)	0	1	2
Hard drive	0.050	(3, 5)	0	1	2
Graphic card	0.025	(3, 5)	0	1	2
Optical drive	0.050	(3, 3)	0	0	1
Chassis	0.025	(1, 2)	0	0	0
Selling price	0.500	($1000, $500)	($1000, $500)	($600, $300)	($350, $150)
Market share			(0.3279, 0.1771)	(0.4906, 0.4861)	(0.1815, 0.3367)

Note: If a cell includes two numbers, the first is of the present new-product market and the second is of the future remanufactured-product market.

remanufacturing. It is expected that all initial sales will become available for buy-back after four years of use (*i.e.* $t = 4$), and the company is planning to conduct remanufacturing for the end-of-life products. To maximize the total life-cycle profit from manufacturing and remanufacturing, the company aims to optimize their product design. To be specific, there are nine product attributes that the company wants to optimize (Table 1), including the central processing unit (CPU), random-access memory (RAM), chassis (case, fan and power supply) and selling price.

The demand for a product is determined by its design (specifications and the selling price) as well as competing product designs. Table 1 shows the target market under consideration in this study. When two numbers are shown in a cell, the first is of the current new-product market and the second is of the future remanufactured-product market.

In the new-product market, there exist three competing products sold at the prices of $1000, $600 and $350. The current market share indicates that customers in the market like the product with medium specifications most (49%) and the highest specifications next (33%). Given the market condition, the expected demand for a new product D_N can be calculated using a conditional multinomial logit choice model, as shown in Equation (7). Here, Q_N denotes the new-product market size, and U_N and U_j denote the customer utility for the new and the competing product j, respectively. In the equation, k is a scaling parameter; as $k \to 0$, all choices have the same demand (Jiao and Zhang 2005). In this study, k was calibrated on the current market share in Table 1 and defined as 6.45.

The utility for the new product U_N is defined as a linear weighted sum of its generational differences x_{Ni} and the selling price p_N (Equation 8). For the calculation, x_{Ni} and p_N are normalized to lie between 0 and 1. The 'Part worth' column in Table 1 shows the weight (or part-worth utility) assumed for each normalized x_{Ni} and p_N, *i.e.* w_{Ni} and w_{Np}. The 'Critical value' column provides the critical values for x_{Ni} and p_N, *i.e.* $\delta_{Ni}^{\max}$ and $p_N^{\max}$. As described in Section 3, the critical values are the maximum generational differences and selling price that customers are willing to accept for a product. In the current study, as an example, the customers of the new-product market will not buy a product if the CPU is more than two generations old.

$$D_N = Q_N \cdot \frac{\exp(kU_N)}{\exp(kU_N) + \sum_{j \in J} \exp(kU_j)} \tag{7}$$

$$U_N = \sum_{i \in I} w_{Ni} x'_{Ni} + w_{Np} p'_N \quad \text{where } x'_{Ni} = 1 - x_{Ni}/\delta_{Ni}^{\max};\ p'_N = 1 - p_N/p_N^{\max} \tag{8}$$

Equation (9) shows the final demand function obtained for the new product. Similarly, the demand function for the remanufactured product is obtained, where Q_R denotes the size of the remanufactured-product market. For simplicity, it was assumed that the part-worth utility does not

Table 2. Parameter settings ($t = 4$).

	$V_i^{\text{new}}(0)$ (\$)	ϕ_i	μ_i	V_i^{matl} (\$)	$r_i(t)$	c_i^{recond} (\$)
CPU	175	0.6733	0.67	5	0.7745	1
RAM	50	0.8378	0.50	5	0.7745	1
Motherboard	150	0.6733	0.67	5	0.5999	1
Hard drive	120	0.1717	1.00	4.5	0.2787	1
Graphic card	100	0.2883	1.00	4.5	0.4646	1
Optical drive	80	0.8088	0.40	3	0.0466	1
Chassis	75	0.1500	0.20	3	0.4646	3

differ between the new- and the remanufactured-product markets. Also, $k = 9.18$ was used for the demand modelling. In this study, Q_N and Q_R are assumed to be 50,000 and 10,000, respectively.

$$\begin{aligned} D_N &= Q_N \cdot (1 + e^{-6.45\cdot(U_N - 0.67)})^{-1} \\ D_R &= Q_R \cdot (1 + e^{-9.18\cdot(U_R - 0.69)})^{-1} \end{aligned} \tag{9}$$

Table 2 provides assumptions on remanufacturing costs and revenues. In Table 2, $V_i^{\text{new}}(0)$ represents the market value of the newest cutting-edge part. In Equation (10), it is used for calculating the cost of purchasing a new part. Adopting the model by Kwak and Kim (2011), the equation assumes that a part's market value depreciates exponentially with its generational difference. The constant parameter ϕ_i reflects a part's own speed of value depreciation. The values of ϕ_i used in this study are given in Table 2.

$$V_i^{\text{new}}(x_i) = V_i^{\text{new}}(0) \cdot e^{-\phi_i \cdot x_i} \tag{10}$$

In Table 2, V_i^{matl} shows the revenue from selling a part to a third party recycler. For simplicity, it is assumed to be the same regardless of the specification. Other processing costs, c^{takeback} and c^{market}, are assumed to be \$58 (\$28 for collection; \$30 for disassembly, inspection and sorting) and \$35, respectively (Bhuie *et al.* 2004; Microsoft 2008). Finally, the annual interest rate is assumed to be 3% (*i.e.* $\theta = 0.03$).

