Varying Lifecycle Lengths Within a Product Take-Back Portfolio

Yuan Zhao
Graduate Research Assistant

Vijitashwa Pandey
Post-Doctoral Researcher

Harrison Kim
Assistant Professor

Deborah Thurston
Gutgsell Professor

Industrial and Enterprise Systems Engineering,
University of Illinois at Urbana-Champaign,
Urbana, IL 61801

Product take-back and reuse is sometimes at odds with the rapidly evolving desires of some customers. For other customers, the environmental benefits of reuse more than compensate for minor drawbacks. "Selling a service" (rather than a product) through leasing enables the manufacturer to control the timing and quality of product take-back but current methods assume a fixed leasing period. What is needed is a method for fine tuning the time span of customers' life cycles in order to provide each market segment the combination of features it most desires. This paper presents a new method for performing long range product planning so that the manufacturer can determine optimal take-back times, end-of-life design decisions, and number of lifecycles. The method first determines a Pareto optimal frontier over price, environmental impact and reliability using a genetic algorithm. Then, a multiattribute utility function is employed to maximize utility across different segments of the market and also across different lifecycles within each segment. Post-optimal studies help determine feasibility of component redesign in addition to parts consolidation. The proposed method is illustrated through an example involving personal computers. [DOI: 10.1115/1.4002142]

1 Introduction and Background

1.1 Product Take-Back Systems. Product stewardship involves everyone—manufacturers, retailers, users, and disposers—taking responsibility for minimizing environmental impacts throughout the lifespan of the product. Product stewardship includes finding effective ways to recapture value and decrease the environmental impacts of already manufactured and used products. Take-back and reuse of such products is an important concept within the product stewardship domain.

Product take-back legislation to close the product lifecycle loop has been enacted in the European Union countries and Japan [1,2]. This legislation mandates that manufacturing companies extend their responsibility for their products beyond the consumer use phase. Williams et al. [3] provided a summary of take-back legislation for packaging, automobiles, and electronic products in several countries and also analyzed the effects of such legislation. The emergence of these existing (and anticipated) take-back laws is a major driving force for manufacturers to incorporate these considerations into product design.

Utilizing recovered products in a remanufacturing operation has potential benefits in addition to compliance with legislation. Energy consumption, material requirements and environmental impacts might be lower than those for newly manufactured products. "Green" products might appeal to more customers and/or enhance corporate image. However, remanufacturing systems are more complex than traditional manufacturing systems. Guide [4] analyzed several complicating characteristics and uncertainties that require significant changes in production and control activities for remanufacturing firms. The major sources of uncertainty are in the timing and quantity of returned products and their components. White et al. [5] presented an overview of end-of-life management challenges in each stage of the recovery process for rapidly obsolete products such as computers and electronics. They pointed out that more complete information about product design, quality and timing can improve the end-of-life opportunities.

Long range product planning can help the manufacturer make end-of-life (EOL) design decisions. Mangun and Thurston [6] developed an EOL decision model where a leasing program (where the manufacturer can control the timing of product take-back) facilitates component reuse, remanufacturing, and recycling over multiple but static-length lifecycles. This paper deals with the critical problem of fine tuning the lifecycle (both the timing and length) in order to best satisfy different customer needs. In addition, post-optimality analyses are performed to gain further insights into redesigning of the product.

1.2 Product Lifecycle. Product lifecycle is a collective term for the stages undergone by a product in its lifespan. In general, the stages include material processing, manufacturing, assembly, transportation, product use (usually the longest phase) and end-of-life management. Life cycle assessment (LCA) requires estimation of environmental impacts throughout all the stages shown in Fig. 1. LCA not only informs strategies that would otherwise be developed without consideration of the environment, it also pinpoints critical areas to focus on in a product's lifecycle. The goal of lifecycle design is to make decisions early during the design process that maximize overall life cycle value-added while minimizing cost and environmental impact [7]. When a product reaches the end of one lifecycle, a number of possible recovery options are available. King et al. [8] compared four alternative strategies to reduce waste within the context of extended producer responsibility. Rose et al. [9] proposed a method for determining feasible strategies from significant product characteristics, and developed a web-based application, end-of-life design advisor. By understanding end-of-life strategies, we can identify redesign improvements based on these results. González and Adenso-Diaz [10] developed a model to simultaneously determine EOL strategy and disassembly sequence based on product structure. The structure is obtained from its bill of materials and the joining geometrical relationship among the components. Other studies also investigated assembly and disassembly aspects of a product. Lambert and Gupta [11] discussed different methods to make a product easy to disassemble and recycle. Behdad et al. [12] presented a model to consider sharing disassembly operations in order to improve the end-of-life strategies for multiple products. Peng and Chung [13] presented a method for nondestructive selective disassembly planning in a dynamic demanufacturing environment with respect to product maintenance. The results can facilitate design for maintainability.

The EOL recovery options often include several discrete choices including direct reuse, remanufacture, recycle, or disposal

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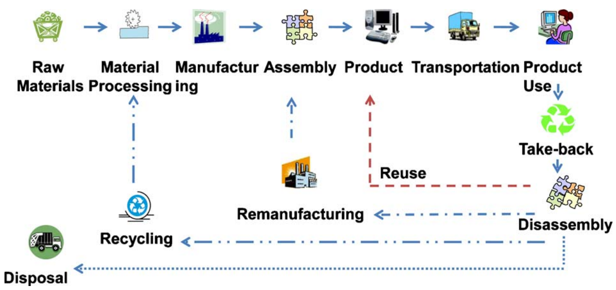

Fig. 1 Product life cycle and end-of-life decisions

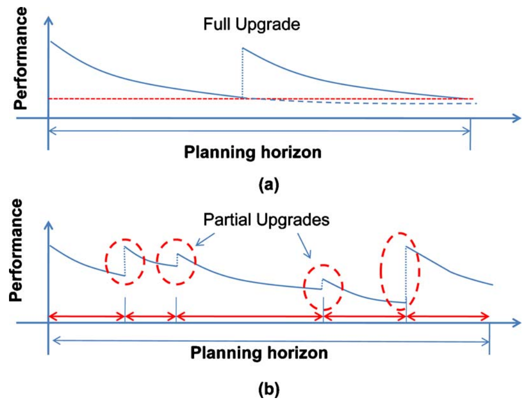

Fig. 2 Effect of partial and complete upgrade on performance within a specified planning horizon

of components, as shown in Fig. 1. Once the product is returned to the manufacturer, the most environmentally benign option is often to reuse the product. However, rapidly evolving technical and customer requirements sometimes make remanufacturing and recycling better options as they allow for upgrades. If a component's material cannot be used in any form, disposal is necessary.

