MODELLING TIME-VARYING VALUE OF AN END-OF-LIFE PRODUCT FOR DESIGN FOR RECOVERY

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ABSTRACT
Estimating residual value of an end-of-life product is an essential preliminary to design for recovery. This paper presents a quantitative model for estimating time-varying value of an end-of-life product. The model estimates the expected economic value of a product by considering two major depreciation factors, physical deterioration and technological obsolescence. The developed model is illustrated with an example of desktop computer and potential applications to design for recovery are presented. The model can contribute to enhancing the residual value of a product and/or improving the way of retrieving the residual value. It can also assist the recovery system design, such as product take-back planning and recovery strategy planning.

Keywords: design for recovery, end-of-life, take-back, product reuse, remanufacturing

1 INTRODUCTION
Product recovery is a process of retrieving residual value from end-of-life products. Although they reached the end-of-use phase, the end-of-life products still contain re-marketable resources, such as reusable parts and recyclable materials. By recovering the resources and reusing or reselling them, a company can make profits as well as contribution to environment protection. Accordingly, product recovery has come into increasing prominence in the industry.
Growing interests in product recovery have made design for recovery a field of rapidly growing interest for product manufacturers. Design for recovery is an engineering design method to make recovery processes more efficiently and effectively. One goal of the method is to maximize recovery profit. It attempts to find the best product design so that maximum economic value can be recovered from the product at the end of life stage.
To improve product design, designers must be able to figure out the current performance of the product and the impact of their design decisions on it. Once they have such capability, they can find out a way to improve the current design. Likewise, in order to implement design for recovery, designers must be able to assess the residual value of a product. Only if the information is given, they can research a way to improve the residual value and/or a better way to recover the value. The difficult part is that product recovery is an uncertain event in the future and there is a lack of models to help estimate the expected future (economic) value of a product from recovery point of view.
This paper presents a quantitative model for estimating time-varying residual value of an end-of-life product. The residual value of a product varies upon time. As time goes, the product experiences physical deterioration and/or technological obsolescence, which in turn changes (depreciates) its residual value [1]. In previous literature [1-7], several approaches have been developed to model the time-varying value of a product. However, the model presented here is distinguished from them in several points. First, most previous methods considered physical deterioration only, not the technological obsolescence. Second, even when both factors are considered, the existing evaluation requires more or less subjective and qualitative inputs from experts or consumers. Third, their evaluation focused on the performance value from the consumers' standpoint, but the present model focuses on the economic value from the manufacturers' standpoint.
The rest of paper is organized as follows. Section 2 presents the model for time value of an end-of-life product. Section 3 describes the time-varying cost advantage of product recovery. Section 4 introduces an application to design for recovery, followed by conclusions in Section 5.

2 A MODEL FOR THE TIME VALUE OF AN END-OF-LIFE PRODUCT

A product can be regarded as a mix of parts. Here, the term "part" refers to any decomposable element of a product. The recovery process under consideration starts from disassembling end-of-life products into parts. Similar products are sent to a central facility and disassembled collectively. After separation, resulting parts are sorted by part type rather than its parent product and inspected if it is reusable or not [8]. Reusable parts are stocked for in-house reuse or resale, while nonreusable parts are shredded and recycled into raw materials.

As can be seen in the description above, a product loses its original identity at the end of its life and changes back into a group of parts. Therefore, it is reasonable to define the product residual value as the sum of part residual values. This section first presents a model for the time-varying value of an end-of-life part, followed by a model for an end-of-life product. An exemplary desktop computer is used for model illustration. Section 2.1 describes the basic notation used in the models.

2.1 Notation

i	parts for product; index $i \in I$
t	returning year; time when the product reaches its end-of-life and returns for recovery
$V_{product}^{eol}(t)$	residual value of an end-of-life product at time *t*
$V_i^{eol}(t)$	residual value of an end-of-life part *i* at time *t*
$PV_{product}^{eol}(t)$	residual value of an end-of-life product at time *t* in present value
$PV_i^{eol}(t)$	residual value of an end-of-life part *i* at time *t* in present value
$R_i(t)$	reliability of part *i* for time period [0, *t*]
$M_i^{eol}(t)$	market value of a unit of *used*, *subject* part *i* at time *t*
$M_{i,\max}^{eol}(t)$	market value of a unit of *used*, *leading-edge* (i.e., *max-generation*) part *i* at time *t*
$M_{i,\max}^{new}(t)$	market value of a unit of *new*, *leading-edge* (i.e., *max-generation*) part *i* at time *t*
$\delta_i(t)$	difference in generation between the leading-edge and the subject parts *i* at *t*
$\gamma_i(t)$	number of successive generations of part *i* being newly released in the market for [0, *t*]
$P_{i,n}(t)$	probability that $\gamma_i(t) = n$
λ_i	constant failure rate for part *i*
θ_i	minimum mean-time-to-failure (MTTF) required for a reusable part *i*
α_i	market value discount for used part *i* relative to new part *i*
π_i	market value trend (i.e., increasing, decreasing, or static) for part *i*; yearly rate
ϕ_i	parameter for exponential value depreciation due to technological obsolescence
μ_i	average frequency per year in which a successive generation of part *i* newly released
r	interest rate per year with continuous compounding