The final optimization model is given in Appendix 1 (see Equation A1). With the initial starting point set as $\mathbf{y}_i = \mathbf{1}, p_N = 1000, p_R = 500, \alpha = 1, \beta_N = 50,000, \beta_R = 10,000$, and all others being zero, the optimization model was solved using the Large-Scale Generalized Reduced Gradient (GRG) Solver of Risk Solver Platform (version 11.0). A personal computer with Intel Core i5 processor (2.53 GHz) and 4 GB RAM was used, and the total solution time was 73 seconds. Table 3 shows the optimization result. The optimal solution satisfied the optimality conditions of the Large-Scale GRG Solver, which means that it is at least a locally optimal solution. The results can be summarized as follows.

- The optimal initial design is to include a cutting-edge CPU, RAM, motherboard, hard drive and chassis, a three-generation-old graphic card and a one-generation-old optical drive. The optimal selling price for the new product is \$999.99, and the corresponding market share is expected to be 20% (or 10,020 units). The total profit expected from the manufacturing stage is approximately \$3.18 million.
- Pursuing remanufacturing can be profitable; it can increase the life-cycle profit by \$72,000. To take advantage of the profit opportunity, the company should take back 1489 units of end-of-life products, which is 14.9% of initial sales. Using the end-of-life products, the company should produce 692 units of remanufactured products. While all other parts are reused in remanufacturing, the RAM and graphic card should be upgraded from two- and seven-generation-old

Table 3. Optimal design of new and remanufactured products ($t = 4$).

	New	Remanufactured
CPU	0	2
RAM	0	0 (upgraded)
Motherboard	0	2
Hard drive	0	4
Graphic card	3	5 (upgraded)
Optical drive	1	2
Chassis	0	0
Price	\$999.99	\$346.24
Production quantity (take-back amount)	10,020 units	692 units (1489 units, $\alpha = 14.86\%$)
Market share	20.04%	6.92%
Total profit (present value)	\$3,250,921 (\$3,178,884 from new, \$72,047 from remanufactured)	

Table 4. Optimal design of new and remanufactured products under a take-back law enforcing a 75% take-back ($t = 4$).

	New	Remanufactured
CPU	0	2
RAM	0	0 (upgraded)
Motherboard	0	2
Hard drive	0	4
Graphic card	3	5 (upgraded)
Optical drive	1	2
Chassis	0	0
Price	\$999.99	\$272.91
Production quantity (take-back amount)	10,020 units	1272 units (7515 units, $\alpha = 75\%$)
Market share	20.04%	12.72%
Total profit (present value)	\$3,136,747 (\$3,178,884 from new, −\$42,127 from remanufactured)	

parts to cutting-edge and five-generation-old parts, respectively. The optimal selling price of the remanufactured product is \$346, and the expected market share is approximately 7%.

Table 4 considers another scenario where there is a take-back law enforcing a 75% collection rate for the initial sales, *i.e.* $\alpha \geq 0.75$. With the additional constraint, the optimization model was solved using the same setting as the previous case with no take-back law. The optimal solution in Table 4 indicates that such legislation would not alter the optimal initial design or design upgrades plan in Table 3 but facilitate more remanufacturing by reducing the selling price of the remanufactured product. Compared with Table 3, the selling price of the remanufactured product is reduced from \$346 to \$273, which increases the expected market share by 5.8%. Conducting remanufacturing, however, is not profitable; rather, it costs approximately \$42,100 (in present value) owing to the increased amount of take-back (from 1489 to 7515 units). Nevertheless, remanufacturing is still recommendable if one considers that the end-of-life treatment would have cost approximately \$210,400 (= 7515 units ×take-back cost \$28/unit), *i.e.* \$187,000 in present value, in case of no remanufacturing and recycling material only.