EOL scenarios can vary depending on the technical characteristics of the returned products. Xing and Belusko [14] proposed the design for upgradability algorithm that can improve the functionality of reused and remanufactured products. The enhanced upgradability can help manufacturers to make long term upgrade plan for multigenerations of a product. If the product is being leased, it is essential to make the optimal decisions not only for one lifecycle but multiple lifecycles together. Dunmade [15], for example, discussed the concept of design for multilifecycles and its link with sustainable design, and applied this concept in the agro-industrial sector. Zhou et al. [16] presented a multilifecycle product recovery model, optimal retirement planning and design selection methods. The method was illustrated via computer monitor and PC. The results can help manufacturers fully incorporate environmental issues in product design and lifecycle planning.

1.3 Research Approach. This paper uses the life cycle design method, which integrates environmental issues into product development by considering all the stages in multiple product life cycles. We apply a multi-objective methodology to the problem of take-back and remanufacturing over multilifecycles. A nondominated sorting genetic algorithm-II (NSGA-II) is employed to define the Pareto optimal frontier. Then, normative multiattribute utility analysis is used to evaluate these nondominated solutions over product attributes.

This paper is organized as follows. Section 2 describes the problem formulation. Section 3 presents a case study using personal computers for a portfolio of four market segments and Sec. 4 summarizes and concludes.

2 Method for Determining Varying Lifecycle Lengths

This section describes a method for determining optimal take-back decisions, including the EOL operations as well as lifecycle lengths for a portfolio of products aimed at different market segments.

2.1 Need for Varying Lifecycles. Reducing the amount of disposed material is an important strategy for reducing environmental impact. However, it is often impractical for the whole product to be reused directly due to reliability and technical obsolescence issues.

Over multiple lifecycles, dispose versus upgrade decisions need to be made many times. Figures 2(*a*) and 2(*b*) illustrate this concept from the perspective of performance. For a given planning horizon, one expects the performance to decrease as a function of time. Since the end user imposes a constraint in terms of minimum acceptable performance, shown with the horizontal line in Fig. 2(*a*), the product may become infeasible within the time horizon. This will require the customer to either purchase a new product or upgrade the existing one. Either of these will result in an increase in the performance level, as shown. The upgrade might have to be done multiple times depending on the length of the planning horizon, the minimum acceptable performance level specified by the customer and the rate of decrease in performance. Of course, there are concomitant costs and environmental impacts of upgrade. In practice, the scenario can be even more complex. The customer wants to optimize products attributes over the whole planning horizon, over multiple lifecycles. One can choose to do a partial upgrade, allow the product to be upgraded well before it becomes infeasible, and also allow for different lifecycle lengths, as shown in Fig. 2(*b*). This will require understanding of the effect of partial upgrade on cost and environmental impact, in addition to performance. At the same time, reuse/upgrade decisions in one lifecycle will affect those in others. As an example, it might be better to delay an upgrade so that the number of lifecycles can be reduced if this has a positive impact on other attributes and vice versa. The driving forces behind the lifecycle decisions are the customers' willingness to make tradeoffs among attributes.

Reliability is used here as a proxy indicator of product performance. It is defined as the probability that a product/component will perform its intended function during a specified period of time under stated conditions [17]. The prediction and control of product reliability play a key role in profitability, especially for products considering component reuse and remanufacturing. For these reused or recycled components, it is necessary to inspect the physical reliability at the end-of-life stage to ensure proper quality in the next generation. Various studies have focused on reliability modeling in product remanufacture and recycle. Shu and Flowers [18] proposed a reliability model to measure the life cycle costs for remanufacturing systems. The model discusses the failure characteristics in series systems when only some parts are replaced. Jiang et al. [19] extended this model to accommodate system population changes.

One issue to consider is that if a component is found to be fully functional at the end of one lifecycle, its physical reliability at the end of the next lifecycle is actually increased. This is because the probability of failure at the end of the second lifecycle is now conditioned on the fact that the component survived the "infant mortality" phase and the first lifecycle. For electronic products, however the perceived performance can be distinct from physical reliability, albeit correlated with time. This is because of continuous technological change and design upgrades inherent to electronic products. As mentioned earlier since we use reliability only as a proxy for performance, we do not make this change in our calculations of reliability. A monotonic decrease in reliability is maintained and signifies that a component is losing value whether or not it has failed physically.

Table 1 Related operations for end-of-life options

Operations	Reuse	Remanufacturing	Recycling	Disposal
(1) Collection	X	X	X	X
(2) Disassembly		X	X	X
(3) Material processing			X	X
(4) Manufacturing			X	X
(5) Assembly		X	X	X
(6) Remanufacturing		X		
(7) Recycling			X	
(8) Disposal				X

In Secs. 2.2–2.4, we discuss the end-of-life decisions and the model used to determine product attributes based on these decisions.

2.2 End-of-Life Design Decisions. The four end-of-life recovery options considered here (reuse, remanufacturing, recycling, and disposal) along with the necessary manufacturing operations are shown in Table 1. Reuse requires that the recovered component undergoes only minor cleaning and refurbishment. In contrast to the other options, reuse is generally the highest level of product recovery in terms of cost and environmental impact reduction [20]. Components can generally be reused only when they retain their full functionality while physical and/or technical obsolescence sometimes limit reuse.

The next option is remanufacturing. Lund [21] defined remanufacturing as an industrial manufacturing process in which a worn-out or discarded product is restored to like-new condition. Recovered components may require some rework (such as milling), repair, or replacement of broken or obsolete parts before they can be employed in the next generation product.

Recycling involves activities by which discarded materials are collected, sorted, shredded, and undergoes a reforming process order to prevent the waste of potentially useful materials [22]. The final EOL option is disposal and replacement with a new component in the next lifecycle. Disposing of these components or products without any resource recovery thus represents a waste of the resources and value-added in previous lifecycle. Although many methods of evaluating and improving remanufacturability or recyclability have been proposed [23–25], many designers are still reluctant to use recycled materials because of uncertain quality or supply standards [26,27].

These four end-of-life design decisions will directly determine the end-of-life processing cost and value, along with the environment impact. We define the controllable binary (0–1) design decision variable set for EOL options $x_{l,i,j}(j=1,2,3,4)$ as follows: $x_{l,i,1}=1$ if component i of product in life cycle l is directly reused, 0 otherwise; $x_{l,i,2}=1$ if component i of product in life cycle l is remanufactured, 0 otherwise; $x_{l,i,3}=1$ if component i of product in life cycle l is recycled, 0 otherwise; $x_{l,i,4}=1$ if component i of product in life cycle l is disposed and replaced with new materials, 0 otherwise.

