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Multi-Criteria Decision-Making for Optimization of Product Disassembly under Multiple Situations

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With growing interest in recovering materials and subassemblies within consumer products at the end of their useful life, there has been an increasing interest in developing decision-making methodologies that determine how to maximize the environmental benefits of end-of-life (EOL) processing while minimizing costs under variable EOL situations. This paper describes a methodology to analyze how product designs and situational variables impact the Pareto set of optimal EOL strategies with the greatest environmental benefit for a given economic cost or profit. Since the determination of this Pareto set via enumeration of all disassembly sequences and EOL fates is prohibitively time-consuming even for relatively simple products, multi-objective genetic algorithms (GA) are utilized to rapidly approximate the Pareto set of optimal EOL trade-offs between cost and environmentally conscious actions. Such rapid calculations of the Pareto set are critical to better understand the influence of situational variables on how disassembly and recycling decisions change under different EOL scenarios (e.g., under variable regulatory, infrastructure, or market situations). To illustrate the methodology, a case study involving the EOL treatment of a coffee maker is described. Impacts of situational variables on trade-offs between recovered energy and cost in Aachen, Germany, and in Ann Arbor, MI, are elucidated, and a means of presenting the results in the form of a multi-situational EOL strategy graph is described. The impact of the European Union Directive regarding Waste Electric and Electronic Equipment (WEEE) on EOL trade-offs between energy recovery and cost was also considered for both locations.

Introduction

Increased demand for consumer electric and electronic products, combined with the accelerated pace at which technology is evolving, has inevitably resulted in an increased amount of obsolete, discarded, broken, or abandoned products that must be treated by society. Consumer electric and electronics products are of particular concern due to high production volumes and characteristically short time scales of technological or stylistic obsolescence leading to landfilling of large amounts of discarded product. Exacerbating this problem is the fact that the components in these products are typically required to fit into a tight enclosing space, which makes disassembly for component recovery a challenging task.

The low economic value of the material composition, high rates of material mixing, and low levels of toxic materials have also discouraged efforts to fully recycle consumer electronics products. For example, it has been estimated that 3.2 million ton of electronic waste is landfilled each year in the United States (*1*). Such high quantities of discarded electronic products create a risk that hazardous metals such as lead, mercury, arsenic, and chromium can reach the environment. The risk is higher for developing countries with limited environmental controls that may ultimately import reused or remanufactured electronic products originating from developed countries (*2*).

It is well-known that recovery of waste electric and electronic equipment for reuse or recycling conserves resources and feedstocks that supply steel, glass, plastic, and precious metals. Such recycling also avoids air and water pollution as well as greenhouse gas emissions associated with materials production and manufacturing. For these reasons, the number of regulatory and voluntary initiatives aiming to increase end-of-life (EOL) reuse and recycling is increasing around the world. Of notable mention is the impending European Union Directive on Waste Electric and Electronic Equipment (WEEE), which will require producers to recycle greater than 50% of consumer products such as cell phones, coffee makers, and computers by 2006 (*3*).

With heightened interest in recycling and reuse inevitable in the coming years, situational factors and uncertainty that impact the economics of EOL options will require increased attention and understanding. For example, it is well-known that product structure, materials, locations of recycling facilities, applicable regulations, geography, and cultural context have a major impact on the economic and environmental benefits of material recovery. To date, a methodology has yet to be described that can quickly and easily quantify the trade-offs between reducing environmental burden and economic costs for optimal EOL strategies, considering all possible disassembly sequences and component fates under multiple situations. Rapid calculation of this set of solutions is necessary so that the impact of situational variables such as recycling costs, labor costs, and transportation distances can be thoroughly understood, leading to improved EOL decision-making and design for minimum EOL environmental impact. Moreover, the availability of a rapid methodology for calculating the optimal EOL trade-offs would present the opportunity to develop a concise set of multi-situational EOL strategy graphs for a given product. Such a concise representation would facilitate the efforts of consumers and decision-makers to maximize the environmental benefit of reuse and recycling efforts at minimum economic cost.

This paper utilizes a multi-objective genetic algorithm (GA) to establish the optimal set of trade-offs between environmental impact and cost for EOL strategies among uncertainty created by situational variables. While the methodology is presented as an EOL decision-making tool, it is general in dimensionality such that it could also be used to simultaneously consider trade-offs related to production costs, product performance, and life cycle environmental impact. Therefore the methodology can serve to accelerate the wider diffusion of green engineering principles such as those proposed by Anastas and Zimmerman (*4*) by providing an approach that engineers can use to quantify and visualize trade-offs between green engineering outcomes, economic variables, and design parameters as they arise.

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Related Research

Several decision variables must be considered when determining the maximum environmental benefit that can be achieved for a given economic cost when a product reaches EOL. These variables include the extent of disassembly, the disassembly sequence (if disassembly occurs), and the EOL fate for removed components as well as the product remainder not disassembled. A number of previous investigations have addressed important aspects of this optimization problem. For instance, Bras and Emblemsväg (*5*) developed an approach to evaluate the economics of disassembly under uncertain conditions using activity based cost modeling. The research investigated the relationship between specific product designs and the economics of EOL treatment, while situational variables were evaluated via Monte Carlo simulation. Rose et al. (*6*) developed a design-oriented decision framework applicable to consumer products. In this case, the research focused on technical product design variables such as expected lifetime and number of parts, and this information was used to select an appropriate EOL strategy at the design stage. Similarly, Caudill et al. (*7*) investigated the application of life cycle analysis techniques to facilitate design for multiple product life cycles.

Relative to the research cited above, the field of disassembly sequence planning (DSP) has generally focused less on product design and EOL management. While material recovery for environmental benefit has been the main motivation for DSP, the primary objective of much of the research has been to maximize the economic returns from disassembly (*8−10*) or to maximize the efficiency of disassembly with respect to disassembly time and the number of components removed (*11−14*). Also, investigations of sensitivity to situational variables have been rare in the DSP literature. Recently however, Erdos et al. (*16*) developed a DSP sensitivity analysis approach that utilizes a disassembly AND/OR graph (*15*) to determine the allowable revenue reduction for a disassembly action that leaves the optimal disassembly sequence unaffected. However, the approach was limited to an evaluation of only the maximum profit disassembly sequence.

Where environmental objectives have been considered in DSP, they have typically been treated either implicitly or as constraints secondary to economic objectives (*17−19*). Therefore more relevant to this investigation is the research performed by Lee et al. (*20*), which did consider economic and environmental variables as dual objectives. In this case, however, the objective function of the optimization problem was based on a weighted sum of economic and environmental variables that was used to establish individual component EOL fates based on only the least cost disassembly sequence. The methodology was not capable of simultaneous consideration of EOL fate and disassembly sequence and did not develop Pareto sets of EOL trade-offs. Such Pareto sets were investigated by Azapagic and Clift (*21*) in a chemical engineering application using a linear programming approach. While effective, the methodology requires multiple simulations to achieve a single Pareto curve. This could limit the use of the methodology for exploring a large number of scenarios as necessary in EOL decision-making.

The methodology presented below is unique in that it explores multi-objective optimization using genetic algorithms to explicitly describe trade-offs between environmental and economic variables. The approach further extends previous research in EOL decision-making by considering optimal sets of trade-offs, including simultaneous consideration of the disassembly sequence, the extent of disassembly, and the fate of EOL components. In addition, the trade-offs are efficiently calculated with reasonably short computational time, which permits extensive sensitivity analysis of trade-offs under multiple situations. The approach presented here is also distinct with respect to the DSP literature in that it takes into account the economic and life cycle environmental impacts of each process involved in product EOL. These processes include transportation, landfilling, shredding, disassembly, and recycling.