2.2 Time-varying value of an end-of-life part

Each part has its own lifetime characteristics. To be specific, each part deteriorates physically or functionally at its own speed and degree. For instance, computer CPUs (central processing unit) are known extremely reliable but easily become obsolete due to the frequent advent of successive models equipped with better performance. In contrast, optical drives (e.g., CD-ROM, DVD drive) are known relatively less reliable, while its technological change happens less frequently. Market conditions also vary for different parts. For example, some parts can have greater value than others depending on the market size, regulations, and consumers' perception on used parts or willingness to buy used parts. Consumers might be willing to buy a used CPU or graphic card, but not a used chassis. Although there could be consumers who want to buy used operating system (OS), it is not allowed for a (re)manufacturer to resell used one. The part value model in this paper estimates the (expected) economic value of an end-of-life part based on these part characteristics. It consists of two sub models to address two major depreciation factors: physical deterioration and technological obsolescence.

Physical deterioration and reusability

Considering reliability of an end-of-life part is a common and essential step in evaluating the residual value. Reliability itself is the probability that a part survives successfully to age *t* [9]. When a constant failure rate λ_i is assumed, the reliability of a part *i* is generally defined by Equation (1).

$$R_i(t) = e^{-\lambda_i t} \quad (1)$$

Reliability gives an estimate for the number of surviving parts at *t*. However, the reliability does not necessarily indicate all the surviving parts are reusable. As Anityasari and Kaebernick (2008) [10] pointed out, the reusability of an end-of-life part must be decided based on the probability of its surviving during the second life. To address this point, this paper introduced a concept of *reusability threshold* which represents the minimum mean-time-to-failure (MTTF) required for an end-of-life part to be approved as a reusable one. The reusability of a part *i* is then defined by Equation (2). Throughout the paper, all parts are equally assumed to have a 3-year threshold (e.g., PC industry). In other words, a (re)manufacturer can reuse or resell only a part that is expected to survive at least three more years.

$$R_i(t) \cdot R_i(\theta \mid t) = R_i(t) \cdot \frac{R_i(t+\theta)}{R_i(t)} = R_i(t+\theta) = e^{-\lambda_i(t+\theta)} \quad (2)$$

Technological obsolescence and secondary market value

In consumer products markets, it is common phenomenon that the value of a formerly cutting-edge unit drops significantly, simultaneous with the release of a successive model with better performance. The more successive models appear the more value the part loses. Figure 1 shows that such value trend from technological obsolescence can be modelled as an exponential depreciation model with a constant parameter ϕ_i.

Figure 1 is a snapshot of market value trends for used hard drives and CPUs (Intel Pentium IV). Figures on the left side represent the value trends in terms of the key performance, i.e., storage size for hard drives and clock speed for CPUs. These figures are redrawn in the right side using the concept of *part generation*; starting from the least-performance part to the leading-edge part with highest performance, generation numbers are assigned. This transformation reveals that both parts have a common value trend—*the part maker value depreciates exponentially by part generation.* Although not shown in the paper, other parts for desktop also show similar trends. The exponential value depreciation can be modelled by Equation (3).

$$M_i^{eol}(t) = M_{i,\max}^{eol}(t) \cdot e^{-\phi_i \cdot \delta_i(t)} = \alpha_i M_{i,\max}^{new}(t) \cdot e^{-\phi_i \cdot \delta_i(t)} \quad (3)$$

In this model, a successive generation is assumed always more advanced, and thus, more valuable than the previous generation. The value depreciation parameter ϕ_i can be estimated by the *least-squares method*. For hard drives and CPUs in Figure 1, ϕ_i of 0.1717 and 0.2133 are obtained with R^2 of 0.9437 and 0.9665, respectively.

Once parameter ϕ_i is obtained, it is possible to estimate the future value of a part, with an assumption that ϕ_i will not change during the time period under consideration. In future value estimation, Equation (3) is used along with Equations (4) and (5) which address the *market value trend* and *generation gap* (i.e., difference in generation between the leading-edge and the subject parts *i*).