2.3 Multilifecycle Product Take-Back Decision Model. In decision analysis, the attributes are defined as "dimensions of value." The attributes can be viewed as the aspects of a product that either partially or completely address customer needs. For each attribute, customers exhibit a range over which they are willing to consider alternatives, and also a degree of willingness to make tradeoffs among attributes. So the term "attribute" rather than "objective" is employed since maximizing or minimizing one attribute is no longer the goal. Rather, maximizing the utility derived from a particular *bundle* or *combination* of attribute is the goal. In this model, product price, environmental impact, and product performance (reliability) are the three attributes influencing customers' choices.

The objective function seeks to minimize a function of product price (P), environmental impact (E), and reliability (R) over multiple lifecycles in the planning horizon.

$$\mathrm{Min}\{P,E,-R\} \tag{1}$$

Constraints

$$\sum_{j=1}^{4} x_{l,i,j} = 1 \quad i=1,\ldots,s \tag{2}$$

$$\sum_{l=1}^{L} a_l = T \quad L \in I \tag{3}$$

The controllable decision variables include the four possible EOL options $x_{l,i,j}$ as described earlier for each component in each lifecycle, as well as the length of each lifecycle a_l. Equation (2) determine that each component undergoes only one of the four EOL options in each life cycle, where s is the number of components. Equation (3) constrains the sum of usage time in the various lifecycles to be equal to the leasing planning horizon (T years) with no time gaps between any two consecutive lifecycles. The number of life cycles (L) is an integer decision variable.

The product price P is the amount of the money that customers are willing to pay for the leasing service (products in all lifecycles). Equation (4) indicates that the price is the sum of manufacturing cost C_l and profit Q_l in all lifecycles. The manufacturing cost in each life cycle C_l is considered as the sum of costs for each component ($i=1,\ldots,s$) in Eq. (5).

$$P = \sum_{l=1}^{L} (C_l + Q_l) \tag{4}$$

$$C_l = \sum_{i=1}^{s} C_{l,i} \tag{5}$$

The end-of-life processing cost for each component depends on the end-of-life decision, as determined by the operations ($c_{l,i,n}$) combinations ($n=1,\ldots 8$) as required in Table 1 and shown in Eqs. (7)–(10).

$$C_{l,i} = \sum_{j=1}^{4} C_{l,i,j} x_{l,i,j} \tag{6}$$

$$C_{l,i,1} = c_{l,i,1} \tag{7}$$

$$C_{l,i,2} = \sum_{n=1,2,5,6} c_{l,i,n} \tag{8}$$

$$C_{l,i,3} = \sum_{n=1,\ldots,5,7} c_{l,i,n} \tag{9}$$

$$C_{l,i,4} = \sum_{n=1,\ldots,5,8} c_{l,i,n} \tag{10}$$

Similarly, the environmental impact E is the sum of environmental impacts in each lifecycle E_l, as shown in Eq. (11). The environmental impact in one life cycle in turn is the sum of environmental impacts for each component, which also depends on EOL decisions, as shown in Eq. (12).

$$E = \sum_{l=1}^{L} E_l \tag{11}$$

$$E_l = \sum_{i=1}^{s} E_{l,i} \tag{12}$$

$$E_{l,i} = \sum_{j=1}^{4} E_{l,i,j} x_{l,i,j} \quad (13)$$

$$E_{l,i,1} = e_{l,i,1} \quad (14)$$

$$E_{l,i,2} = \sum_{n=1,2,5,6} e_{l,i,n} \quad (15)$$

$$E_{l,i,3} = \sum_{n=1,\ldots,5,7} e_{l,i,n} \quad (16)$$

$$E_{l,i,4} = \sum_{n=1,\ldots,5,8} e_{l,i,n} \quad (17)$$

These impact values are expressed as millipoints units (mPt) and estimated from widely used commercial software, SIMAPRO [28]. SIMAPRO can analyze and monitor environmental performance of products based on life cycle analysis methods. The software evaluates environmental impact based on the inputs of component materials and operations (energy consumption, transportation, processing, usage, waste treatment, and so on), separates them into different categories (greenhouse effect, ozone layer depletion, acidification, eutrophication, heavy metals, carcinogens, winter smog, summer smog, pesticides, energy, and solids) and normalizes them to ecopoints or mPt using the "distance-to-target" principle [6,29]. In this paper, we only consider the environmental impact of the manufacturing process, transportation and disposal. We do not consider impacts during the use phase since the total planning horizon for each scenario is considered constant.

In this paper, the component end-of-life age $t_{l,i}$ depends on its age $t_{l-1,i}$ when it entered the present life cycle, decisions made $x_{l,i,j}$ regarding its refurbishment or upgrade, and length of use time a_l in the current life cycle. The function g represents the effects of design decisions $x_{l,i,j}$ and the returned component's age on outgoing component age. For, example, remanufacturing will improve the effective age of a component. We will make specific assumptions about these effects in the PC example section.

$$t_{l,i} = g(t_{l-1,i}, x_{l,i,j}) + a_l \quad (18)$$

At the end of a particular lifecycle, the component reliability $R_{l,i}$ is represented by the two parameter (characteristic life θ_i and slope of the Weibull reliability curve b_i) Weibull distribution, as shown in Eq. (19), where we only consider the useful life stage in the model.

$$R_{l,i} = \exp\left\{-\left[\frac{t_{l,i}}{\theta_i}\right]^{b_i}\right\} \quad (19)$$

This information provides input to the failure mode function, which estimates overall product reliability at the end of the lifecycle. In this paper, we consider the end-of-life reliability of the product R_l is a function of the reliability of each component based on product failure mode information, as shown in Eq. (20).

$$R_l = f(R_{l,1}, \ldots, R_{l,s}) \quad (20)$$

We assume that there is no time gap between any two life cycles. We conservatively define overall reliability as the lowest product reliability (Eq. (21)) in all life cycles as the reliability attribute value R.

$$R = \min\{R_l\} \quad (21)$$

2.4 NSGA-II. As discussed, in our model, we consider component level design decisions in order to control and optimize the product attributes. Evaluating a product comprising 12 components with 4 possible EOL decisions requires consideration of a total number of possible product configurations of 4^{12}, for just one life cycle. Evaluating multiple lifecycles increases the complexity even further. For example, more than 10^{72} solutions are possible if each component can be reused, remanufactured, recycled, or replaced for ten possible lifecycles. Obviously, this is a large number and exhaustive enumeration and comparison of all the solutions is not possible. We employ heuristics in solving the optimization problem for the set of the three attributes of price, environmental impact, and reliability. This determines the Pareto optimal frontier, a manageable number of nondominated solutions. The stochastic search methods—Genetic Algorithms [30]—in particular, have been successfully employed to solve complex engineering problems involving multiple objectives. A number of multi-objective algorithms have been proposed in literature [31,32] and we choose the elitist NSGA-II proposed by Deb et al. [33]. The algorithm is efficient in approximating the Pareto frontier, which considers attributes separately and does not employ information about customer tradeoff behavior over multiple attributes [34]. The algorithm has found several applications in product design. A mass customization decision making problem is addressed in Ref. [34] while an extension to the algorithm is utilized in Ref. [29] for reuse decision making. After the Pareto optimal frontier is defined, the utility function is employed to identify the best set of tradeoffs.