5. Discussion: Extension to design for green profit

In previous sections, the proposed model considers only the economic perspective of life-cycle design. This section discusses an extension of the model to a bi-objective model that has two conflicting objectives: to maximize the life-cycle profit (*i.e.* f_1) and to maximize the *environmental-impact saving* (*i.e.* f_2).

$$\begin{aligned}
&\text{maximize} f_2 : E^{\text{takeback}} + E^{\text{reman}} \\
&\text{where} \\
&E^{\text{takeback}} = e^{\text{disposal}} \cdot \alpha \cdot \beta_N \\
&- \left(e^{\text{takeback}} \cdot S_R + \sum_{i \in I} [S_R - y_i \cdot l_i \cdot R_i(t) - y_i \cdot (1 - l_i) \cdot \beta_R] \cdot e_i^{\text{matl}}(x_{Ri}) \right) \\
&E^{\text{reman}} = \sum_{i \in I} e_i^{\text{new}}(x_{Ri}) \cdot \beta_R - \left(\begin{array}{l} \sum_{i \in I} [(1 - y_i) \cdot \beta_R + y_i \cdot l_i \cdot (\beta_R - R_t(t))] \cdot e_i^{\text{new}}(x_{Ri}) \\ + \sum_{i \in I} [y_i \cdot l_i \cdot R_i(t) + y_i \cdot (1 - l_i) \cdot \beta_R] \cdot e_i^{\text{recond}} \end{array} \right)
\end{aligned} \tag{11}$$

Environmental-impact saving is the concept proposed in Kwak, Koritz, and Kim (2013). It indicates 'how much environmental impact can be avoided by producing remanufactured products, as compared to the case when only new products are produced'. Adopting the concept of environmental saving, the second objective can be formulated as shown in Equation (11). The environmental advantage of remanufacturing originates from two sources. First, by taking back end-of-life products, companies can reduce the amount of waste that must be disposed of. Secondly, by utilizing the parts from the end-of-life products, companies can produce products in 'same-as-new' condition using reduced resources and energy. E^{takeback} and E^{reman} in Equation (11) represent the impact saving from the two sources, respectively.

In this article, the ε*-constraint approach* (Andersson 2000; Mavrotas 2009) was used to consider the two objectives simultaneously. In the ε-constraint approach, one of the objective functions is optimized using the other objective functions as constraints. For instance, the bi-objective problem in Equation (12) can be reformulated as Equation (13), where the second objective f_2 is incorporated into the constraint part of the model and bounded from below by ε. (It should be noted that the solution space in Equations 12 and 13 is limited to $f_1 \geq 0$: the decision maker in this article is a profit-seeking company.)

$$\begin{aligned}
&\max_x [f_1(x), f_2(x)] \\
&\text{subject to} \\
&g_l(x) \leq 0 \quad l = 1, 2, \ldots, L \\
&h_m(x) = 0 \quad m = 1, 2, \ldots, M \\
&f_1 \geq 0
\end{aligned} \tag{12}$$

$$\begin{aligned}
&\max_x f_1(x) \\
&\text{subject to} \\
&g_l(x) \leq 0 \quad l = 1, 2, \ldots, L \\
&h_m(x) = 0 \quad m = 1, 2, \ldots, M \\
&f_1 \geq 0 \\
&f_2(x) \geq \varepsilon \\
&\varepsilon = f_2(x_1{}^*) + (f_2(x_2{}^*) - f_2(x_1{}^*)) \cdot \eta \\
&0 \leq \eta \leq 1
\end{aligned} \tag{13}$$

Table 5. Parameter settings for environmental consideration ($t = 4$).

	e_i^{new} (kg CO_2e)	e_i^{recond} (kg CO_2e)	e_i^{matl} (kg CO_2e)
CPU	5.92	1.18	0.0051
RAM	7.59	1.52	0.0015
Motherboard	169.00	33.80	0.0044
Hard drive	12.30	2.46	0.0035
Graphic card	50.20	10.04	0.0029
Optical drive	17.10	3.42	0.0023
Chassis	56.20	11.24	0.0022

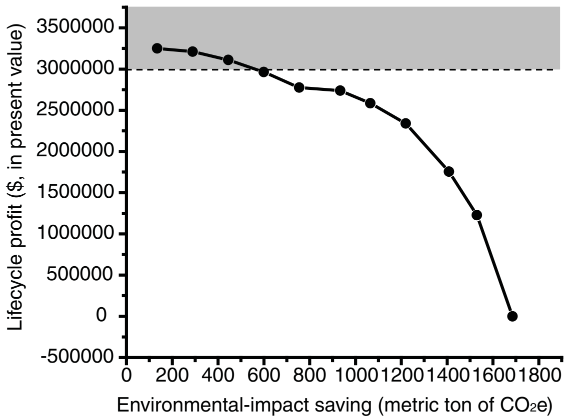

Figure 4. Efficient frontier of the bi-objective optimization. The grey area indicates the opportunities for green profit, compared with the case of selling the new product only.