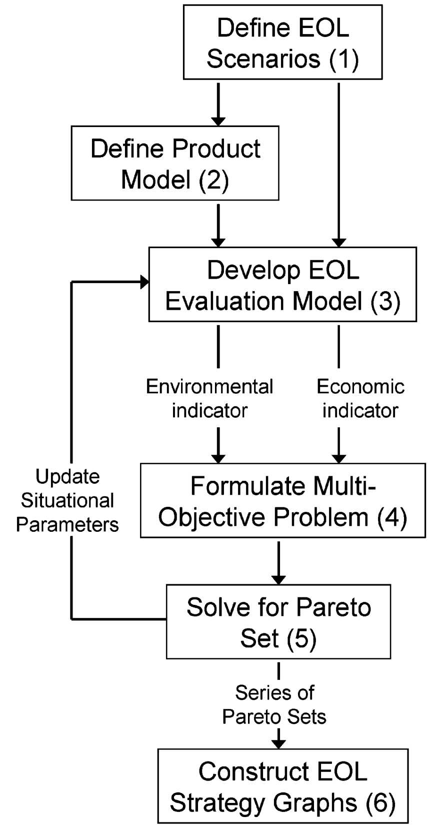


FIGURE 1. Methodology for calculationg EOL trade-off sets for multiple situations.

Methodology for Calculating EOL Trade-off Sets

The three primary objectives of this research can be summarized as follows: (i) develop a methodology to rapidly calculate the optimal set of trade-offs between economic investment and environmental improvement at EOL; (ii) use the methodology to investigate how situational variables can impact the optimal set of EOL trade-offs; and (iii) determine if the optimal set of EOL trade-offs, and its sensitivity to situational variables, can be usefully represented in a graphical form that facilitates EOL decision-making under uncertainty. This section describes the following six-step approach to achieve these objectives:

1. Define the situational variables and EOL scenarios of interest;
2. Define the product structure and the feasible set of disassembly sequences and times;
3. Develop environmental and economic assessment models of EOL options;
4. Formulate a multi-objective optimization problem based on models and metrics for product disassembly, EOL economics, and EOL environmental impact;
5. Calculate optimal trade-off sets and perform sensitivity analysis for situational variables;
6. Interpret results and construct multi-situational EOL strategy graphs.

The relationship between these six steps is illustrated in Figure 1. In the methodology development, the following definitions are utilized:

• Disassembly Sequence: The order in which components or subassemblies are removed from the product assembly.

• EOL Strategy: The set of all EOL decisions, consisting of the disassembly sequence (if disassembly occurs), the EOL fate of each removed component, and the EOL fate of the product remainder not disassembled (e.g., shred, landfill, etc.).

• Situational Variable: A variable defining an influential aspect of the context under which the EOL strategy is conducted (e.g., labor cost, recycled material revenue, transportation distance, etc.).

• Scenario/Situation: The set of all situational variables necessary to adequately model the context under which disassembly will take place.

Task 1: Define Situational Variables and EOL Scenarios. Situational variables that must be defined include *market variables* such as recycling prices, transportation prices, and labor prices; *infrastructure variables* such as transportation distances and recycling/remanufacturing technology; and *regulatory variables* such as take-back legislation, taxation, and subsidies. In the problem formation below, the vector **s** defines the set of situational variables necessary to describe a scenario.

Task 2: Define the Product Structure and the Feasible Set of Disassembly Sequences and Times. The next step of the methodology is to determine the feasible disassembly sequences and disassembly times, which can be derived from the following subtasks:

2a. Define the Set of Components along with Their Masses and Material Compositions. These values determine the economic and environmental characteristics of EOL processing. The set of components in the product is denoted as $C = \{c_1, c_2, ..., c_n\}$ below.

2b. Define a Liaison Graph of the Components. A liaison graph of components in C is a undirected graph $G = (C, L)$, where $L = \{\{c_i, c_j\}|c_i, c_j \in C\}$ is a set of *liaisons* representing physical contacts between two components in the product. This graph can provide a visual depiction of physical relationships between each component, which can be produced by manual or computer analysis of an existing physical product (*22*).

2c. Evaluate Opportunities To Define Component Subassemblies. A subassembly refers to a subset of components in C that can be removed simultaneously by one disassembly action. This can increase the computational speed of the analysis, while also increasing the intuitive value of results. A set of subassemblies can be represented as a partition $A = \{a_1, a_2, ..., a_m\}$ of component set C (*9, 23, 24*).

2d. Define a Precedence Matrix. A precedence matrix mathematically defines the physical relationships between components and subassemblies. The matrix permits the numerical determination of which disassembly sequences are feasible. It is defined as an $m \times m$ matrix $\mathbf{P} = (p_{ij})$ where

$$p_{ij} = \begin{cases} 1 & \text{if disassembly of } a_i \text{ can precede disassembly of } a_j \\ -1 & \text{if disassembly of } a_j \text{ can precede disassembly of } a_i \\ \text{nil} & \text{if } a_i = a_j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

2e. Evaluate Product Disassembly Times To Estimate Disassembly Labor Cost. Several methods exist for estimating required disassembly times, including studies based on the time required to manually perform common disassembly tasks (*35*). In the following, it is assumed that the disassembly is a linear sequence of removing one subassembly at a time (i.e., no parallel disassembly). Accordingly, a disassembly sequence is denoted as a list of l distinct subassemblies to be removed with $d = \langle d_1, d_2, ..., d_l \rangle \in A^l$ and with length $l \in [1, m]$ allowed to vary. While the linearity assumption greatly reduces the complexity of evaluating product disassembly times, the assumption is not specifically required and can be relaxed when necessary.

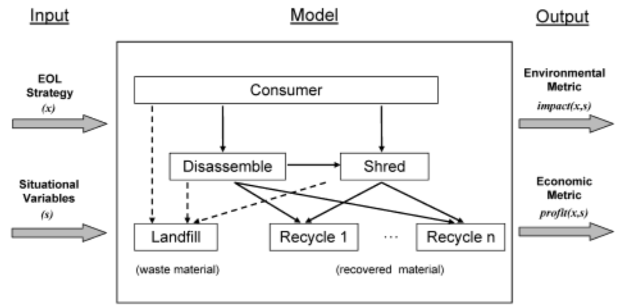


FIGURE 2. EOL evaluation model for calculating econominc and environmental metrics.

Task 3: Develop Model of EOL Economic and Environmental Impacts. Figure 2 illustrates a model-based estimation of EOL cost and environmental impact, using a given EOL strategy $\boldsymbol{x}$ and situational variables $\boldsymbol{s}$ as inputs. To gain a more complete picture of EOL impacts on the environment, in-use, upstream, and downstream environmental impacts are all presumed to be accounted for in the EOL model. As shown in Figure 2, the model must account for all transportation (arrows) and process activities (boxes) that occur during the execution of a given EOL strategy. This includes energy that can be saved by utilizing recycling processes as well as the energy spent to enable recycling. In a similar manner, the model must also evaluate the costs and revenue associated with disassembly, transportation, recycling, and disposal for each possible EOL strategy.

Task 4: Formulate Multi-Objective Optimization Problem. The economic and environmental metrics calculated by the EOL model (Figure 2) represent the objective functions for the optimization problem. The objectives are both functions of the EOL strategy $\boldsymbol{x}$ and the situational variables $\boldsymbol{s}$. If E is the set of EOL options, then the design variable is EOL strategy $\boldsymbol{x} = (d, eol(d_1), eol(d_2), ..., eol(d_l), eol_r)$, where d is a disassembly sequence, $eol(d_i)$ is the EOL fate of the subassembly d_i in d, and eol_r is the EOL fate of the reminder r in the product. More specifically

$$eol(a) = (e_1, e_2, ..., e_k) \in E^k;\ a = \{ac_1, ac_2, ..., ac_k\} \in d \quad (2)$$

$$eol_r \in E;\ r = \{c|c \in C, c \notin U_{a \in d} a\} \quad (3)$$

where e_i is the EOL fate of component ac_i in subassembly a. [In eqs 2 and 3, symbol "$\in$" in $a \in d$ is informally used to represent that subassembly a is contained in sequence d.]