3 Personal Computer Example and Results

The model presented in here is applied to personal computers; however, the general model structure can be employed for other products as well. Electronic waste represents only 2% of America's trash in landfills; however, it equals 70% of overall toxic waste [35].

3.1 Baseline Results. This section presents an example involving personal computers with 12 components for a portfolio of four different market segments. These components are easily separable modules such as the hard drive or the video card. While disassembly of the components into more subcomponents is possible, we show later that consolidating into a smaller number of components (less than 12) does not affect the results significantly.

Failure mode information is required when we want to find product reliability based on the component reliability information. It is important to consider component dependencies and criticality. The selection of the critical components is discussed within maximum entropy reliability [36]. In this personal computer example, we assume product failure mode occurs when one of the critical components (mother board, hard drive, or video card) fails, or when three of the remaining noncritical components fail together. Recall the discussion in Sec. 2.3 regarding the effects of end-of-life decisions made on component in terms of age. We assume, for our example that the option of recycling recovers 90% of the original component value in terms of its age and remanufacturing recovers 50%. The reused component would keep the output age from the previous lifecycle and disposed component with replacement would be brand new. All component inputs are new at the beginning of the first lifecycle.

We first generate the Pareto optimal frontier over price, environmental impact and reliability.

The NSGA-II algorithm for this problem is programmed in MATLAB. A two-bit string represents the four possible design decisions for each component in a lifecycle, resulting in 24 bits for the product. In addition, one location in the chromosome using real numbers is added to represent the length of the lifecycle. Hence, the total length of the chromosome is 25* (number of life cycles). The population size varies according to the number of lifecycles to account for the increase in problem size. The algorithm searches for solutions from a population set instead of a single point. Two-point crossover is used with probability 0.85; the probability of mutation is fixed at 0.02, and is implemented using the distribution of time-to-next-mutation to gain speedup. These operators can provide adequate mixing of solutions to promote solution diversity and can allow the algorithm to investigate

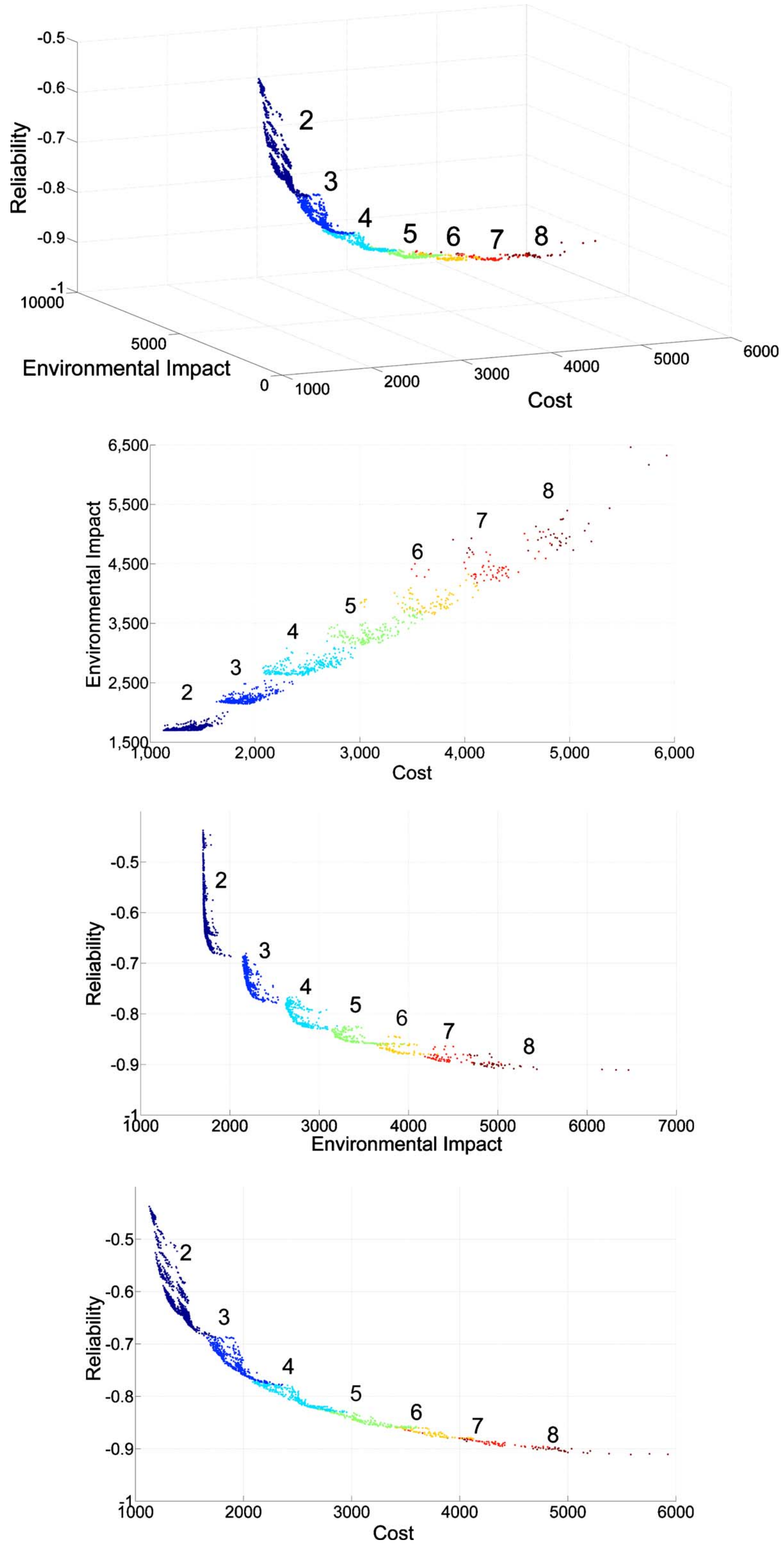

Fig. 3 The Pareto frontier over price, environmental impact, and reliability and projections

the solution space efficiently, converging to the optimal solutions quickly. Crowding and elitism are also utilized to allow effective evolution in the NSGA-II [33].

The algorithm iteratively searches for better solutions, and each solution is compared with a set of nondominated solutions. The algorithm finally converges when further improvement in the Pareto frontier is not possible. The Pareto frontier is shown in Fig. 3. In addition to the initial 3D plot, two dimensional projections are plotted showing pairs of attributes.