The lower bound ε can be set by a two-step approach. First, by solving Equation (12) with only one objective at a time (*i.e.* first, maximizing the life-cycle profit, and next, maximizing the environmental-impact saving), calculate the two extremes of the efficient frontier (*i.e.* a set of Pareto optimal solutions); this gives the range of f_2, *i.e.* the lower bound $f_2(x_1^*)$ and the upper bound $f_2(x_2^*)$. Next, apply a value of η between 0 and 1. By progressively increasing the η value, different points on the efficient frontier can be sampled. If $\eta = 0$, the resulting optimum of Equation (13) is the same as the independent maximum of f_1. If $\eta = 1$, the resulting optimum is the same as the independent maximum of f_2.

To demonstrate, the developed bi-objective model is applied to the desktop case. As the measure for the environmental impact, global warming potential (GWP), which quantifies the greenhouse gas emissions to air, was used. The unit of GWP is kilograms of carbon dioxide equivalent (hereinafter kg CO_2e). The environmental impact parameters used for the optimization are shown in Table 5. In addition, $e^{disposal}$ and $e^{takeback}$ are assumed to be 1.488 and 0.658, respectively. Life-cycle assessment (LCA) was conducted to estimate the impact parameters using SimaPro 7.3 and the ecoinvent database. More details on LCA and its applications can be found in Keoleian (1993), Guinée *et al.* (2011), Rebitzer *et al.* (2004) and Goedkoop and Spriensma (2000).

Figure 4 and Table 6 show the optimization results. By progressively changing the η value from 0 to 1 with 0.1 increment, a total 11 points on the efficient frontier is sampled. Here, $\eta = 0$ represents the single-objective problem of maximizing the life-cycle profit, which returns the optimal solution identical to Table 3. As η increases, more environmental consideration is made, and $\eta = 1$ represents another single-objective problem of maximizing the environmental saving.

Table 6. Optimal design of new and remanufactured (Reman.) products ($t = 4$) with two objectives.

	New	Reman.	New	Reman.	New	Reman.
	$\eta = 0$		$\eta = 0.2$		$\eta = 0.4$	
CPU	0	2	0	2	0	2
RAM	0	0 (upgraded)	0	0 (upgraded)	0	0 (upgraded)
Motherboard	0	2	0	2	0	2
Hard drive	0	4	0	4	0	4
Graphic card	3	5 (upgraded)	3	5 (upgraded)	3	5 (upgraded)
Optical drive	1	2	1	2	1	2
Chassis	0	0	0	0	0	0
Price	\$999.99	\$346.24	\$999.99	\$195.22	\$999.99	\$112.24
Production quantity	10,020 units	692 units	10,020 units	2,292 units	10,020 units	3,891 units
(take-back amount)		(1,489 units)		(4,933 units)		(8,380 units)
Market share	20.04%	6.92%	20.04%	22.92%	20.04%	38.91%
Total profit	\$3,250,921		\$3,109,977		\$2,774,972	
(present value)	(\$3,178,874, \$72,047)		(\$3,178,874, −\$68,898)		(\$3,178,884, −\$403,903)	
Total environmental saving	134,196kg CO_2e		444,475kg CO_2e		754,582kg CO_2e	
	$\eta = 0.6$		$\eta = 0.8$		$\eta = 1$	
CPU	0	2	0	2	0	1 (upgraded)
RAM	0	0 (upgraded)	0	0 (upgraded)	0	0 (upgraded)
Motherboard	0	2	0	2	0	2
Hard drive	0	4	0	4	0	4
Graphic card	1	5	1	5	1	5
Optical drive	1	2	1	2	1	1 (upgraded)
Chassis	0	0	0	0	0	0
Price	\$999.99	\$82.80	\$963.79	\$3.81	\$852.90	\$0.06
Production quantity	10,909 units	4,549 units	11,937 units	6,328 units	15,479 units	7,529 units
(take-back amount)		(9,790 units)		(11,937 units)		(15,479 units)
Market share	21.82%	45.49%	23.87%	63.28%	30.96%	75.29%
Total profit	\$2,584,829		\$1,756,122		\$118.03	
(present value)	(\$3,102,546, −\$517,717)		(\$2,962,818, −\$1,206,697)		(\$2,125,497, −\$2,125,379)	
Total environmental saving	1,064,863 kg CO_2e		1,407,720 kg CO_2e		1,685,161 kg CO_2e	

Among the 11 points, Table 6 shows detailed results for six points. The results can be summarized as follows.

- Until $\eta = 0.4$, the optimal initial designs are the same, as explained in Table 3. The desktop should include a cutting-edge CPU, RAM, motherboard, hard drive and chassis, a three-generation-old graphic card and a one-generation-old optical drive. The optimal selling price for the new product is \$999.99, and the corresponding market share is expected to be 20% (or 10,020 units). At the end-of-life stage, the RAM and graphic card should be upgraded to cutting-edge and five-generation-old parts, respectively, while all other parts are reused in remanufacturing. As the η value progressively increases, changes are observed in the optimal take-back rate, remanufacturing quantity and selling price for the remanufactured product. When the company aims to maximize its profit only (*i.e.* $\eta = 0$), the optimal take-back rate and remanufacturing quantity are 14.9% and 692 units, respectively; the corresponding selling price for the remanufactured product is \$346. However, as more environmental consideration is made, more remanufacturing is pursued. When $\eta = 0.4$, the optimal take-back rate and remanufacturing quantity increase to 83.6% and 3891 units while the optimal selling price decreases to \$112. Even though the total life-cycle profit decreases by 14.6% (from 3.25 to 2.77 million dollars), a huge environmental saving is observed; the total saving increases from 134 to 755 tonnes of CO_2e by 462.3%.