The fundamental constraint in the problem is that all disassembly sequences and EOL fates in x must be geometrically and technically feasible. The precedence matrix $\mathbf{P} = (p_{ij})$ imposes a constraint on the disassembly sequence d of design variable $\boldsymbol{x}$ as $precedences(\boldsymbol{x})$ = TRUE, where the function $precedences(\boldsymbol{x})$ returns the truth value of the statement "$\forall\ a_i, a_j \in d(x), a_i\ p\ a_j; p_{ij} = 0 \vee p_{ij} = 1$", which can be implemented as a computer algorithm. The constraint for technical feasibility of the EOL options in $eol(d_i)$ and eol_r can be similarly denoted as $eol\_feasibility(\boldsymbol{x}, \boldsymbol{s})$ = TRUE. Technical feasibility issues include the availability of recycling technology for a specific material, or for the feasibility of remanufacturing or reuse as EOL options. Therefore $eol\_feasibility(\boldsymbol{x}, \boldsymbol{s})$ is a function of both $\boldsymbol{x}$ and $\boldsymbol{s}$, unlike $precedences(\boldsymbol{x})$ which is only a function of $\boldsymbol{x}$. Other constraints that can be considered include WEEE-type regulations such as targets for component recovery and recycling, denoted as *regulations*($\boldsymbol{x}$, $\boldsymbol{s}$) = TRUE. In summary, the optimization problem can be stated as:

$$\begin{aligned}&\text{minimize } \ impact(\boldsymbol{x}, \boldsymbol{s})\\&\text{maximize } \ profit(\boldsymbol{x}, \boldsymbol{s})\end{aligned} \tag{4}$$

subject to:

$$\begin{aligned}&precedences(\boldsymbol{x}) = \text{TRUE}\\&eol\_feasibility(\boldsymbol{x}, \boldsymbol{s}) = \text{TRUE}\\&regulations(\boldsymbol{x}, \boldsymbol{s}) = \text{TRUE}\\&\boldsymbol{x} = (d, eol(d_1), \ldots, eol(d_l), eol_r) \in A^l \times E^{|d_1|} \times \quad \times E^{|d_l|} \times E\\&1 \le l \le m; \ \ l \in \mathbf{Z}\end{aligned}$$

Due to the combinatorial nature of eq 4, solving it requires a discrete optimization algorithm. This is because simple enumeration is computationally too expensive even for simple products with relatively small n and m. As such, a multi-objective GA was chosen because of its robustness to discrete problems and efficiency in handling multi-objective problems without predefined weights or bounds on objective functions. The particular implementation used in the case study below is based on the Non-Dominated Sorting Genetic Algorithm (NSGA-II) (*25, 26*). A detailed comparison of NSGA-II with a conventional method of Pareto surface generation for a complex engineering design problem is given in ref *33*.

Task 5: Calculate Optimal Trade-off Sets and Conduct Sensitivity Analysis. Figure 3 provides a typical trade-off set that results from the solution to eq 4. The data represent the optimal set of trade-offs between recovered energy and cost for the EOL treatment of a coffee maker in Ann Arbor, MI, for the prevailing conditions of March 2002. In the case study, recovered energy is defined as the difference between the energy required to produce virgin material and the energy required to produce recycled material. The specific details of the case study and model are described in the next section.

Each point on the curves shown in Figure 3 (called Pareto curves) represents an optimal disassembly and recycling (D/R) strategy. Strategy P is the maximum profit D/R strategy, and strategy E is the maximum recovered energy D/R strategy. Usually, Strategy E involves complete disassembly and recycling of all recyclable components, as long as energy requirements for transportation and recycling are not excessive. In the coffee maker case study presented below, D/R strategies always have greater potential for energy recovery than direct landfilling or direct shredding and recycling (S/R).

Figure 3 also defines a strategy M, which is the EOL strategy closest to costing \$0.03/kW-h energy recovery (1 kW-h = 3.6 MJ). This cost is approximately equal to the cost of electricity charged to residential users in the United States (*34*). Strategy M can be used to compare different product designs and EOL situations for their maximum "economical" energy recovery under the supposition that the recovered energy could be sold on the open market. While recovered energy is not an entity which can be sold, Strategy M does provide an indication of the point where society "breaks even" with respect to energy production versus energy savings. Similarly, it should be noted that the concept of cost/profit at EOL utilized here is taken from the perspective of total profit/loss that can be achieved at EOL. It is most applicable for the case where an entity (e.g., a producer) is directly responsible for all EOL handling after the product is discarded by the consumer.

As shown in Figure 3, direct S/R of the coffee maker is the only strategy that achieves positive revenue at EOL in the Ann Arbor base case. However the profit is marginal and direct S/R cannot recover as much energy as the D/R strategies defined by the set bounded by strategies P and E. Compared to D/R, directly landfilling the coffee maker imposes less EOL cost but is also the only EOL strategy that is characterized by net energy consumption.

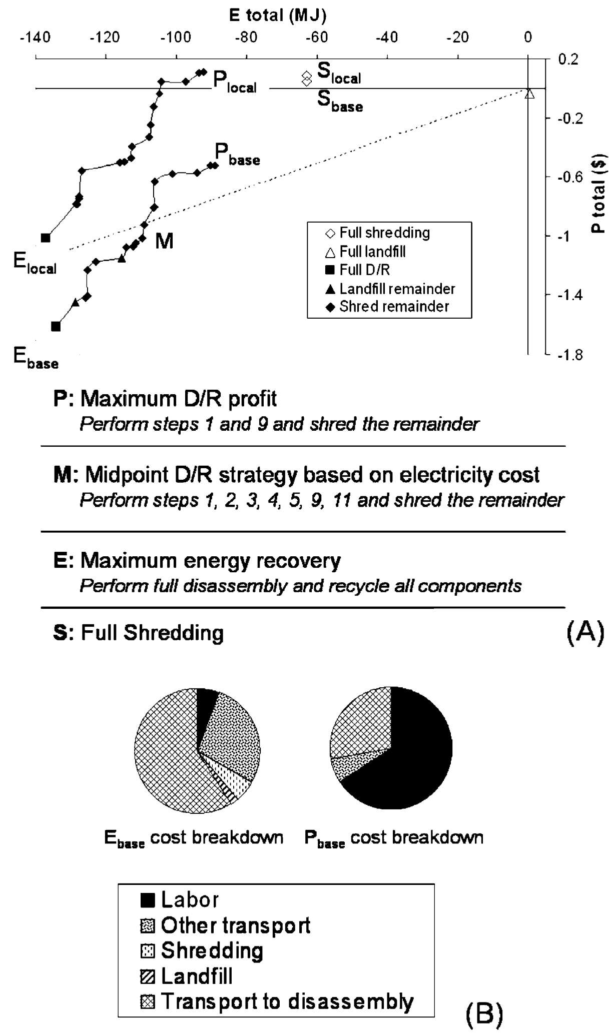


FIGURE 3. (A) Optimal EOL strategy set for Ann Arbor base case scenario with and without local disassembly (P, E, S_{local} and P, E, S_{base}, respectively). (B) Cost distribution for strategies P and E for Ann Arbor base case without local disassembly. negative E represents net positive recovered energy at EOL.

Task 6: Interpret Results and Construct Multi-Situation EOL Strategy Graphs. Once a Pareto set has been determined for a single base case, it is possible to re-run the optimization routine with new situational variables (or product designs) in order to understand their influence on the EOL Pareto set. For instance, Figure 3 also illustrates the impact of reducing the transportation distance between the consumer and the EOL processing center. Once such impacts are understood, it is possible to develop a "multi-situational EOL strategy graph", which illustrates the "tipping scenarios" where optimal EOL decisions change due to changes in EOL situational variables. Examples of EOL strategy graphs are provided in the case study below.