In general, the values of these attributes increase as the number of lifecycles increases. The data points are represented by different colors indicating the optimal number of lifecycles, ranging

Table 2 Acceptable attribute range for each market segment and attribute

Market segment	Price (per year) $(P_{p,\min}, P_{p,\max})$ ($)	Environmental impact (per year) $(E_{p,\min}, E_{p,\max})$ (mPt)	Reliability $(R_{p,\min}, R_{p,\max})$
Technophile	600–1000	420–1280	0.84–0.9999
Utilitarian	50–600	210–900	0.60–0.85
Green	500–1000	105–700	0.50–0.80
Neutral	13–1068	105–1579	0.64–0.95

from 2 to 8 lifecycles, for these nondominated solutions. After arriving at the nondominated solutions on the optimal Pareto frontier, now we need to determine, which solution on the frontier represents the best tradeoffs among price, environmental impact and reliability for each market segment.

Here, we consider a product portfolio composed of four product variants to cover four different market segments: *technophile customers*, who put more emphasis on the performance of the product and can spend more money to achieve it; *utilitarian customers*, who want to spend less but buy relatively higher performance product; *green customers*, who are willing to sacrifice a certain level of performance to reduce the environmental impact; and *neutral customers*, who do not have significant preferences on one specific attribute. Customer preferences are reflected by two parameters; the ranges over which each segment is willing to consider tradeoffs in each attribute (Table 2) and the scaling constants, which reflect willingness to make tradeoffs among the attributes, shown in Table 3. For price and environmental impact, the values in Table 2 are averaged over time. Then we move on to develop optimal multilifecycle strategies to meet specific customer preferences in each market segment.

The nondominated solutions are now evaluated to determine the best combination of price, environmental impact and reliability using utility theory. Various approaches have demonstrated the importance of applying utility theory in engineering decision making [37,38]. The multiplicative utility function [39] in Eq. (22) is used to evaluate the desirability of attribute tradeoffs. The total planning horizon T is 10 years. $P_{p,\max}, P_{p,\min}$ define the tolerable range for price, $E_{p,\max}, E_{p,\min}$ define the tolerable range for environmental impact, and $R_{p,\max}, R_{p,\min}$ define the tolerable range for reliability. The single attribute utility (U_P, U_E, U_R) of each attribute is normalized between 0 and 1 over the acceptable range as shown in Eqs. (23)–(25).

$$\max\ U_p = \frac{1}{K}\left[\left\{\prod_{a\in\{P,E,R\}} (Kk_a U_a + 1)\right\} - 1\right] \tag{22}$$

$$U_P = \frac{P_{p,\max} - P}{P_{p,\max} - P_{p,\min}} \tag{23}$$

$$U_E = \frac{E_{p,\max} - E}{E_{p,\max} - E_{p,\min}} \tag{24}$$

$$U_R = \frac{R - R_{p,\min}}{R_{p,\max} - R_{p,\min}} \tag{25}$$

Table 3 Scaling constants for each market segment

Market segment	Price	Environmental impact	Reliability
Technophile	0.30	0.10	0.80
Utilitarian	0.70	0.35	0.45
Green	0.15	0.85	0.15
Neutral	0.50	0.50	0.50

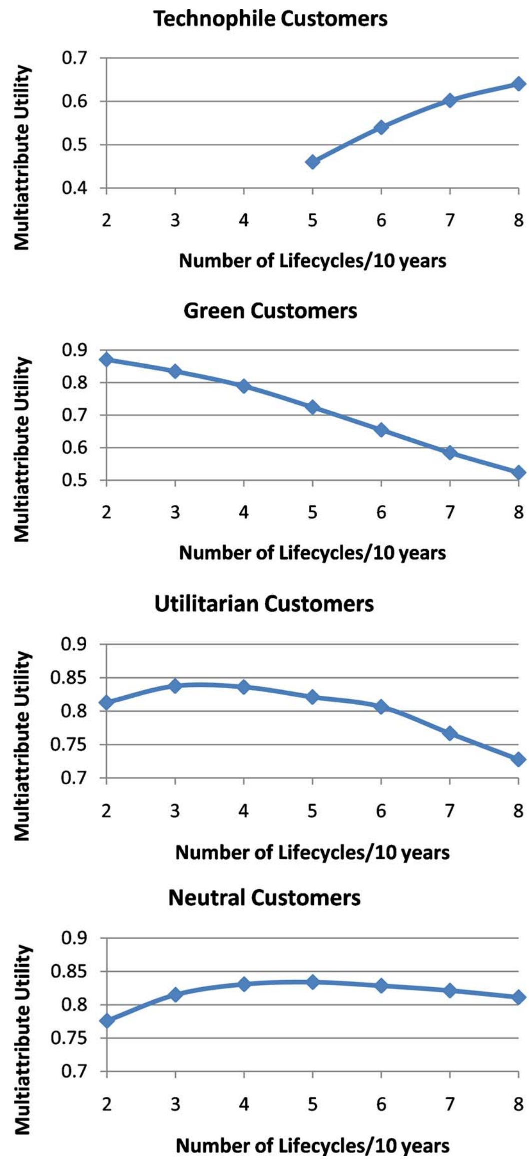

Fig. 4 Multiattribute utility for nondominated solutions with respect to the number of lifecycles over 10 years for each market segment

Figure 4 shows the results of using Eq. (22) to estimate the multiattribute utility of each point on the Pareto optimal frontier for each of the four market segments. We only show the highest utility solutions (optima) in terms of different of number of lifecycles. Multiattribute utility is shown with respect to the optimal number of lifecycles in the 10 year planning horizon. A greater number of lifecycles corresponds to a shorter average lifecycle. Details for the optimal solutions for each market segment are shown in Tables 4–7 in the following (Ru—Reuse; Rm—remanufacturing; Rc—recycling; Rn—disposal; LC—life cycle).

The differences in preferences across the market segments as shown in Tables 2 and 3 are reflected in differences in optimal take-back profiles for each segment. The technophile segment places more emphasis on reliability, as reflected in a higher reliability cutoff and scaling constant. The result is shown in Fig. 4(i). Solutions where the number of lifecycles is less than five are infeasible since they would fall below the acceptable range for reliability. As the number of lifecycles increases, utility increases since the average usage time is decreasing, thereby improving reliability. The optimal multiattribute solution for this market seg-

Table 4 Optimal decisions for technophile market segment

	Design decisions							
Component	LC 1	LC 2	LC 3	LC 4	LC 5	LC 6	LC 7	LC 8
Monitor	Rn	Ru	Ru	Rc	Ru	Rm	Rm	Ru
Floppy drive	Rn	Rm	Rn	Ru	Rn	Rc	Rn	Rc
Keyboard	Rn	Ru	Rn	Rm	Rm	Rc	Ru	Rm
Hard drive	Rn	Rn	Rn	Rc	Rn	Rn	Rn	Rc
CD-ROM	Rn	Rc	Rn	Rm	Rc	Rc	Ru	Rn
Mother board	Rn	Rc	Rc	Rc	Rn	Rc	Rc	Rc
Power supply	Rn	Rc	Ru	Rc	Rm	Ru	Ru	Ru
Sound card	Rn	Rc	Rc	Ru	Rc	Rm	Ru	Rc
Video card	Rn	Rc	Rc	Rn	Rn	Rm	Rc	Rc
Modem	Rn	Ru	Ru	Rn	Rc	Rc	Rm	Ru
Cables	Rn	Rc	Ru	Rc	Ru	Rc	Rm	Ru
Housing	Rn	Rm	Ru	Rc	Ru	Rn	Rc	Rc
Usage time (years)	1.41	1.29	1.25	1.26	1.27	1.12	1.20	1.20
Product attributes	P: 5381.1 E: 5436.4 R: 0.909							
Utility	0.640							

ment is 8 lifecycles over the 10 year planning horizon.