- If $\eta = 0.6$, more weight is given to the environmental saving, and the optimal initial design and upgrade plan are changed to enable more remanufacturing. To be more specific, 'overdesign' of graphic card is chosen at the initial design stage, and the new product includes a one-generation-old graphic card instead of a three-generation-old one. Accordingly, no upgrade is needed at the end-of-life stage, which enables the cost of purchasing spare parts to be reduced.
- When $\eta = 0.8$, the selling price for the new product decreases to \$964, and the new product sales increase accordingly. As more products are released to the market, more end-of-life products are taken back and allowed to meet the increasing demand for the remanufactured product.
- If the company aims to maximize its environmental-impact saving ($\eta = 1$), it should increase the remanufacturing quantity even more. To secure enough reusable parts, more end-of-life products have to be returned, which requires increase new product sales by offering a cheaper price (*i.e.* \$853). To increase the market share, the upgrade plan for the remanufactured product also changes. More parts upgrading is conducted, and the selling price for the remanufactured product decreases almost to zero. Consequently, approximately 7500 units of the remanufactured product are produced, and the total environmental-impact saving reaches 1685 tonnes of CO_2e.

Figure 4 plots and compares different points on the efficient frontier. As explained in Section 4, if the company sells only the new product and no remanufacturing is conducted, the total life-cycle profit is expected to be approximately 3 million dollars in present value (*i.e.* \$3,178,874 – \$187,000 = 2,991,936). Given the case as the reference point, the grey area in Figure 4 represents the opportunities where the company can achieve a 'green profit' (Kwak 2012). The solutions in the grey area show that the company can actually make a green profit with the optimal life-cycle design that considers both initial manufacturing and end-of-life remanufacturing simultaneously.

6. Conclusion

Product design determines both the current profit from manufacturing and the future profit from remanufacturing. To maximize the total life-cycle profit, design decisions must be carefully made considering both stages together. To help in such design for life-cycle profit, this article proposed a nonlinear mixed integer programming model. Considering trends in product obsolescence and customer preferences, the model optimizes both the initial design and design upgrades at the end-of-life stage and also provides corresponding production strategies. The model and its potential applications are illustrated with an example of a desktop computer. Its extension to a model for green-profit maximization is also discussed and demonstrated.

The proposed optimization model can serve as a useful tool for life-cycle thinking in product design, especially in the concept design stage where design specifications and abstract embodiment of a product are determined. Moreover, the model provides essential information for configuration and detail design stages. The model helps designers to identify which parts are expected to be reused or upgraded at the end-of-life stage. Understanding future paths of each part is important in elaborating product design, since parts for (reuse in) remanufacturing and parts for recycling have different design concerns, in terms of, for example, compatibility with (physically or functionally) adjacent parts, ease of assembly and disassembly, security of technology and the protection of intellectual property, and liability for improper disposal. By providing estimates for future paths of parts inside, the proposed model can help to elaborate product design from a life-cycle perspective.

In the future, the model should be improved to incorporate market trend estimation. The inputs needed for the proposed model (*e.g.* customer preference trend, reusability of parts decreasing over time and part market value trend) may bring challenges to prediction. Although such future prediction was 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.* Tucker and Kim 2011; Ma, Kwak, and Kim 2012) may provide a promising solution to this challenge. Another potentially productive line of research would be to improve the current model for uncertainty consideration. Uncertainty is an important aspect in design for life cycle because many parameters are stochastic and uncontrollable in reality. Future work should include the development of a stochastic model that can deal effectively with such uncertainties and provide a robust design solution. The mixed integer programming model proposed in this article is simple, but it is one of the first attempts to integrate design optimization of new and remanufactured products and provides a great foundation for a variety of studies in the future.