Case Study: Situationally Optimal EOL Trade-offs for Coffee Maker

To understand the utility of the methodology proposed above, the optimal set of EOL trade-offs for a typical coffee maker was investigated under multiple situations. A coffee maker was selected as the target product due to the existence of published LCA research on the product (*27*) and the availability of educational materials related to this case study (*28*). In this example, the trade-off between total EOL cost and total energy recovered/spent at EOL was considered. While not a direct indicator of environmental impact, energy

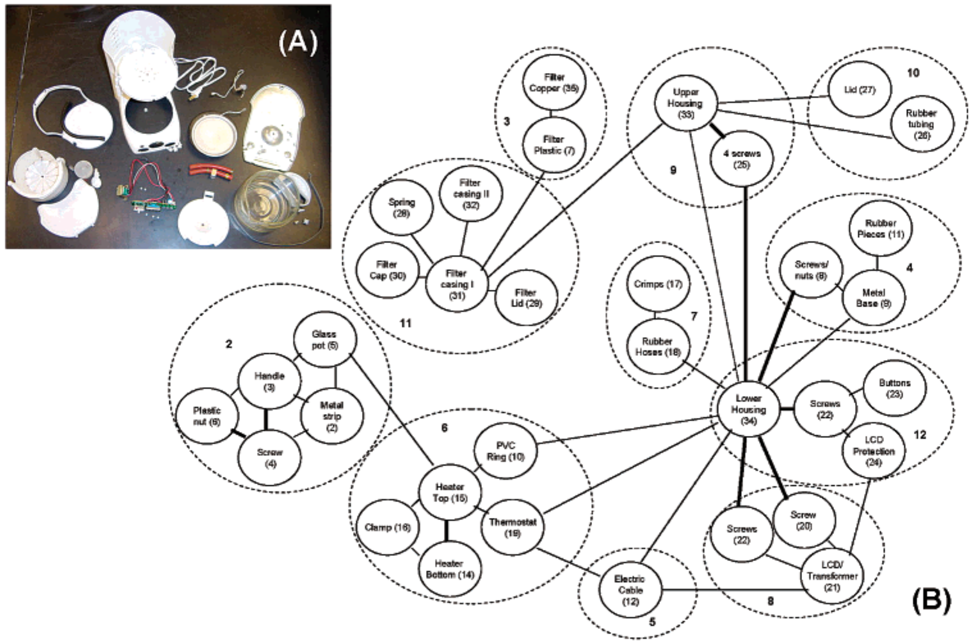


FIGURE 4. (A) Photograph of the disassembled coffee maker. (B) Coffee maker liaison grraph. Each node represents one of 35 components, and each line represents a physical connection. A darkened line indicates a relationship that requires a tool for seperation. The 35 components are grouped into subassemblies as shown by dotted lines.

TABLE 1. Example Values for Situational Variables in the Ann Arbor and Aachen base cases (*38*)

	Ann Arbor	Aachen	per
labor rate	\$ 20.00	\$25.00	h
transportation cost	\$ 0.23	\$ 0.30	t km
plastic value	\$ 0.06	\$ 0.06	kg
aluminum	\$ 0.98	\$ 0.98	kg
steel	\$ 0.22	\$ 0.22	kg
glass	\$ 0.03	\$ 0.03	kg
electronics	\$ 0.19	\$ 0.19	kg
rubber			kg
copper	\$ 1.23	\$ 1.23	kg
landfill	\$ 0.02	\$ 0.20	kg

TABLE 2. Example Destinations and Distances to Recycling Facilities from the EOL Processing Center for Ann Arbor and Aachen Base Cases (*44*, *38*)

	United States		Germany	
facility	distance (km)	destination	distance (km)	destination
plastics	40	Dundee, MI	5	Aachen
glass	70	Dearborn, MI	5	Aachen
steel	480	Glassport, MI	80	Grevenbroich
aluminum	990	Piscataway, NJ	80	Grevenbroich
landfill	8	Ann Arbor, MI	21	Aachen
disassembly facility	1300	Washington, DC	10	Aachen
shredding facility	80	Detroit, MI	50	Essen
electronics recycling	270	Elkton, OH	50	Essen

consumption has good correlation with environmental metrics such as fossil fuel consumption, global warming potential, and emissions of criteria air pollutants. While the specific nature of this correlation is dependent on the energy source mix used to drive specific activities, it is notable that the GA-based methodology described above is general enough to handle all such environmental variables simultaneously.

Task 1: Define EOL Scenarios for Coffee Maker. Two baseline EOL scenarios were considered in the case study: Aachen, Germany, and Ann Arbor, MI. For both scenarios, the following situational variables were acquired in March 2002 and utilized in the analysis: recycled material prices (*29*, *30*), labor rates (*31*), transportation distances and prices (*32*, *35*), and tipping fees (*36*). Recycled material prices for Aachen and Ann Arbor were assumed to be the same, which is reasonable based on data from recent years (*30*). All situational variable values used in the case study are listed in Table 1.

Two EOL fates were considered for each component of the coffee maker: landfill and recycling. In the case study, reuse of components was not considered since the coffee maker components are unlikely candidates for reuse under current economic and regulatory conditions. However, the general analysis methodology can easily handle cases where product reuse and remanufacturing are viable EOL options.

It was assumed that available landfill, transportation, recycling, and shredding technologies in Germany and the United States were technically identical with respect to environmental emissions and energy consumption/recovery. Recovered energy was also assumed to be identical for Germany and the United States.

Table 2 lists the assumed distances from the consumer to the EOL processing facility, and the distances from the EOL processing facility to recycling, shredding, and landfill locations for both Ann Arbor and Aachen. In 2002, an EOL processing center (capable of material separation and nondestructive disassembly) was present near Aachen but not near Ann Arbor. For the Ann Arbor case, this processing was assumed to occur at the original manufacturer, resulting in a large initial transport distance for disassembly. This distance was later reduced by considering the hypothetical presence of an EOL processing facility near Ann Arbor, which to date does not exist.

Task 2: Define the Coffee Maker Structure and Its Disassembly Sequences and Times. A mathematical representation of the coffee maker photographed in Figure 4A was constructed that describes its material composition,

TABLE 3. Precedence Matrix for Each of the 12 Disassembly Steps

	1	2	3	4	5	6	7	8	9	10	11	12
1	nil	1	0	1	1	1	1	1	1	1	1	1
2	−1	nil	0	0	0	0	0	0	0	0	0	0
3	0	0	nil	0	0	0	0	0	0	0	1	0
4	−1	0	0	nil	1	1	1	1	0	0	0	1
5	−1	0	0	−1	nil	0	1	1	0	0	0	1
6	−1	0	0	−1	0	nil	1	0	0	0	0	0
7	−1	0	0	−1	−1	−1	nil	0	0	0	0	0
8	−1	0	0	−1	−1	0	0	nil	0	0	0	1
9	−1	0	0	0	0	0	0	0	nil	1	0	0
10	−1	0	0	0	0	0	0	0	−1	nil	0	0
11	−1	0	−1	0	0	0	0	0	0	0	nil	0
12	−1	0	0	−1	−1	0	0	−1	0	0	0	nil

[a] The matrix **P** is defined where $P_{ij} = 1$ if step i must be done before step j, −1 if step j must be done before step i, nil if $i = j$, and 0 otherwise.

TABLE 4. Labor Times for the 12 Coffee Maker Disassembly Steps

step	component group	time (s)
1	remove glass jug	2
2	glass jug	22
3	coffee filter	2
4	metal base	53
5	electric cable	9
6	3 crimps	28
7	hot plate	19
8	transformer	32
9	lid, tubing	9
10	4 screws	32
11	spring	16
12	LCD protection	37
	total	260

feasible disassembly sequences, and disassembly times. The 35 components of the coffee maker were grouped as shown in Figure 4B and can be broadly characterized by seven material categories: thermoplastics, steel, aluminum, copper, rubber, electronics, and glass.

The liaison graph shown in Figure 4B indicates that the total disassembly can be achieved via 12 disassembly steps. The precedence among disassembly steps was defined in the precedence matrix shown in Table 3. The disassembly times were estimated based on the MOST system (*37*). The MOST predictions for the disassembly of the coffee maker were validated by empirical time studies (*38*), with disassembly times listed in Table 4. For this coffee maker, it was found that the disassembly time for a given component was reasonably independent of the disassembly sequence undertaken. Therefore, it was assumed that the time for any disassembly sequence could be modeled as the sum of the disassembly times for each component removed.