$$M_{i,\max}^{new}(t) = e^{\pi_i t} \cdot M_{i,\max}^{new}(0) \quad (4)$$

$$\delta_i(t) = \delta_i(0) + \gamma_i(t) \quad (5)$$

There could be an industry-wise trend in the market value for a part. Taking the computer industry as an example, the original retail price of computers continues its decreasing trend, despite dramatic improvements in technical specifications. The average laptop price was $3,000 in 1999, but it was $720 in 2009 [11]. Likewise, the market price of a part can have increasing, decreasing, or static trend, which is represented by π_i in Equation (4). Equation (5) calculates the generation gap of part *i* at time *t* by adding up the current generation gap (i.e., $\delta_i(0)$) and the total number of future-generations that will appear by time *t* (i.e., $\gamma_i(t)$). Since $\gamma_i(t)$ is a stochastic process representing the total number of "event" (new generation) that occur by time *t*, this paper assumes it a Poisson process having rate μ_i. Accordingly, the number of new generation by time *t* is Poisson distributed with mean $\mu_i t$ and Equation (6) is obtained [12]. Finally, the mean market value of a unit of end-of-life part is obtained by Equation (7).

$$P_{i,n}(t) = P\{\gamma_i(t) = n\} = (\mu_i t)^n \frac{e^{-\mu_i t}}{n!}, \; n = 0, 1, 2, \cdots \quad (6)$$

$$E\left[M_i^{eol}(t)\right] = \sum_{n=0}^{\infty} \alpha_i M_{i,\max}^{new}(t) \cdot e^{-\phi_i(\delta_i(0)+n)} \cdot P_{i,n}(t) \tag{7}$$

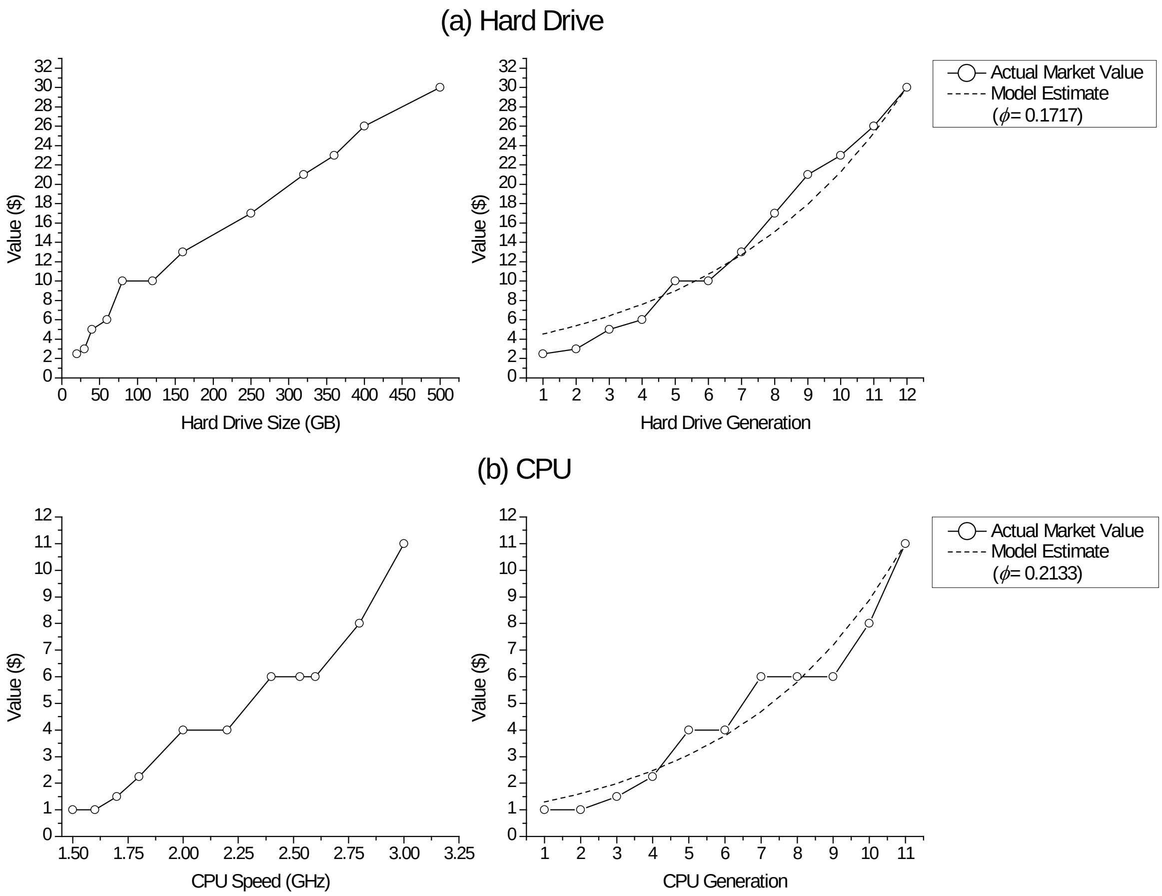

Figure 1. Examples of exponential value depreciation: used hard drive and CPU

Value of an end-of-life part

The (mean) residual value of an end-of-life part *i* is defined by Equation (8) where the reusability of the part is multiplied by the part market value. In this equation, nonreusable parts are not included with an assumption that their economic value to (re)manufacturer is zero. Nonreusable parts are recycled for material recovery. In practice, (re)manufacturers do not perform material recovery but transfer parts to third-party recyclers. They might be paid by recyclers for the parts but this paper assumes that the amount is insignificant (=0). The present model therefore only considers reusable parts and their market value. If the value from material recovery is significant, however, Equation (8) can be elaborated into Equation (9) where $S_i(t)$ denotes the unit value from material recovery of a part *i*.