Nomenclature

i	Index for part; $i \in I$
N, R	Index for the new ($= N$) and the remanufactured ($= R$) products, respectively
Π_N, Π_R	Profit from selling the new and the remanufactured products, respectively
x_{Ni}, x_{Ri}	Specification of part i of the new and the remanufactured products, respectively
p_N, p_R	Selling price of the new and the remanufactured products, respectively
β_N, β_R	Production quantity of the new and the remanufactured products, respectively
D_N, D_R	Demand size (in units) for the new and the remanufactured products, respectively
t	Product end-of-life year; time (in years) when the product returns for remanufacturing
α	Take-back rate at year t
S_R	Supply of the end-of-life product (in units) at year t
y_i	Binary variable indicating whether part i of the remanufactured product maintains its original specification ($y_i = 1$) or upgrades its specification ($y_i = 0$)
$\delta_i\ (t)$	Generational difference of part i of the end-of-life product at year t
u_i	Generational difference of part i being newly decided when the part i is to be upgraded
l_i	Binary decision variable indicating whether part i needs new part purchase ($= 1$) or not ($= 0$)
$R_i\ (t)$	Number of units of reusable part i available for remanufacturing at year t
$r_i\ (t)$	Reusability of part i of the end-of-life product at year t
μ_i	Average frequency per year in which a successive generation of part i newly released
$C_N^{\text{part}}, C_R^{\text{part}}$	Total cost of purchasing (or manufacturing) parts for the new and the remanufactured products, respectively
$C_N^{\text{market}}, C_R^{\text{market}}$	Total cost of assembling and distributing the new and the remanufactured products, respectively
$C_R^{\text{takeback}}, C_R^{\text{recond}}$	Total cost of take-back and reconditioning, respectively
$V_i^{\text{new}}(x_i)$	Market value of purchasing a new part i when the part's specification is x_i
$V_i^{\text{matl}}(x_i)$	Market value of recycling a used part i when the part's specification is x_i
M_R^{recycle}	Total revenue from recycling (*i.e.* material recovery)
c^{takeback}	Unit cost of taking back (buying back) the end-of-life product at year t
c_i^{recond}	Unit cost of reconditioning operations for a reusable part i
c^{market}	Unit cost of assembling and distributing a product
E^{takeback}	Environmental-impact saving from taking back $\alpha \cdot \beta_N$ units of the end-of-life product
E^{reman}	Environmental-impact saving from producing β_R units of the remanufactured product
$e^{\text{disposal}}, e^{\text{takeback}}$	Unit environmental impact of discarding and taking back the end-of-life product
$e_i^{\text{new}}(x_i)$	Unit environmental impact of purchasing a new part i when the part's specification is x_i
$e_i^{\text{recond}}(x_i)$	Unit environmental impact of reconditioning a used part i when the part's specification is x_i
$e_i^{\text{matl}}(x_i)$	Unit environmental impact of recycling a used part i when the part's specification is x_i
Q_N, Q_R	Market size (in units) for the new and the remanufactured products, respectively
M	Big M; a very large positive number
θ	Annual interest rate
$\delta_{Ni}^{\max}, \delta_{Ri}^{\max}$	Maximum value that the generational difference of part i can have for the new and the remanufactured products, respectively
$p_N^{\max}, p_R^{\max}$	Maximum selling price that customers are willing to consider for purchasing the new and the remanufactured products, respectively

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References

Andersson, J. 2000. *A Survey of Multiobjective Optimization in Engineering Design*. Technical Report no. LiTH-IKP-R-1097, Department of Mechanical Engineering, Linköping University.

Ben-Akiva, M., and S. Lerman. 1985. *Discrete Choice Analysis: Theory and Application to Travel Deman*. Cambridge, MA: MIT Press.

Bhuie, A. K., O. A. Ogunseitan, J.-D. M. Saphores, and A. A. Shapiro. 2004. "Environmental and Economic Trade-Offs in Consumer Electronic Products Recycling: A Case Study of Cell Phones and Computers." *Proceedings of the IEEE International Symposium on Electronics and the Environment* 74–79 (http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=1299691).

Chung, W. H., G. E. Okudan, and R. A. Wysk. 2010. "An Optimal Upgrade Strategy for Product Users Considering Future Uncertainty." *Proceedings of the IIE Annual Conference and Expo 2010 (IERC 2010)*. Cancun, Mexico.

Frischknecht, B. D., K. Whitefoot, and P. Y. Papalambros. 2010. "On the Suitability of Econometric Demand Models in Design for Market Systems." *Journal of Mechanical Design, Transactions of the ASME* 132 (12): 121007-1–121007-11.

Goedkoop, M., and S. Spriensma. 2000. *The Eco-Indicator 99: A Damage Oriented Method for Life Cycle Impact Assessment*. Amersfoort, The Netherlands: PRe Consultants.

Green, P. E., A. M. Krieger, and Y. Wind. 2001. "Thirty Years of Conjoint Analysis: Reflections and Prospects." *Interfaces* 31 (3): S56–S73.

Gu, X., J. E. Renaud, L. M. Ashe, S. M. Batill, A. S. Budhiraja, and L. J. Krajewski. 2002. "Decision-Based Collaborative Optimization." *Journal of Mechanical Design* 124 (1): 1–13.

Guide, V. D. R., R. H. Teunter, and L. N. Van Wassenhove. 2003. "Matching Demand and Supply to Maximize Profits from Remanufacturing." *Manufacturing and Service Operations Management* 5 (4): 303–316.