Task 3: Model of EOL Cost and Recovered Energy for Coffee Maker. The in-use, upstream, and downstream energy consumption associated with individual EOL processes was estimated using information listed in existing life cycle inventory (LCI) databases. The primary source of LCI data was the BUWAL 250 database (*39*). LCI data for the production and EOL treatment of copper, rubber, and electronics was estimated using the IDEMAT LCI database (*40*). The production and recycling energy data for thermoplastics was estimated based on data provided by the Association of Plastics Manufacturers of Europe (*41*). Although all LCI data were acquired in Western Europe, it was assumed that the data were representative of similar technical processes utilized in the United States. The following paragraphs outline calculations and assumptions utilized in the EOL cost and energy recovery models for the coffee maker.

TABLE 5. Recovered Energy Values for Recycling Coffee Maker Materials[a]

composition	recovered energy (MJ/kg)
plastic[b] (PP)	62
aluminum	140
steel	19
glass	2
scrap electronics	50
rubber	10
copper	85

[a] Derived from refs *39* and *40*. [b] The coffee maker includes small polystyrene parts (comprising less than 0.5% of the coffee maker mass) that were not considered in the analysis.

Transportation. The energy required for transporting 1 t of material a distance of 1 km (by 40-t truck) was estimated to be 1.2 MJ (*39*). The total energy consumed $E_i^{\mathrm{trans}}(\boldsymbol{x}, \boldsymbol{s})$ (MJ) for transportation segment i was therefore calculated as

$$E_i^{n}(\boldsymbol{x}, \boldsymbol{s}) = \Delta E^{\mathrm{trans}}(\boldsymbol{s}) \times D_i(\boldsymbol{s}) \times M_i(\boldsymbol{x}, \boldsymbol{s}) \tag{5}$$

where $\Delta E^{\mathrm{trans}}(\boldsymbol{s})$ is the energy consumption coefficient (1.2 MJ t^{-1} km^{-1}), $D_i(\boldsymbol{s})$ is the distance traveled (km), and $M_i(\boldsymbol{x}, \boldsymbol{s})$ is the weight of the materials being transported (kg) for transportation segment i.

Shredding. Shredding processes separate an input flow of materials into output material flows for recycling and a waste flow that is suitable for incineration or landfill. For this case study, it is assumed that only metals can be recovered via shredding (100% efficiency assumed). The remainder of the product is assumed to be landfilled. The total energy $E^{\mathrm{shred}}(\boldsymbol{x}, \boldsymbol{s})$ (MJ) required to shred $M^{\mathrm{shred}}(\boldsymbol{x}, \boldsymbol{s})$ (kg) of material is calculated by

$$E^{\mathrm{shred}}(\boldsymbol{x}, \boldsymbol{s}) = \Delta E^{\mathrm{shred}}(\boldsymbol{s}) \times M^{\mathrm{shred}}(\boldsymbol{x}, \boldsymbol{s}) \tag{6}$$

where $\Delta E^{\mathrm{shred}}(\boldsymbol{s})$ (MJ/kg) is estimated as 1, accounting for energy required to perform shredding, magnetic separation, cyclone separation, and agglomeration (*39*).

Recycling. Each of the seven materials defined in the coffee maker is sent to an appropriate facility for recycling based on distances defined in scenario $\boldsymbol{s}$. The recycling process converts scrap into recycled material through the consumption of energy and auxiliary inputs. The result is a flow of recycled material that is assumed to offset the production of materials from virgin resources (primary recycling is assumed). The total energy consumption (negative of recovered energy), $E_i^{\mathrm{recycle}}(\boldsymbol{x}, \boldsymbol{s})$ (MJ), in the process of recycling material i is defined by

$$E_i^{\mathrm{recycle}}(\boldsymbol{x}, \boldsymbol{s}) = \{\Delta E_i^{\mathrm{recycle}}(\mathrm{s}) - \Delta E_i^{\mathrm{production}}(\boldsymbol{s}) \times \eta_i\} \times M_i^{\mathrm{recycle}}(\boldsymbol{x}, \boldsymbol{s}) \tag{7}$$

where $\Delta E_i^{\mathrm{recycle}}(\mathrm{s})$ (MJ/kg) is the process energy required to recycle material i, $\Delta E_i^{\mathrm{production}}(\mathrm{s})$ (MJ/kg) is the energy required to produce material i from virgin sources, η_i is the efficiency of the recycling process (kg of output material/kg of input material), and $M_i^{\mathrm{recycle}}(\boldsymbol{x}, \boldsymbol{s})$ (kg) is the weight of material i being recycled. Table 5 summarizes the assumed recovered energy potentials for the primary recycling of each material.

Landfill. The energy required to landfill material is based on the movement of materials on site, the use of machinery, and the continuous treatment of wastewater at the landfill. The total amount of energy $E^{\mathrm{landfill}}(\boldsymbol{x}, \boldsymbol{s})$ (MJ) required to landfill $M^{\mathrm{landfill}}(\boldsymbol{x},\boldsymbol{s})$ (kg) of material is defined as

$$E^{\mathrm{landfill}}(\boldsymbol{x}, \boldsymbol{s}) = \Delta E^{\mathrm{landfill}}(\boldsymbol{s}) \times M^{\mathrm{landfill}}(\boldsymbol{x}, \boldsymbol{s}) \tag{8}$$

TABLE 6. Definition of a Genetic Algorithm Chromosome Representing Decision Variable x in eq 4[a]

	1	2	3−14	15−49
position name	sequence length	remainder fate	disassembly sequence	component fates
crossover method	arithmetic	uniform	single point	uniform
possible values	0−11	0 = landfill, 1 = recycle, −1 = not removed	1−12, −1	0 = landfill, 1 = recycle, −1 = not removed
P	1	1	1, 9, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1	−1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, −1, 1, −1, −1, −1, −1, −1, −1, −1, 1, −1, −1
E	11	−1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1

[a] The table also lists the profit maximum D/R strategy (P) and the maximum recovered energy D/R strategy (E) for the Ann Arbor base case (Pareto set shown in Figure 3).

where $\Delta E^{\text{landfill}}(\boldsymbol{x}, \boldsymbol{s})$ (MJ/kg) is the energy required for landfilling a given mass of material, estimated to be approximately 20 000 based on the landfilling of polypropylene (*41*). Although landfilling energy consumption is known to vary based on material composition (*39*), this variation was found to be negligible and hence not considered in the analysis.

Model of Energy Consumption and Total Profit. Based on the discussion above, the total energy consumption for a given EOL strategy was modeled as

$$E^{\text{total}}(\boldsymbol{x}, \boldsymbol{s}) = \sum_{i \in T} E_i^{\text{trans}}(\boldsymbol{x}, \boldsymbol{s}) + E^{\text{shred}}(\boldsymbol{x}, \boldsymbol{s}) + \sum_{i \in M} E_i^{\text{recycle}}(\boldsymbol{x}, \boldsymbol{s}) + E^{\text{landfill}}(\boldsymbol{x}, \boldsymbol{s}) \quad (9)$$

where T and M are sets of the transportation segments and the seven materials, respectively. The total profit (revenue minus cost) $P^{\text{total}}(\boldsymbol{x}, \boldsymbol{s})$ ($US) for EOL strategy $\boldsymbol{x}$ is similarly calculated as

$$P^{\text{total}}(\boldsymbol{x}, \boldsymbol{s}) = \sum_{i \in M} P_i^{\text{recycle}}(\boldsymbol{x}, \boldsymbol{s}) - \sum_{i \in T} C_i^{\text{trans}}(\boldsymbol{x}, \boldsymbol{s}) - C^{\text{landfill}}(\boldsymbol{x}, \boldsymbol{s}) - C^{\text{shred}}(\boldsymbol{x}, \boldsymbol{s}) - C^{\text{disassembly}}(\boldsymbol{x}, \boldsymbol{s}) \quad (10)$$

where $P_i^{\text{recycle}}(\boldsymbol{x}, \boldsymbol{s})$ is the revenue generated from recycling, $C_i^{\text{trans}}(\boldsymbol{x}, \boldsymbol{s})$ is the cost of each transportation activity, $C^{\text{landfill}}(\boldsymbol{x}, \boldsymbol{s})$ is the cost of landfilling, $C^{\text{shred}}(\boldsymbol{x}, \boldsymbol{s})$ is the cost of shredding, and $C^{\text{disassembly}}(\boldsymbol{x}, \boldsymbol{s})$ is the labor cost for disassembly.