Equation (10) discounts the future value into the present one (at time 0) by means of *r*, an interest rate per year with continuous compounding—$1 deposited at rate *r* grows to e^{rt} at time *t*.

$$V_i^{eol}(t) = R_i(t+\theta) \cdot M_i^{eol}(t) \tag{8.1}$$

$$E\left[V_i^{eol}(t)\right] = R_i(t+\theta) \cdot E\left[M_i^{eol}(t)\right] \tag{8.2}$$

$$V_i^{eol}(t) = R_i(t+\theta) \cdot \max\left(M_i^{eol}(t), S_i(t)\right) + (1 - R_i(t+\theta)) \cdot S_i(t) \tag{9.1}$$

$$E\left[V_i^{eol}(t)\right] = R_i(t+\theta) \cdot E\left[\max\left(M_i^{eol}(t), S_i(t)\right)\right] + (1 - R_i(t+\theta)) \cdot S_i(t) \tag{9.2}$$

$$PV_i^{eol}(t) = V_i^{eol}(t) \cdot e^{-rt} \tag{10.1}$$

$$E\left[PV_i^{eol}(t)\right] = E\left[V_i^{eol}(t)\right] \cdot e^{-rt} \tag{10.2}$$

2.3 Time-varying value of an end-of-life product

Product residual value is defined as the sum of parts' residual values, as can be seen in Equation (11). Similar to the part residual value, the present residual value of an end-of-life product is obtained by Equation (12).

$$V_{product}^{eol}(t) = \sum_i V_i^{eol}(t) \tag{11.1}$$

$$E\left[V_{product}^{eol}(t)\right] = \sum_i E\left[V_i^{eol}(t)\right] \tag{11.2}$$

$$PV_{product}^{eol}(t) = V_{product}^{eol}(t) \cdot e^{-rt} \tag{12.1}$$

$$E\left[PV_{product}^{eol}(t)\right] = E\left[V_{product}^{eol}(t)\right] \cdot e^{-rt} \tag{12.2}$$

For illustration, the developed model is applied to an exemplary mainstream desktop, *Desktop X* in Table 1. The reliability parameters are assigned based on previous literature [13] and online product-review website (*www.pcworld.com* [14]). Market data for ϕ_i and μ_i is obtained from online marketplaces and price comparison portal, such as *ebay.com* and *pricewatch.com*, and Kwak et al. (2010) [11]. However, it should be noted that the data used for this paper is just for illustration and needs additional data collection and calibration to have meaning as the industry representative.

To incorporate the uncertainty from the Poisson process γ_i(t), simulation has been conducted varying the returning time t from 0 to 15. For simulation, a software *Risk Solver Platform for Excel* is used throughout the paper. The results are shown in Figure 2. All values in the figure are mean values from 2,000 trials each and adjusted to the present values ($t=0$). Referring to the federal funds rate trend, r=0.03 is applied for the adjustment.

Table 1. Exemplary product information: Desktop X

Part i	λ_i	ϕ_i	μ_i	$\delta_i(0)$	α_i	π_i	$M_{i,\max}^{new}(0)$
CPU	0.0018	0.6733(0.2133)*	0.5(4)	0	0.75	0.00	175
RAM	0.0147	0.8378	1	0	0.65	0.00	50
Motherboard	0.0302	0.2133	4.5	0	0.65	0.00	150
Hard drive	0.0633	0.1717	2	0	0.65	0.00	120
Graphic Card	0.0390	0.2883	2	0	0.70	0.00	100
Optical Drive	0.1372	0.8088	0.5	0	0.70	0.00	80
Chassis (Case)	0.0438	0.1500	0.2	0	0.20	0.00	75
Operating System	0.0000	0.5926	0.5	0	0.00	0.00	50

* CPU is modeled to have two types of technological obsolescence: One by major change in CPU platform (e.g., *Core2* to *Core i*) and the other by minor change (in parenthesis) in clock speed.