Guinée, J. B., R. Heijungs, G. Huppes, A. Zamagni, P. Masoni, R. Buonamici, T. Ekvall, and T. Rydberg. 2011. "Life Cycle Assessment: Past, Present, and Future." *Environmental Science & Technology* 45 (1): 90–96.

Hazelrigg, G. A. 1998. "A Framework for Decision-Based Engineering Design." *Journal of Mechanical Design* 120 (4): 653–658.

Jiao, J., and Y. Zhang. 2005. "Product Portfolio Planning with Customer-Engineering Interaction." *IIE Transactions* 37 (9): 801–814.

Keoleian, G. A. 1993. "The Application of Life Cycle Assessment to Design." *Journal of Cleaner Production* 1 (3–4): 143–149.

Kerr, W., and C. Ryan. 2001. "Eco-Efficiency Gains from Remanufacturing: A Case Study of Photocopier Remanufacturing at Fuji Xerox Australia." *Journal of Cleaner Production* 9 (1): 75–81.

Kumar, D. K. D., W. Chen, and H. M. Kim. 2006. "Multilevel Optimization for Enterprise-Driven Decision-Based Product Design." In *Decision Making in Engineering Design*, edited by E. L. Kemper, C. Wei, and C. S. Linda, 203–215. New York: ASME Press.

Kwak, M. and Kim, H. 2010. "Evaluating end-of-life recovery profit by a simultaneous consideration of product design and recovery network design." *Journal of Mechanical Design* 132 (7): 071001-1–071001-17.

Kwak, M. and Kim, H. 2011. "Assessing product family design from an end-of-life perspective." *Engineering Optimization* 43 (3): 233–255.

Kwak, M. 2012. *Green Profit Design for Lifecycle*. Doctoral dissertation, University of Illinois at Urbana-Champaign. Retrieved from: http://hdl.handle.net/2142/34247

Kwak, M., and H. Kim. 2011. "Modelling Time-Varying Value of an End-of-Life Product for Design for Recovery." *Proceedings of ICED 2011*.

Kwak, M., and H. Kim. 2013. "Market Positioning of Remanufactured Products with Optimal Planning for Part Upgrades." *Journal of Mechanical Design* 135 (1): 011007-1–011007-10.

Kwak, M., K. Koritz, and H. Kim. 2013. "Green Profit Maximization through Joint Pricing and Production Planning of New and Remanufactured Products." *Proceedings of ASME IDETC/CIE 2013*.

Lund, R. T. 1984. *Remanufacturing: The Experience of the United States and Implications for Developing Countries*. Washington, DC: World Bank.

Ma, J., M. Kwak, and H. Kim. 2012. "Pre-Life and End-of-Life Combined Profit Optimization with Predictive Product Lifecycle Design." *Proceedings of the ASME 2012 IDETC/CIE*.

Mavrotas, G. 2009. "Effective Implementation of the *e*-Constraint Method in Multi-Objective Mathematical Programming Problems." *Applied Mathematics and Computation* 213 (2): 455–465.

Microsoft. 2008. *The Enterprise PC Lifecycle*. Microsoft Corporation. http://download.microsoft.com/download/1/A/7/1A765767-7CC2-4604-8F18-C8954D548F09/Enterprise%20PC%20Lifecycle%20(Desktop%20Opt)%20-%20whitepaper.pdf

Östlin, J., E. Sundin, and M. Björkman. 2009. "Product Life-Cycle Implications for Remanufacturing Strategies." *Journal of Cleaner Production* 17 (11): 999–1009.

Rachaniotis, N. P., and C. P. Pappis. 2008. "Preventive Maintenance and Upgrade System: Optimizing the Whole Performance System by Components' Replacement or Rearrangement." *International Journal of Production Economics* 112 (1): 236–244.

Rebitzer, G., T. Ekvall, R. Frischknecht, D. Hunkeler, G. Norris, T. Rydberg, W.-P. Schmidt, S. Suh, B. P. Weidema, and D. W. Pennington. 2004. "Life Cycle Assessment: Part 1: Framework, Goal and Scope Definition, Inventory Analysis, and Applications." *Environment International* 30 (5): 701–720.