Task 4: Formulate Multi-Objective EOL Strategy Optimization Problem for Coffee Maker. The two objective functions of the formulation in eq 4 are defined as follows:

$$\text{impact}(\boldsymbol{x}, \boldsymbol{s}) \equiv E^{\text{total}}(\boldsymbol{x}, \boldsymbol{s}) \quad (11)$$

$$\text{profit}(\boldsymbol{x}, \boldsymbol{s}) \equiv P^{\text{total}}(\boldsymbol{x}, \boldsymbol{s}) \quad (12)$$

Since the sequence length l is a variable, the design variable $\boldsymbol{x}$ defined in eq 4 is variable in size. However in the GA algorithm, $\boldsymbol{x}$ is represented as a constant-size vector of dimension $(2 + n + m)$ denoted $\mathbf{g} = (g_1, g_2, ..., g_{2+n+m})$. Therefore, depending on the sequence length specified in g_1, only a subset of the elements in $\mathbf{g}$ is actually used for the evaluation of the objective functions in eqs 11 and 12. As a consequence, it is necessary to apply a standard repair operator for permutation (*42*) to elements g_3−g_{14} following each one-point crossover operation used in the GA in order to maintain a valid sequence in $\mathbf{g}$. Further implementation details can be found in ref *43*. Since the coffee maker has 35 components ($n = 35$) and 12 subassemblies ($m = 12$), the vector $\mathbf{g}$ has 49 elements, whose descriptions, ranges, and crossover methods are given in Table 6.

Task 5: Calculate Optimal Trade-off Sets and Conduct Sensitivity Analysis. To achieve efficient convergence to a high-quality Pareto curve, the two optimal EOL strategies P and E (obtained by separate optimization runs) were included in the starting population of the multi-objective GA (NSGA-II algorithm). The remaining 498 members of the population were seeded at random, and the genetic algorithm was run through 50 generations. This technique proved to be very effective in finding a wide spread, with dense Pareto points, as shown below.

The Pareto set bounded by Strategies P and E for the Ann Arbor base case was introduced in Figure 3. The figure also illustrates the cost breakdown for strategies P and E, and it is seen that while transportation to the EOL processing facility is the dominant cost component for strategy P, labor cost is the dominant cost component for strategy E. A sensitivity analysis for the Ann Arbor and Aachen base cases with respect to transportation, labor costs, and WEEE regulations is provided in the following paragraphs.

Sensitivity Analysis for Transportation (*Ann Arbor*). Figure 3 illustrates that if the distance to the disassembly processing center is too large, or if transportation is too costly, profitable D/R cannot be achieved for the Ann Arbor base case. However if the disassembly processing facility is located closer to Ann Arbor, profitable D/R can be achieved as shown in Figure 5. Figure 5 illustrates how the optimal set of EOL strategies varies with transportation costs for the case of a local disassembly processing center available in Ann Arbor. Under a local disassembly scenario, strategy P is more profitable than direct S/R or direct landfilling and recovers approximately 50% more energy than direct S/R. For this case, strategy P involves performing disassembly steps 1 and 9 to remove and recycle the upper housing (see Figure 4). The product remainder is shredded and recycled.

With local disassembly in Ann Arbor, the D/R strategies are inherently less sensitive to transportation costs. In this case, the maximum profit strategy P does not change unless transportation costs increase by more than 125%. With this increase, the optimal EOL strategy changes to strategy P_{250}. Strategy P_{250} involves performing only disassembly Step 3, which removes the copper portion of the filter for recycling. The product remainder in this case is landfilled, which results in a drop in recovered energy of approximately two-thirds relative to strategy P.

Interestingly, the distances from the EOL processing facility to the individual metals and plastics recycling centers had no impact on the set of optimal EOL strategies and little impact on total costs, within a significant bound of the Ann Arbor base case scenario. More specifically, if these distances were changed within the range of 0−200% of their initial values (individually or simultaneously), there were no changes observed in the optimal D/R strategy set. Similarly, it was found that the mode of transportation did not have an impact on the optimal set of D/R solutions. Changing between rail, large truck, and small truck modes of transport

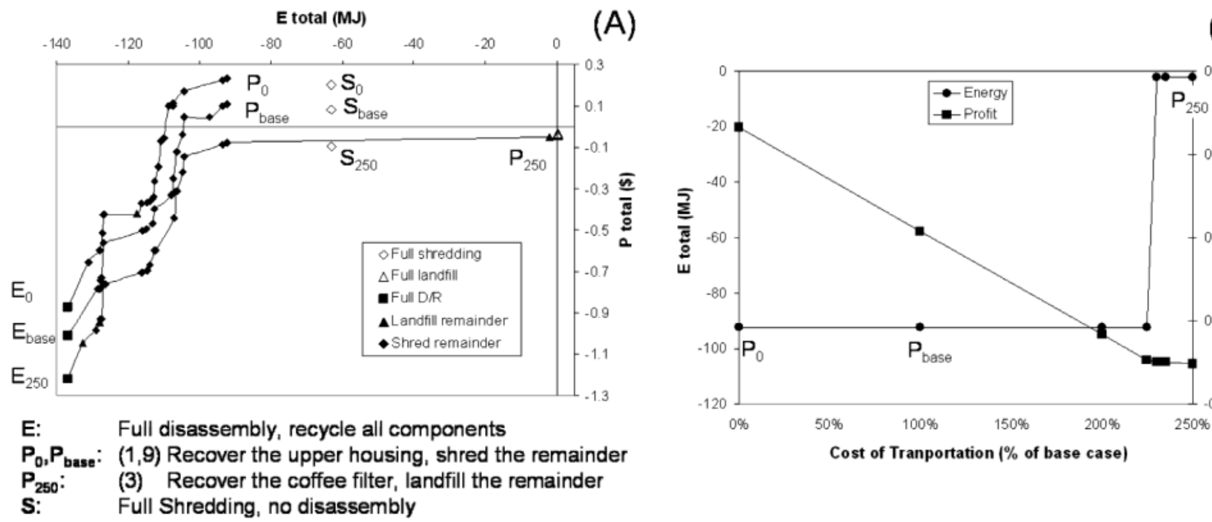


FIGURE 5. (A) Impact of transportation cost on Pareto set assuming Ann Arbor base case with localized disassmembly. Costs are varied from 0% to 250% of base case value. (B) Maximum profit and recovered energy for D/R strategies as transportation costs vary. The strategy changes from P_{base} to P_{250} near 225% of the base case value. Subscripts denote value of transportation cost as percentage of base case.

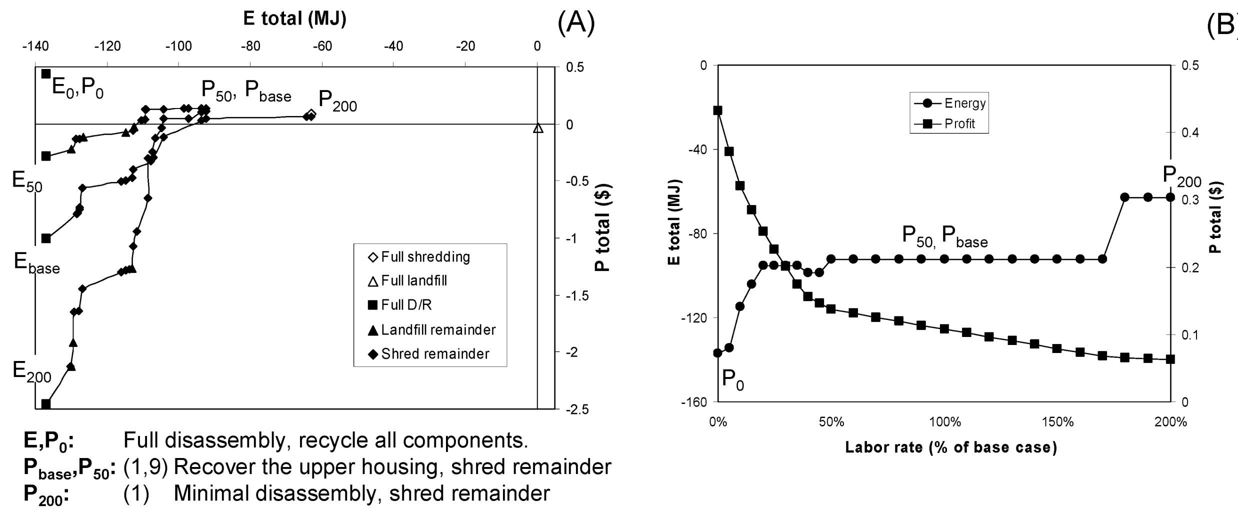


FIGURE 6. (A) Impact of labor cost on Pareto set assuming Ann Arbor base case with localized disassembly. Costs are varied from 0% to 200% of the base case value. (B) Minimum cost and recovered energy for D/R strategies as labor costs vary. Subscripts denote value of labor cost as percentage of base case.