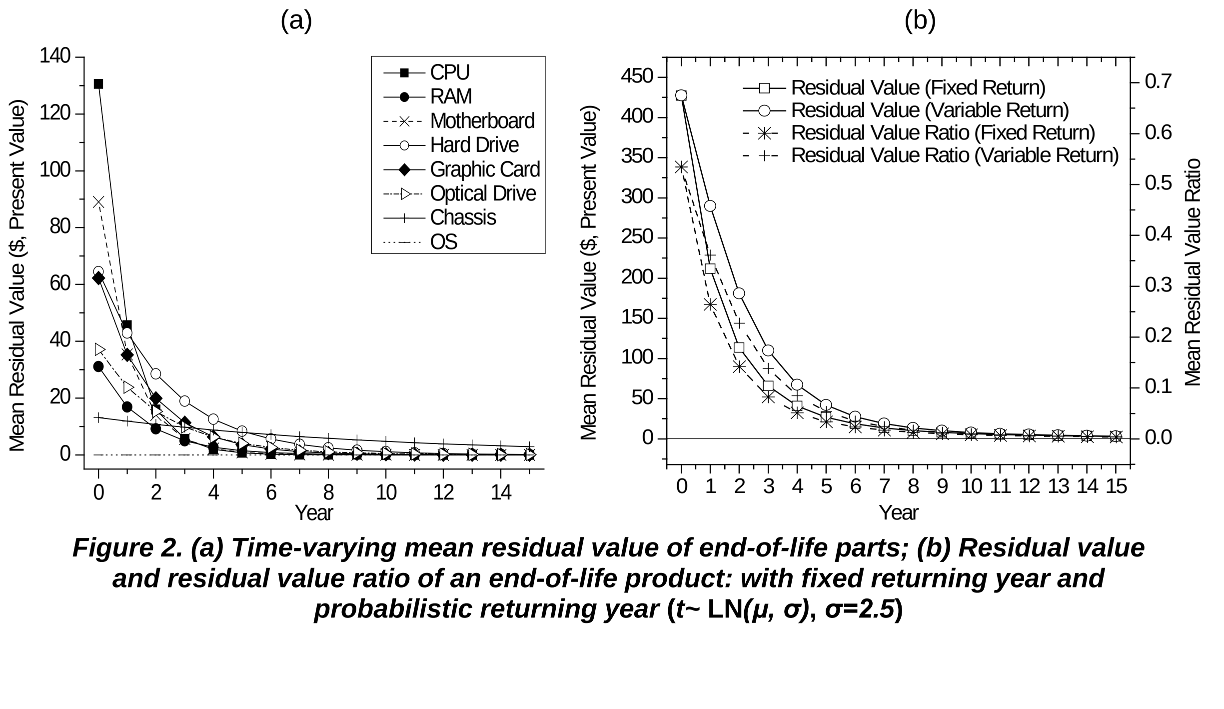

Figure 2. (a) Time-varying mean residual value of end-of-life parts; (b) Residual value and residual value ratio of an end-of-life product: with fixed returning year and probabilistic returning year (t~ LN(μ, σ), σ=2.5)

Figure 2(a) shows how the mean residual value of an end-of-life part varies as the returning year *t* changes. The CPU and motherboard lose their value so rapidly that only less than 10% of its original value—$175 and $150, respectively—remains if the product returns after two years. If the product returns after five years, they have almost no value. The hard drive shows relatively gradual depreciation. When the product returns after two years, approximately 25% of the original value can be recovered. Also, positive residual value is expected even until 10 years later. The chassis loses more than 80% of its value at the beginning, because people rarely prefer used chassis. However, its value depreciates slowly and keeps positive value for long lifetime. As to the OS, reusing is assumed not allowed; thus, it has no value regardless of the returning time.

One interesting point is that the part with most value is changing upon *t*. When $t \leq 1$, the CPU is the most valuable part and the motherboard is the next. However, when $1 \leq t \leq 5$, the most valuable part is changed to the hard drive. The second place is also changed to the graphic card until *t*=3 and again to the chassis after that. When product ages more than six years old, the chassis has the highest residual value. **These results imply that designers must consider the returning year *t* in implementing design for recovery. Parts worthwhile to recover depend on the timing, and so does the optimal product design.**

Figure 2(b) describes how the mean residual value of an end-of-life *Desktop X* changes over time. The second y-axis on the right side represents the mean residual value ratio, that is, the ratio of the mean residual value to the original product value ($800). When product returns at the end of the second year, the desktop still retains about $110 which corresponds to 13-14% of residual value ratio. If the product is more than five years old, the residual value is even below 2.5% of the original value.

Figure 2(b) can be used in planning product take-back. As an example, suppose that recovering a desktop costs $10/unit in present value. Then a reasonable take-back strategy is to collect *Desktop X* before it becomes eight years old in which the residual value begins to be less than $10. Figure 2(b) also helps quickly figure out the upper limit of the buyback price. For instance, when the recovery cost is $10, the maximum buyback price for a five-years-old desktop is about $17. If pays more, recovery cannot be profitable on average.

Until now, only the return with a fixed return has been considered. With the proposed model, a variable return also can be considered. For example, Figure 2(b) shows the residual value of *Desktop X* when *t* is a lognormal random variable with different means and the standard deviation of 2.5. In this case, variable returns show a higher mean residual value than fixed returns, although the overall patterns are similar.

3 TIME-VARYING COST ADVANTAGE OF PRODUCT RECOVERY

To retrieve the residual value from an end-of-life product, (re)manufacturers must pay recovery cost, such as cost of disassembling, inspecting, purchasing spare parts, etc. The point is that the recovery cost, the value retrieved, and the recovery profit can differ according to what recovery strategy is adopted. This section demonstrates that the developed model can help compare different recovery strategies in terms of the recovery cost and profit.