In contrast, Fig. 4(ii) shows that for the green market segment, multiattribute utility increases as the number of lifecycles decrease from eight to two over the 10 year planning horizon. The optimal solution is two lifecycles. This is due to the fact that longer lifecycles result in lower overall environmental impact for which this market segment is willing to sacrifice a certain level of reliability. The results for the other two customer groups (Figs. 4(iii) and 4(iv)) lie between these two extremes as expected. The optimal number of life cycles is three and five for utilitarian and neutral customers, respectively.

3.2 Design Insights

3.2.1 Change of Component Reliability. Analysis of the results can provide important insights into component level design decision problems. From the optimal solutions for the four market segment shown in Tables 4–7, we can see that the critical components—hard drive, motherboard, and video card—are mostly disposed or recycled (which reduces their effective age to near zero or zero for purposes of improving reliability estimation). Noncritical components are mostly reused or remanufactured in the optimal solution for utilitarian and neutral customers. In the case of green customers since the optimal number of life cycles is only two, recycling can recover most of the component value without significantly increasing cost. Knowing ahead of time which components will be reused (rather than recycled), the designer can redesign those components in order to further enhance their reusability.

An immediate question that might arise in the mind of designers is whether these decisions can be influenced by modifying the reliability functions of components. For our case study, we modify the characteristic life of components to see its effects on the overall utility of the manufacturer. We consider a critical component (hard disk) for our analysis. Simulation results (Table 8) show that when the characteristic life of the two components is doubled, the utilitarian customers utility would increase from $0.837(U_1)$ to $0.867(U_2)$ and three attribute new values are 2017.0, 2268.6, and 0.800.

While this result is intuitive if the redesign cost is free, it opens up the avenue to perform a cost-benefit analysis. One can determine how much cost is incurred in increasing the reliability by a given amount. In the case of the hard disk, for example, improving the mechanical elements or the platter material [40] can improve reliability substantially since the electronics are usually considered robust. If the cost-benefit analysis shows that cost per product offsets the utility less than the increase in reliability, re-

Table 5 Optimal decisions for green market segment

	Design decisions	
Component	LC 1	LC 2
Monitor	Rn	Ru
Floppy drive	Rn	Rm
Keyboard	Rn	Rm
Hard drive	Rn	Rc
CD-ROM	Rn	Rm
Motherboard	Rn	Rc
Power supply	Rn	Ru
Sound card	Rn	Rc
Video card	Rn	Rc
Modem	Rn	Rc
Cables	Rn	Rm
Housing	Rn	Ru
Usage time (years)	5.47	4.53
Final product attributes	P: 1521.7 E: 1750.6 R: 0.663	
Utility	0.871	

Table 6 Optimal decisions for utilitarian market segment

	Design decisions		
Component	LC 1	LC 2	LC 3
Monitor	Rn	Ru	Ru
Floppy drive	Rn	Ru	Rc
Keyboard	Rn	Rm	Rm
Hard Drive	Rn	Rc	Rc
CD-ROM	Rn	Ru	Rc
Motherboard	Rn	Rc	Rc
Power supply	Rn	Ru	Ru
Sound card	Rn	Rc	Ru
Video card	Rn	Rc	Rc
Modem	Rn	Rc	Ru
Cables	Rn	Ru	Rc
Housing	Rn	Ru	Ru
Usage time (years)	3.92	3.06	3.03
Product attributes		P: 1986.5 E: 2234.6 R: 0.758	
Utility		0.837	

Table 7 Optimal decisions for neutral market segment

Component	Design decisions LC 1	LC 2	LC 3	LC 4	LC 5
Monitor	Rn	Ru	Ru	Ru	Ru
Floppy drive	Rn	Ru	Rc	Ru	Rc
Keyboard	Rn	Ru	Rm	Rn	Rm
Hard Drive	Rn	Rc	Rn	Rc	Rn
CD-ROM	Rn	Rm	Rc	Rc	Rn
Motherboard	Rn	Rc	Rc	Rc	Rc
Power supply	Rn	Ru	Ru	Ru	Rm
Sound card	Rn	Ru	Rn	Ru	Ru
Video card	Rn	Rc	Rc	Rc	Rc
Modem	Rn	Ru	Ru	Rc	Rc
Cables	Rn	Ru	Ru	Rc	Ru
Housing	Rn	Ru	Rc	Rm	Ru
Usage time (years)	2.28	1.92	1.87	1.90	2.03
Product attributes			P: 3124.3 E: 3322.5 R: 0.853		
Utility			0.833		

design can be undertaken.

The isoutility curves of the utilitarian customers are shown in Fig. 5, for a constant environmental impact. To estimate the price increase customers would accept in order to improve reliability, we consider a movement from U_1 to U_2 ($U_2 > U_1$). We first find on the isoutility line a point with utility U_1 that is directly above U_2. We then move along the vertical direction (price axis) with the same reliability in U_2 until we reach the point on the isoutility line with U_1. The monetary difference in these two prices is the maximum acceptable redesign cost for the reliability change.

In this case study, to determine this price change, we first fix $U_1 = 0.837$, then use the multiattribute Eq. (22) to determine that the new price is \$2473. Therefore, the manufacturer can spend up to \$2473−\$2017=\$456 per product over the planning horizon to improve hard disk reliability through redesign. If the redesign cost is less than the monetary difference, the redesign would improve customers' utility.

3.2.2 Parts Consolidation. Parts consolidation refers to combining of components into one module so that installation into and disassembly from the product is facilitated. In addition, other benefits can also be attributed to parts consolidation such as better tolerances, less inventory and better aesthetics in the case of outer housings, among others. However, parts consolidation removes the freedom that a manufacturer has in terms of decisions they can make while reusing and thus fine tuning the product's performance.