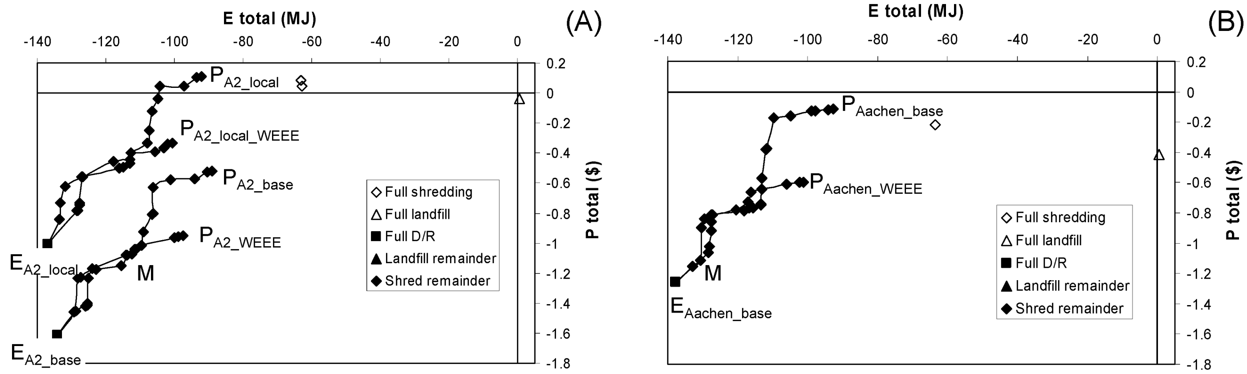
(*39*) results in only small cost and energy recovery shifts for the Pareto set.

Impact of Labor Cost on D/R Strategies (*Ann Arbor*). Figure 6A shows that the labor cost changes the slope of the P−E Pareto set significantly. This is expected since increasing energy recovery requires additional labor for disassembly. The result is higher costs and a steeper Pareto curve under high labor rates.

As shown in both panels A and B of Figure 6, under the hypothetical case of labor costs approaching zero, strategy E (complete disassembly and recycling) is also the profit maximizing strategy P (i.e., strategies E_0 and P_0 are equivalent in Figure 6A). This is not true of transportation costs. As transportation costs approach zero, strategies E and P are still separated by approximately 50 MJ, as seen in Figure 5A. The result suggests that if localized disassembly facilities exist, efforts to reduce labor costs in the disassembly system might be more effective in aligning environmental and economic objectives than focusing on minimizing transportation distances to material recycling facilities (distances that are relatively large, as shown in Table 2).

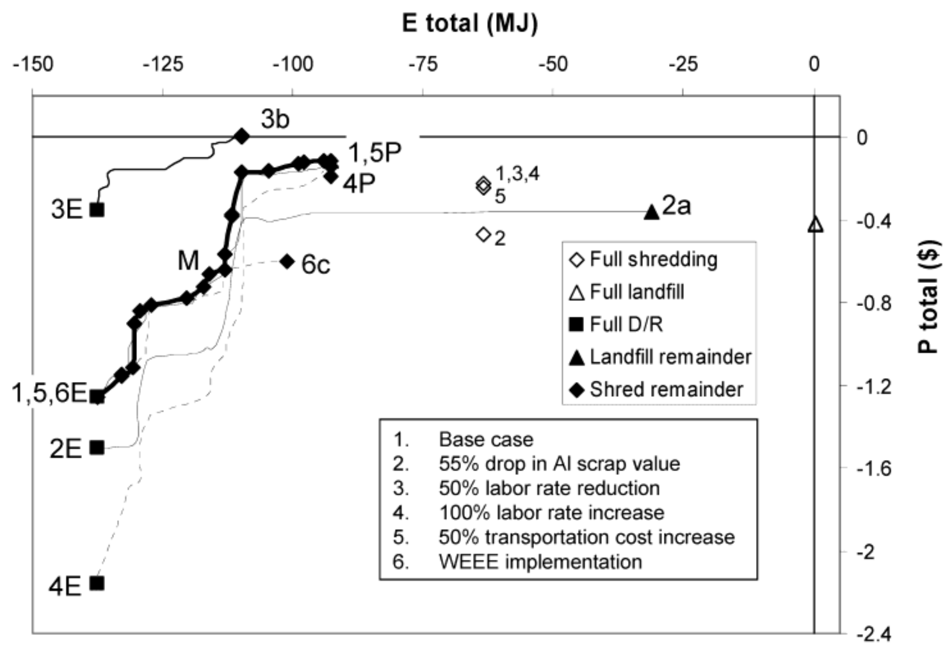
Impact of Recycling Targets on D/R Strategies (*Ann Arbor and Aachen*). To investigate the impact of regulatory targets on the EOL Pareto sets, the imposition of the European Union (EU) Directive on WEEE was investigated under both Ann Arbor and Aachen scenarios. It was assumed that the imposition of WEEE regulations would require greater than 50% of the mass of the coffee maker to be recycled and that the removal and recovery of the coffee maker liquid crystal display (LCD), transformer, and electrical cord would also be required.

Imposing WEEE regulations on the Ann Arbor scenario results in the removal of the direct landfill, direct S/R, and several D/R strategies from the Pareto set. As shown in Figure 7A, the regulations mostly impact minimum cost D/R strategies (e.g., Strategy P), while D/R strategies focused on energy recovery already recycle a high percentage of the coffee maker and are therefore less affected. It is important to note that while WEEE regulations force the cost of feasible D/R solutions to increase, especially relative to strategy P, they address environmental concerns related to toxics in the environment and not just energy recovery. Therefore, a dimension of environmental improvement is affected that is not captured by energy recovery alone. To capture such affects, additional metrics can be added to the objective function in eq 4, as the NSGA-based methodology is general



(A)		(B)	
E:	Full disassembly, recycle all components.	**E:**	Full disassembly, recycle all components.
P:	(1,9) Recover the upper housing, shred remainder	**P:**	(1,9) Recover the upper housing, shred remainder
P_{WEEE}:	(1,4,8,9) Recover WEEE components, shred remainder	**P_{WEEE}:**	(1,4,8,9) Recover WEEE components, shred remainder
M:	(1,2,3,4,5,9,11), shred remainder	**M:**	(1,2,3,4,5,8,9,10,11,12), shred the remainder.

FIGURE 7. (A) Ann Arbor scenarios with and without WEEE regulation. (B) Aachen base case with and without WEEE regulation.



E: Full disassembly. Recycle all components
M: Perform steps 1, 2, 3, 9, 11 and shred the remainder
P: Perform steps 1, 2, 3, 4, 5, 8, 9, 10, 11 and shred the remainder

a: Perform steps 1, 3, 9 and landfill the remainder
b: Perform steps 1, 2, 3, 9, 11 and shred the remainder
c: Perform steps 1, 4, 5, 8, 9 and shred the remainder

FIGURE 8. Example multi-situational EOL strategy graph for Ann Arbor.

in dimensionality and can be utilized for establishing Pareto sets, which consider trade-offs between more than two environmental and economic metrics simultaneously.