3.1 Notation

$\delta_i^{target}(t)$	generation gap between the *leading-edge* and the *target-level* parts *i* at *t*
$M_{i,target}^{new}(t)$	market value of an unit of *new*, *target-level* part *i* at time *t*
$C_{product}^{1}(t)$	cost of new production without recovery at *t*
$C_{product}^{2}(t)$	cost of new production with part resale at *t*
$C_{product}^{3}(t)$	cost of remanufacturing without part resale at *t*
$C_{product}^{4}(t)$	cost of remanufacturing with part resale with part resale at *t*
$C_i^{material}(t)$	cost of purchasing *new*, *target-level* part *i* in short for remanufacturing at *t*
$C_i^{proc}(t)$	cost of processing an end-of-life part *i* for recovery at *t*
$I_i^{resale}(t)$	income from reselling an end-of-life part *i* after remanufacturing at *t*

3.2 Time-varying cost of recovery strategies

Suppose a company plans to offer a product with following target specifications: $\delta_i^{target}(t)$ ={0, 1, 1, 1, 1, 1, 1, 1, 1}. This indicates that the company wants to release a product with the newest model of CPU with the second-fastest speed, and a set of previously leading-edge (one-generation old) RAM, motherboard, hard drive, and so on. The company just released *Desktop X* comprising of all up-to-date parts, which is expected to return at *t* for recovery. Then, there are three recovery strategies that the company can choose from, alongside the new production:

- *New production*: no recovery is conducted. A product is made with new parts only.
- *New production with part resale*: a product is produced using new parts. At the same time, recovery is performed to retrieve reusable parts and resell them in the second-hand market.
- *Remanufacturing*: product recovery is performed. A product is produced by reassembling reusable parts from the recovery and new parts where necessary. If any reusable parts remain, they are sent to recycler with no income.
- *Remanufacturing with part resale*: remanufacturing is performed. If any reusable parts remain after remanufacturing, they are sold in the second-hand market for additional income.

In this paper, it is assumed that remanufacturing is performed based on product conformity. In other words, in remanufacturing a product, both a target-level part ($\delta_i(t) = \delta_i^{target}(t)$) and one with an above-target specification ($\delta_i(t) < \delta_i^{target}(t)$, i.e., product with newer parts than required) can be used. Accordingly, the mean ratio of the end-of-life part that can be used in remanufacturing—part which is *reusable* and also *conforms to the target*—can be estimated as shown in Figure 3.

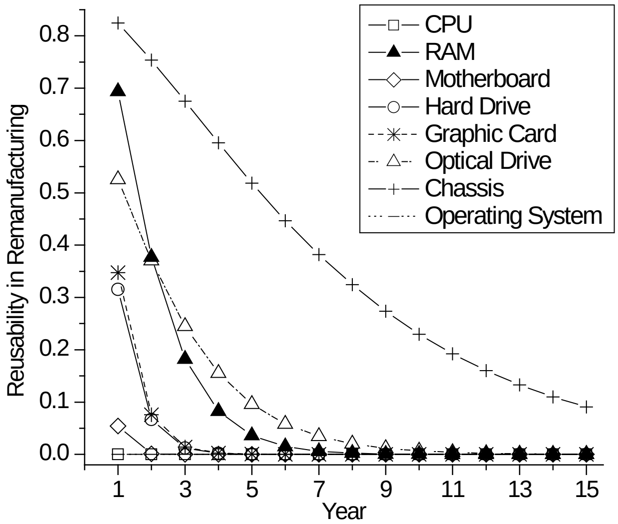

Figure 3. Mean ratio of reusable parts given target specifications for (re)manufacturing

The (re)manufacturing cost of a target-satisfying product can be modelled as can be seen in Equations (13)–(19). All costs can be adjusted to the present value by multiplying e^{-rt}. In this PC illustration, the processing cost is assumed as \$4 for a whole product [15] and apportioned to each part based on the part residual value at *t*. The hard drive has additional processing cost of \$2 for data deletion. Other parameters are identical to ones in Table 1.

$$C^1_{product}(t) = \sum_{i \in I} M^{new}_{i,target}(t) \tag{13}$$

$$C^2_{product}(t) = \sum_{i \in I} \left(M^{new}_{i,target}(t) + C^{proc}_i(t) - V^{eol}_i(t) \right) \tag{14}$$

$$C^3_{product}(t) = \sum_{i \in I} \left(C^{proc}_i(t) + C^{material}_i(t) \right) \tag{15}$$

$$C^4_{product}(t) = \sum_{i \in I} \left(C^{proc}_i(t) + C^{material}_i(t) - I^{resale}_i(t) \right) \tag{16}$$

$$M^{new}_{i,target}(t) = M^{new}_{i,\max} \cdot e^{-\phi_i \delta_i^{target}(t)} \tag{17}$$

$$C^{material}_i(t) = \begin{cases} (1 - R_i(t+\theta)) \cdot M^{new}_{i,target}(t) & if \ \delta_i(t) \le \delta_i^{target}(t) \\ M^{new}_{i,target}(t) & else \end{cases} \tag{18}$$

$$I^{resale}_i(t) = \begin{cases} 0 & if \ \delta_i(t) \le \delta_i^{target}(t) \\ V^{eol}_i(t) & else \end{cases} \tag{19}$$