As an example, in our simulations, we consider that integrating the sound card, video card and modem to reduce the number of components from 12 to 10 based on the physical proximity and integrability into one module. It means the decisions are the same within each product for these three components. The results (Table 8) show that the customers' utility would not be significantly influenced by this change, showing that such parts consolidation should be undertaken.

Table 8 The utility comparison for redesign components and parts consolidation

	Technophile	Green	Utilitarian	Neutral
Base	0.640	0.871	0.837	0.833
Redesign component (hard drive)	0.711	0.884	0.867	0.853
Parts consolidation	0.64	0.87	0.837	0.829

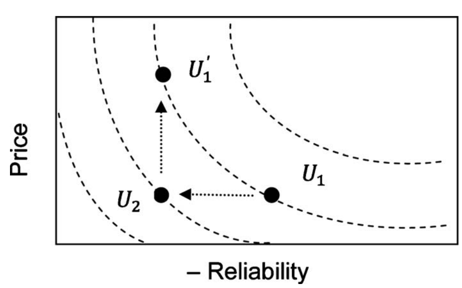

Fig. 5 Isoutility curve for utilitarian customers

3.2.3 Legislation Constraints. This section explores the impact of varying degrees of take-back legislation. The absence of legislation should improve the manufacturer's utility since the manufacturer does not have to expend resources on collection or disposal.

Earlier in this paper, take-back legislation was assumed to be imposed on manufacturers to enforce collection of products after they have been used by customers. We consider the following two alternative scenarios: (1) the manufacturer is not required to collect used products, hence the overall cost for manufacturing is decreased and (2) stricter legislation is enacted and the cost for disposal of some hazardous materials, such as lead, is increased. The environmental impact can be assumed to remain constant in both scenarios as the product is ultimately disposed of in the landfill, even though the decision to do so is made by the customer.

Figure 6 shows the results of repeating the analysis under these scenarios. We assume that the customer tradeoff behavior remains the same as in the baseline case presented earlier. Figure 6 shows that the utility changes in the utilitarian market segment under the two different legislative scenarios. Comparing the results to the baseline case, we find that the customers' utility increases slightly when there is no take-back legislation and decreases slightly with more stringent legislation. In addition, the effects of legislation on product take-back would greatly influence the utilitarian customers' utility since they are more sensitive to the price that they pay for the products (Fig. 6).

3.2.4 Change in Customer Preference. We also perform sensitivity analysis to investigate the effect of changes in customer preferences due either to uncertainties in the initial preference assessment, or to changes in preferences over time. Table 9 shows the results. It is anticipated that environmental consciousness will continue to spread throughout the general market. For the neutral customer group, we keep other parameters constant and revise the

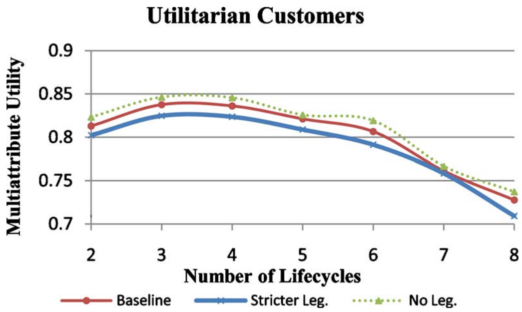

Fig. 6 Effect of changes in legislation for utilitarian market segment

acceptable environment impact range from [105, 1579] to [105, 900] (per year), reflecting a reduction in the maximum acceptable environmental impact. Comparing the magnitude of utility when different utility functions are employed is not meaningful, so we compare only the resulting optimal decision outcomes. Compared with the baseline case, Table 9 shows that the optimal solution calls for fewer lifecycles and fewer new components in order to decrease the environment impact. Similar results are seen for other market segments.

4 Conclusions and Future Work

In this paper, we proposed a methodology to establish more efficient closed-loop, multiple life cycle product stewardship. A multiple life cycle design decision model was created to help manufacturers identify component level decisions to accommodate flexibility in the number of lifecycles according to different customer needs. The methodology proposed in this paper enables the decision maker to identify a set of nondominated solutions first and then make optimal decisions based on different customers' tradeoff preferences over multiple attributes.

The challenge for the future work is to more accurately evaluate the reused and remanufactured products' retained functionality, as well as their potential to satisfy dynamically changing customer requirements. Although returned products may still be in good condition in terms of physical reliability, customers often upgrade their products in order to acquire innovative new technology. Hence, it is necessary to consider some performance indicator (and its degradation over time) other than reliability and age. In addition, we need to predict accurate cost and environmental impact information for future life cycles in a larger scale product take-back system. This will be challenging as the high variability of remanufacturing and recycling operations will be greatly influenced by as yet unknown technological innovations and changes in customer preferences. Rapid development in data collection, storage, and analysis methods can aid in modeling and predicting these manufacturing and marketing trends.

Table 9 Optimal decisions for neutral customers when acceptable environmental impact decreases

Component	Design decisions			
	LC 1	LC 2	LC 3	LC 4
Monitor	RN	RU	RU	RU
Floppy drive	RN	RC	RC	RU
Keyboard	RN	RM	RC	RM
Hard drive	RN	RC	RC	RC
CD-ROM	RN	RN	RC	RC
Motherboard	RN	RC	RC	RC
Power supply	RN	RU	RU	RU
Sound card	RN	RU	RN	RC
Video card	RN	RC	RC	RC
Modem	RN	RC	RU	RC
Cables	RN	RU	RU	RC
Housing	RN	RM	RC	RU
Usage time (years)	2.89	2.39	2.40	2.32
Product attributes	P: 2605.2 E: 2782.3 R: 0.82			
Utility	0.803			