Figure 7B illustrates the optimal trade-off sets for the Aachen situation with and without WEEE regulations. Relative to the existing Ann Arbor situation, which does not have a localized disassembly facility, the WEEE regulations are less costly to achieve in Aachen. As shown previously, the difference between Ann Arbor and Aachen is primarily due to transportation requirements to the EOL processing facility. This is because labor and recycled material values are otherwise similar for both Aachen and Ann Arbor, and direct landfill options are no longer an EOL option under WEEE.

Interestingly, the Pareto set of EOL strategies for Aachen prove to be the same as the existing Ann Arbor scenario under WEEE. However, the implementation of these regulations also leads to a net cost at EOL under both situations. While this net cost at EOL can be addressed through product design, it is important to keep in mind any possible life cycle implications (e.g., production and use-phase environmental impacts) that might result from design changes. If desired, the model presented in Figure 2 could be modified to address such impacts, which would come to the fore when comparing alternative coffee maker designs under multiple use and EOL situations.

Task 6: Construct Multi-Situational Strategy Graphs for Coffee Maker. Figures 8 and 9 illustrate multi-situational strategy graphs constructed for the Ann Arbor and Aachen base cases. Least cost and maximum recovered energy strategies are labeled for each trade-off set. The trade-off sets are provided for the base case along with five other scenarios featuring differences in material scrap values, transportation infrastructure, labor costs, and WEEE regulations. In the graphs, the number represents the scenario

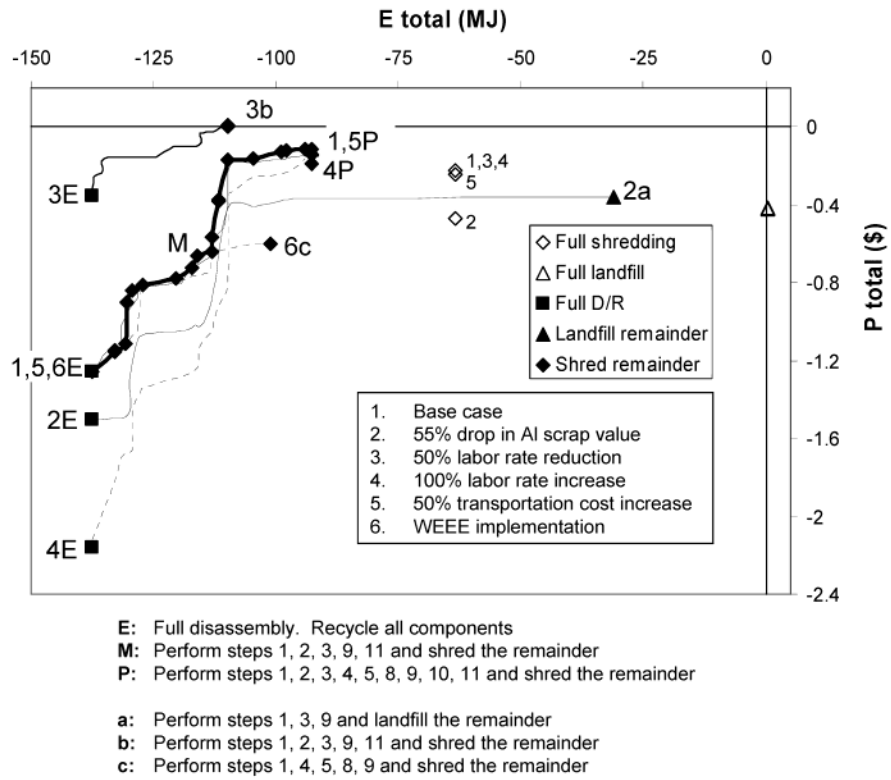


FIGURE 9. Example multi-situational EOL strategy graph for Aachen.

investigated, and the letter corresponds to a specific EOL strategy (i.e., disassembly sequence, EOL fate of removed components, and fate of product remainder). For all cases, the maximum recovered energy strategy (strategy E) is complete disassembly and recycling. For least cost strategies, the optimal EOL strategies change significantly, and strategy P is used only for the EOL strategy corresponding to the base case. If a scenario causes a change in the least cost strategy, then a letter is assigned to the strategy. For example, "6c" in Figure 9 represents the least cost EOL strategy c for scenario 6 (WEEE regulation) in Aachen. The symbols corresponding to each point represent the fate of the remainder of the product not disassembled for recycling.

A comparison of Figures 8 and 9 provides significant insight regarding the impact of situational factors on trade-offs between cost and energy recovery in Aachen versus Ann Arbor. The results show that, for Aachen, reducing the labor cost by 50% has the most significant impact on reducing EOL costs for the scenarios investigated. For Ann Arbor, reducing labor costs by 50% has little impact on least cost EOL treatment, although the slope of the trade-off curve changes such that the cost difference between the least cost and the maximum energy recovery strategies is relatively low. For Ann Arbor, providing for a localized disassembly facility is a greater priority than reducing labor costs, as discussed previously.

Both Ann Arbor and Aachen feature a shift in the least cost EOL strategy as aluminum scrap values fall. In this case, Ann Arbor is more sensitive to aluminum scrap prices, as only a 30% reduction in scrap aluminum prices is required to change the least cost EOL strategy. This is in contrast to 55% for Aachen (see scenario 2 in Figures 8 and 9). As shown in Figures 8 and 9, the strategy changes considerably from strategy P as aluminum scrap prices fall. For Aachen, the strategy shifts to removing and recycling the upper housing and the coffee filter. For Ann Arbor, only the coffee filter is removed and recycled. In both cases, the remainder is landfilled.

Inspection of the multi-situational EOL strategy graphs shown in Figures 8 and 9 reveals that the level of uncertainty in cost increases with recovered energy under variable situations. Within the scope of this research, this result was found to be general due to increasing labor costs and transportation with greater D/R and diminishing returns associated with greater recovery of materials with low recycling values. At the same time, it was found that uncertainty due to situational variables has the greatest impact on least cost D/R strategies. With respect to EOL strategy, the least environmental burden strategies were found to be most robust.

Summary and Conclusions

This paper has described a six-step methodology to analyze how product designs and situational variables impact the Pareto set of optimal EOL strategies with the least environmental impact for a given economic cost or profit. Since the determination of this Pareto set via enumeration of all disassembly sequences and EOL fates is prohibitively time-consuming even for relatively simple products, multi-objective GA were utilized to rapidly approximate the Pareto set of optimal EOL trade-offs between cost and environmentally conscious disassembly and recycling efforts. To achieve efficient convergence of the multi-objective GA to a high-quality Pareto curve, the two optimal EOL strategies for maximum profit and minimum environmental burden (obtained by separate optimization runs) were included in the starting population of the GA, which was used to solve the problem. This technique proved to be very effective in finding a well-populated Pareto curve, with relatively low computation time, which permitted the large number of simulations necessary for understanding the impact of situational variables on EOL trade-offs between reduced environmental impact and increased cost.

The six-step methodology was applied to the EOL treatment of a coffee maker. An analysis of the Pareto optimal set of EOL strategies achieving maximum recovered energy for minimum cost was conducted for scenarios in Aachen, Germany, and Ann Arbor, MI. The results revealed the importance of localized EOL processing for minimizing transportation costs, which would serve to be critical for any cost-effective implementation of legislation in the United States similar to the European Directive on Waste Electric and Electronic Equipment. In the United States, minimizing the distance to an EOL processing center was found to be more important than minimizing distances between metals and plastics recycling facilities and the EOL processing center. Once localized disassembly facilities exist, the minimization of labor costs was found to provide the largest impact on bringing economic and environmental objectives together. For the specific coffee maker investigated in this research, it was found that maximum energy recovery was achieved through complete disassembly and recycling; while the maximum profit (least cost) strategy was more sensitive to EOL situational variables. In addition to transportation distances and the cost of labor, the revenue generated from recycling aluminum had a major impact on the optimal EOL strategy. While the driving variables for EOL strategy changes were common to both Ann Arbor and Aachen, a significant amount of variation in the Pareto sets for the two locations was observed. Such EOL strategy differences were reduced under WEEE, simulated both in Aachen and Ann Arbor, due to the prescriptive nature of the regulations.

Acknowledgments

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