Figure 4(a) compares the cost of different (re)manufacturing strategies. Here, all π_i is set as zero and all cost values are adjusted to the present value. Accordingly, all strategies have decreasing tails as *t* increases. The figure shows that all three recovery strategies have a significant cost advantage over new production, even though the degree decreases continuously and finally disappears as *t* increases. It is observed that the remanufacturing costs more than the new production cost when *t* is 15 or greater. Among the three recovery strategies, remanufacturing with part resale incurs the lowest cost. The second place changes according to *t*. When $t < 5$ or t >10, new production with part resale performs better than remanufacturing; when $5 \leq t \leq 10$, remanufacturing is slightly more economical than new production with part resale.

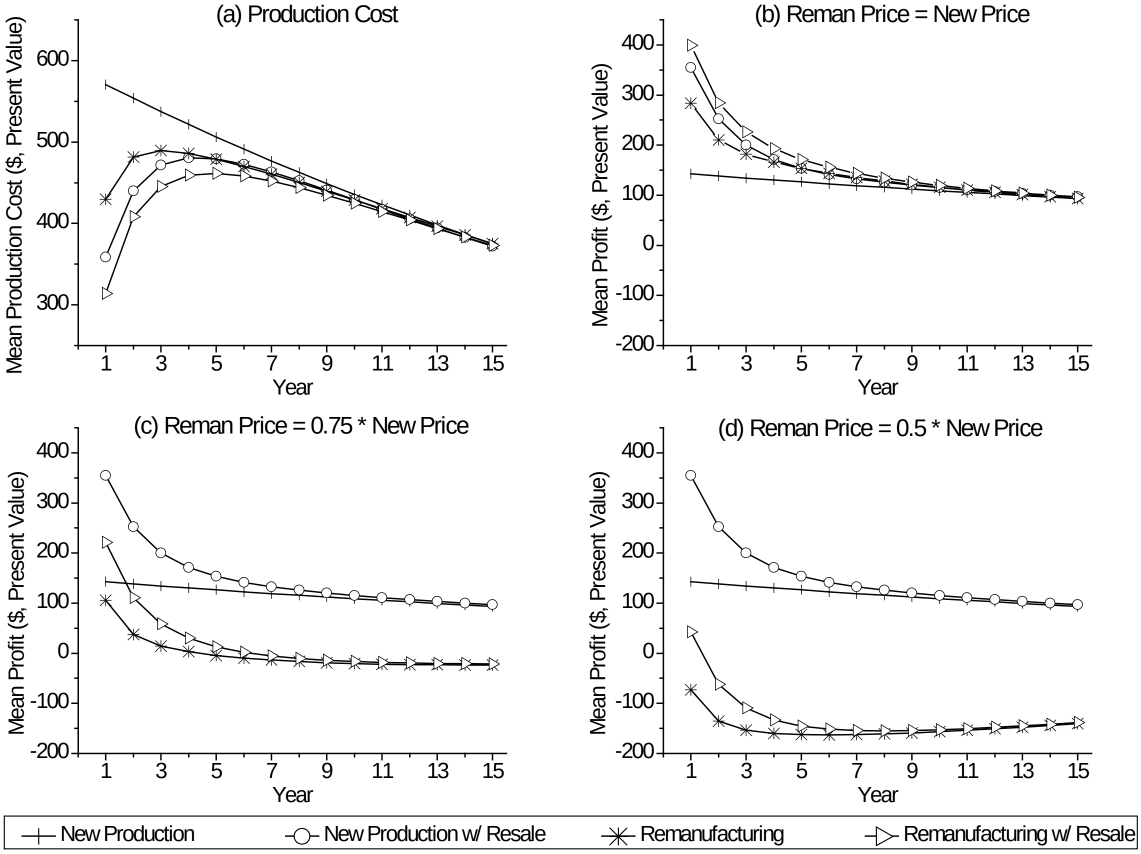

Figure 4. Time-varying advantage of (re)manufacturing strategies

Figures 4(b) to 4(d) compare the recovery profit of different strategies. Suppose that a new product can be sold at the price with 25% gross margin (=1.25*$C^{1}_{product}$) and remanufacturing is instantaneous—product return, remanufacturing, and the sale happen at the same time. As can be seen in Figure 4(b), the previous order of the strategies in Figure (a) remains the same if the remanufactured product is sold at the same price as the new product: remanufacturing with part resale is the best and new production is the worst. However, if a price discount for remanufactured product exists, different results can appear. In Figures 4(c) and (d) where 75% and 50% price discounts are assumed respectively, the best strategy is new production with part resale. Also it becomes harder for remanufacturing strategies to achieve profit. In case of a 50% price discount, remanufacturing even cannot be profitable regardless of *t*.