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References

[1] European Union Directive, 1999, "Landfill of Waste," Council Directive 1999/31/EC, Official Journal of the European Communities, Apr. 26, L182, Vol. 42, 16.7.1999, pp. 1–19.
[2] European Union Directive, 2002, "Waste Electrical and Electronic Equipment (WEEE)," Directive 2002/96/EC of the European Parliament and of the Council, Official Journal L 037, Jan. 27, 13/02/2003, pp. 0024–0039.
[3] Williams, J., Shu, L., and Murayama, T., 2000, "Current Status of Extended Producer Responsibility Legislation and Effects on Product Design," Proceedings of ASME Japan–USA Symposium on Flexible Automation, Ann Arbor, MI.
[4] Guide, V. D. R., 2000, "Production Planning and Control for Remanufacturing: Industry Practice and Research Needs," J. Operations Manage., **18**(4), pp. 467–483.
[5] White, C., Masanet, E., Rosen, C., and Beckman, S., 2003, "Product Recovery With Some Byte: An Overview of Management Challenges and Environmental Consequences in Reverse Manufacturing for the Computer Industry," J. Cleaner Prod., **11**, pp. 445–458.
[6] Mangun, D., and Thurston, D. L., 2002, "Incorporating Component Reuse, Remanufacture and Recycle into Product Portfolio Design," IEEE Trans. Eng. Manage., **49**(4), pp. 479–490.
[7] Ishii, K., Eubanks, C. F., and DiMarco, P., 1994, "Design for Product Retirement and Material Life-Cycle," Mater. Des., **15**(4), pp. 225–233.
[8] King, A. M., Stuart, C. B., Winnie, I., and Chris, A. M., 2006, "Reducing Waste: Repair, Recondition, Remanufacture or Recycle?," Sustain. Dev., **14**(4), pp. 257–267.
[9] Rose, C. M., Kurt, A. B., and Ishii, K., 1999, "Determining End-of-Life Strategies as a Part of Product Definition, ISEE-1999," Proceedings of the 1999 IEEE International Symposium on Electronics and the Environment, pp. 219–224.
[10] González, B., and Adenso-Diaz, B., 2005, "A Bill of Materials-Based Approach for EOL Decision Making in Design for the Environment," Int. J. Prod. Res., **43**(10), pp. 2071–2099.
[11] Lambert, A. J. D., and Gupta, S. M., 2005, *Disassembly Modeling for Assembly, Maintenance, Reuse, and Recycling*, CRC Press, Boca Raton, FL.
[12] Behdad, S., Kwak, M., Kim, H., and Thurston, D., 2010, "Simultaneous Selective Disassembly and End-of-Life Decision Making for Multiple Products That Share Disassembly Operations," ASME J. Mech. Des., **132**(4), p. 041002.
[13] Peng, Q., and Chung, C., 2007, "Selected Disassembly Planning for Product Maintainability," Proceedings of ASME International Design Engineering Technical Conferences, Las Vegas NV.
[14] Xing, K., and Belusko, M., 2008, "Design for Upgradability Algorithm: Configuring Durable Products for Competitive Reutilization," ASME J. Mech. Des., **130**(11), p. 111102.
[15] Dunmade, I., 2006, "Design for Multi-lifecycle: A Sustainable Design Concept Applied to an Agro-Industrial Development Project," 2006 ASAE Annual Meeting, Paper No. 068059.
[16] Zhou, M., Caudill, R., Sebastian, D., Zhang, B., "Multi-Lifecycle Product Recovery for Electronic Products," 1999, J. Electron. Manuf., **9**(1), pp. 1–15.
[17] Reliability Engineering, http://en.wikipedia.org/wiki/-Reliability_engineering
[18] Shu, L. H., and Flowers, W. C., 1998, "Reliability Modeling in Design for Remanufacture," ASME J. Mech. Des., **120**(4), pp. 620–627.
[19] Jiang, Z. H., Shu, L. H., and Benhabib, B., 2000, "Reliability Analysis of Non-Constant-Size Part Populations in Design for Remanufacture," ASME J. Mech. Des., **122**(2), pp. 172–178.
[20] Kara, S., Mazhar, M. I., and Kaebernick, H., 2004, "Lifetime Prediction of Components for Reuse: An Overview," Int. J. Environ. Technol. Manage., **4**(4), pp. 323–348.
[21] Lund, R., 1998, "Remanufacturing: An American Resource," Proceedings of the Fifth International Congress Environmentally Conscious Design and Manufacturing, Rochester Institute of Technology, Rochester, NY, Jun. 16–17.
[22] National Recycling Coalition, 1999, Buy Recycled Guidebook, http://www.greenbiz.com/files/document/-O16F4773.pdf
[23] Yuzo, H., Takayuki, N., and Toshijiro, O., 2001, *Recyclability Evaluation Method (REM) and Its Applications*, Second International Symposium on Environmentally Conscious Design and Inverse Manufacturing (EcoDesign'01),

p. 315.
[24] Desai, A., and Mital, A., 2003, "Evaluation of Disassemblability to Enable Design for Disassembly in Mass Production," Int. J. Ind. Ergonom., **32**, pp. 265–281.
[25] Ishii, K., 1996, "Materials Selection Issues in Design for Recyclability," Proceedings of the Second International Ecobalance Conference, Tsukuba, Japan.
[26] Chick, A., and Micklethwaite, P., 2003, "Recycled Tigers' Teeth?: Obstacles to UK Designers Specifying Recycled Products and Materials," Fifth European Academy of Design Conference, Barcelona, Spain, Apr. 28–30.
[27] Hammond, R., Amezquita, T., and Bras, B. A., 1998, "Issues in the Automotive Parts Remanufacturing Industry: Discussion of Results From Surveys Performed Among Remanufacturers," International Journal of Engineering Design and Automation - Special issue on Environmentally Conscious Design and Manufacturing, **4**(1), pp. 27–46.
[28] PRé Consultants Company, 2010 SimaPro LCA software, http://www.pre.nl/simapro/
[29] Pandey, V., and Thurston, D., 2007, "Non-Dominated Strategies for Decision Based Design for Product Reuse," Proceedings of ASME International Design Engineering Technical Conferences, Las Vegas, NV, USA.
[30] Goldberg, D. E., 1989, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, New York.
[31] Zitzler, E., Deb, K., and Thiele, L., 2000, "Comparison of Multiobjective Evolutionary Algorithms: Empirical Results," Evol. Comput., **8**(2), pp. 173–195.
[32] Deb, K., 2001, *Multi-Objective Optimization Using Evolutionary Algorithms*, Wiley, Chichester, UK.
[33] Deb, K., Pratap, A., Agrawal, S., and Meyarivan, T., 2002, "A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II," IEEE Trans. Evol. Comput., **6**(2), pp. 182–197.
[34] Jolly, M., Winward, P., Pandey, V., and Thurston, D. L., 2006, "Mass Customization Optimization Using Social Network Based Product Architecture Representation," Proceedings of ASME 2006 IDETC/CIE, Philadelphia, Sep. 10–13.
[35] Natural Resources Council of Maine, 2008, "Maine's E-Waste Program," Progress Report On Maine's Electronic Waste Law, http://www.nrcm.org/documents/ewaste_report2008.pdf
[36] Pandey, V., and Thurston, D., 2009, "Effective Age of Remanufactured Products: An Entropy Approach," ASME J. Mech. Des., **131**(3), p. 031008.
[37] Li, H., and Azram, S., 2002, "An Approach for Product Line Design Selection Under Uncertainty and Competition," ASME J. Mech. Des., **124**(3), pp. 385–392.
[38] Wassenaar, H. J., and Chen, W., 2003, "An Approach to Decision-Based Design With Discrete Choice Analysis for Demand Modeling," ASME J. Mech. Des., **125**(3), pp. 490–497.
[39] Keeney, R., and Raiffa, H., 1993, *Decisions With Multiple Objectives*, Cambridge University Press, Cambridge, UK.
[40] http://www.pcguide.com/ref/hdd/perf/qual/issues.htm