Sand, J. C., and P. Gu. 2006. "AdaptEx: Extending Product Life Cycles through Strategic Product Upgrades." In *Advances in Design*, edited by H. A. Elmaraghy and W. H. Elmaraghy, 111–119, London: Springer.
Sundin, E., and B. Bras. 2005. "Making Functional Sales Environmentally and Economically Beneficial through Product Remanufacturing." *Journal of Cleaner Production* 13 (9): 913–925.
Tsubouchi, K., and S. Takata. 2007. "Module-Based Model Change Planning for Improving Reusability in Consideration of Customer Satisfaction." *Proceedings of the 14th CIRP-LCE*.
Tucker, C., and H. Kim. 2011. "Trend Mining for Predictive Product Design." *Journal of Mechanical Design* 133 (11): 111008-1–111008-11.
Umeda, Y., S. Kondoh, and T. Sugino. 2006. "Analysis of Reusability using 'Marginal Reuse Rate'." *Annals of the CIRP-Manufacturing Technology* 55 (1): 41–44.
Wassenaar, H. J., and W. Chen. 2003. "An Approach to Decision-Based Design with Discrete Choice Analysis for Demand Modeling." *Journal of Mechanical Design* 125 (3): 490–497.
Zhao, Y., V. Pandey, H. Kim, and D. Thurston. 2010. "Varying Lifecycle Lengths within a Product Take-back Portfolio." *Journal of Mechanical Design* 132 (9): 091012-1–091012-10.
Zhao, Y., and D. Thurston. 2010. "Integrating End-of-Life and Initial Profit Considerations in Product Life Cycle Design." *Proceedings of the ASME 2010 IDETC/CIE*.

Appendix 1

$$
\begin{aligned}
&\text{maximize } \Pi_N + (1+\theta)^{-t} \cdot \Pi_R \\
&\text{with respect to } x_{Ni},\ p_N,\ \beta_N,\ x_{Ri},\ p_R,\ \beta_R,\ \alpha,\ y_i,\ l_i,\ u_i,\ \delta_i(t) \\
&\text{where} \\
&\Pi_N = p_N \cdot \beta_N - (C_N^{\text{part}} + C_N^{\text{market}}) \\
&\Pi_R = p_R \cdot \beta_R + M_R^{\text{recycle}} - (C_R^{\text{takeback}} + C_R^{\text{part}} + C_R^{\text{recond}} + C_R^{\text{market}}) \\
&C_N^{\text{part}} = \beta_N \cdot \sum_{i\in I} V_i^{\text{new}}(x_{Ni}) \\
&C_N^{\text{market}} = c^{\text{market}} \cdot \beta_N \\
&C_R^{\text{takeback}} = c^{\text{takeback}} \cdot S_R \\
&C_R^{\text{part}} = \sum_{i\in I} [(1-y_i)\cdot \beta_R + y_i \cdot l_i \cdot (\beta_R - R_t(t))] \cdot V_i^{\text{new}}(x_{Ri}) \\
&C_R^{\text{recond}} = \sum_{i\in I} [y_i \cdot l_i \cdot R_i(t) + y_i \cdot (1-l_i)\cdot \beta_R] \cdot c_i^{\text{recond}} \\
&C_R^{\text{market}} = c^{\text{market}} \cdot \beta_R \\
&M_R^{\text{recycle}} = \sum_{i\in I} [S_R - y_i \cdot l_i \cdot R_i(t) - y_i \cdot (1-l_i) \cdot \beta_R] \cdot V_i^{\text{matl}}(x_{Ri}) \\
&S_R = \alpha \cdot \beta_N \\
&\text{subject to} \\
&D_N = Q_N \cdot (1 + e^{-6.45\cdot(U_N - 0.67)})^{-1} \\
&D_R = Q_R \cdot (1 + e^{-9.18\cdot(U_R - 0.69)})^{-1} \\
&U_N = \sum_{i\in I} [w_{Ni} \cdot (1 - x_{Ni}/\delta_{Ni}^{\max}) + w_{Np} \cdot (1 - p_N/p_N^{\max})] \\
&U_R = \sum_{i\in I} [w_{Ri} \cdot (1 - x_{Ri}/\delta_{Ri}^{\max}) + w_{Rp} \cdot (1 - p_R/p_R^{\max})] \\
&\beta_N \le D_N;\ \beta_R \le D_R;\ \beta_R \le S_R \\
&x_{Ri} = \delta_i(t) \cdot y_i + u_i \quad \forall i \\
&\delta_i(t) \le x_{Ni} + \mu_i \cdot t \quad \forall i
\end{aligned}
\tag{A1}
$$

$$\delta_i(t) \geq (x_{Ni} + \mu_i \cdot t) - 1 + \varepsilon \quad \forall i$$

$$\sum_{i \in I} y_i \cdot u_i = 0$$

$$R_i(t) = r_i(t) \cdot S_R \quad \forall i$$

$$\beta_R - R_i(t) \leq M \cdot l_i \quad \forall i$$

$$\beta_R - R_i(t) \geq M \cdot (l_i - 1) \quad \forall i$$

$$x_{Ni} \leq \delta_{Ni}^{\max};\ x_{Ri} \leq \delta_{Ri}^{\max};\ 0 \leq p_N \leq p_N^{\max};\ 0 \leq p_R \leq p_R^{\max}$$

$$\beta_N,\ \beta_R,\ x_{Ni},\ x_{Ri},\ u_i \in \text{non-negative integer}$$

$$y_i, l_i \in \{0, 1\} \quad \forall i$$

$$0 \leq \alpha \leq 1$$