4 APPLICATION TO DESIGN FOR RECOVERY

This section presents an application of the model to design for recovery. Different parts have different lifetime characteristics. Designers must choose the best combination of parts such that the total profit from the product lifecycle can be maximized. In this section, a mathematical model is presented which decides an optimal part mix with maximum expected lifecycle profit. The model maximizes the summation of initial production cost (negative), sales price, and end-of-life residual value. For simplification, the sales profits are assumed to be fixed and identical for any combinations. In other words, consumers do not recognize the difference between part alternatives. The problem is then defined as below, which is formulated by Equations (20)-(23):

- *Minimizing*: production cost of a product less its expected end-of-life residual value
- *Find*: an optimal mix of parts
- *Given*: part alternatives and their current value and lifetime characteristics (Table 2), distribution of returning year *t*
- *Constraint*: only one alternative *j* is chosen for each part type *i* (Equation (21)); the CPU and motherboard must be compatible with each other (Equation (22)).

In this example, the current design is equipped with the newest parts. Therefore, $\delta_i(0)$=0 and $M_{ij}^{new}(0) = M_{ij,\max}^{new}(0)$. Returning time *t* is assumed to be lognormally distributed with mean and standard deviation of 7 and 2.5, respectively. With that, the problem is solved and the optimal solution is shown in the last column of Table 2.

$$minimize \sum_i \sum_j M_{ij}^{new}(0) \cdot x_{ij} - \sum_i \sum_j E\left[V_{ij}^{eol}(t)\right] \cdot x_{ij} \cdot e^{-rt} \quad (20)$$

$$s.t. \quad \sum_j x_{ij} = 1 \qquad \forall i \quad (21)$$

$$x_{1j} = x_{3j} \qquad \forall j \quad (22)$$

$$x_{ij} \in \{0, 1\} \quad (23)$$

Table 2. Design for Lifecycle: Finding an optimal part mix

Part *i*	*j*	λ_i	ϕ_i	μ_i	$\delta_i(0)$	α	π_i	$M_{ij,\max}^{new}(0)$	Variable	Decision
CPU	1	0.01	0.60 (0.20)	0.5 (4)	0 (0)	0.75	0.05	150	x_{11}	0
	2	0.03	0.50 (0.30)	0.5 (2)	0 (0)	0.75	0.05	150	x_{12}	1
	3	0.03	0.60 (0.20)	0.5 (4)	0 (0)	0.75	0.05	145	x_{13}	0
RAM	1	0.01	0.75	1	0	0.65	0.05	50	x_{21}	0
	2	0.02	0.75	1	0	0.65	0.05	35	x_{22}	1
Motherboard	1	0.03	0.40	4.5	0	0.65	0.05	150	x_{31}	0
	2	0.05	0.40	2.5	0	0.65	0.05	100	x_{32}	1
	3	0.05	0.40	4.5	0	0.65	0.05	120	x_{33}	0
Hard Drive	1	0.05	0.15	2	0	0.65	0.05	100	x_{41}	1
	2	0.03	0.15	2	0	0.65	0.05	120	x_{42}	0
Graphic Card	1	0.05	0.20	2	0	0.70	0.00	110	x_{51}	0
	2	0.05	0.40	2	0	0.70	0.00	100	x_{52}	0
	3	0.05	0.20	3	0	0.70	0.00	100	x_{53}	1
Optical Drive	1	0.10	0.80	0.5	0	0.70	0.05	80	x_{61}	0
	2	0.15	0.80	0.5	0	0.70	0.05	75	x_{62}	1
Chassis	1	0.05	0.15	0.2	0	0.20	0.00	50	x_{71}	1
OS	1	0.00	0.59	0.5	0	0.00	0.00	75	x_{81}	1

5 CONCLUSIONS

This paper addresses time-varying value of an end-of-life product. A quantitative model is presented which estimates the (mean) time-varying value by incorporating two major depreciation factors, physical deterioration and technological obsolescence. The model illustration with desktop computers shows possible applications to design for recovery. It can be used in enhancing the residual value of a product and/or improving the way of retrieving the residual value. It is also possible to use the model for the recovery system design, such as product take-back planning and recovery strategy planning.

In the future, the value depreciation parameters, ϕ_i and μ_i , can be studied further. In the presented model, they are defined as static parameters not varying over time, but can be elaborated as stochastic variables. Another potentially productive line of research would be to integrate this company-perspective model with a consumer-perspective model. Value models from consumer's standpoint can help clarify the link between product design and the lifecycle profit.

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