Chapter 22
Sustainability and Life Cycle Product Design

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This chapter addresses problems that arise during product design for sustainability and the life cycle. A description of the problem itself is provided from an industrial engineering viewpoint. The first section describes the problem elements, including the need to expand the set of conflicting objectives under consideration, the need to consider the entire product life cycle, the need to employ new data acquisition tools, and the need to investigate the complex role of consumer behavior before, during, and after the point of purchase. Subsequent sections summarize work the authors have done towards solving these problems. A general mathematical programming framework is first presented. This chapter highlights several instances of the benefits of bringing the logic and mathematical rigor of industrial engineering methods to these problems. The authors' previous contributions to sustainable design are presented and include defining the concept of the product life cycle from a decision-based design point of view, developing different types of decision-making techniques for engineering design (both subjective and objective), normative decision analytic methods (e.g., multiattribute utility, constrained optimization), methods for environmentally conscious design to cover new environmental objectives (e.g., connection of design with the end-of-use phase), and immersive computing technologies to address challenges with information-intensive design procedures. The final section presents methods to consider heterogeneous consumer behavior during product selection, use, and disposal.

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22.1 Introduction

Design for sustainability is more complicated that simply “doing the right thing.” First, one must define which thing(s) should even be considered. Then, information about the current and possible future states of those things must be gathered. That information must then be analyzed, or processed in some way. Finally, decisions must be made on the basis of that analysis and action taken.

Industrial engineering provides the toolbox needed to tackle such problems. This toolbox includes a broad set of mathematical models that can be used to predict, control, and generally make things better. This chapter presents an overview of research conducted by the authors that employs industrial engineering tools towards the goal of making sustainable design as efficient, profitable, and sustainable as possible.

The engineering design process plays a significant role in both causing and solving sustainability problems. In the past, the traditional design process started with a set of technical performance specifications posed in terms of hard constraints. Then, the designer would create a configuration to satisfy these constraints. This step was often considered to be an art, rather than a science.

This configuration would then be evaluated, most often on the basis of cost to manufacture. What followed was an iterative configure/evaluate/reconfigure to improve/evaluate loop. Externalities such as environmental impacts were not considered, and the time frame of analysis typically encompassed only the manufacturing process, from the cost of materials entering the plant to the manufacturing cost of the finished product leaving the plant.

More recently, the engineering design process has employed mathematical modeling approaches to make the design process itself more efficient. For example, the axiomatic design and the design structure matrix approach (Suh 1998; Tokunaga and Fujimura 2016) illuminate dependence relationships among physical design parameters and performance metrics, enabling designers to see how they might reconfigure the product to improve performance in one area without degrading performance in another. Also, normative decision analysis has brought mathematical rigor to the design evaluation process by formally modeling the decision-maker’s willingness to make tradeoffs (Thurston 1991), the effect that uncertainty has on overall design utility, and integrating normative decision-making into constrained optimization (Thurston et al. 1994).

Design for sustainability poses new challenges that are not trivial. The time frame for analysis has been expanded quite significantly from just the manufacturing process to now include impacts occurring prior to manufacturing (such as those resulting from raw material extraction and processing), as well as during the consumer-use and end-of-life stages. The list of performance metrics has also expanded, from primarily cost (and perhaps quality) to now include environmental impacts before, during, and after the manufacturing process, including air, water, solid waste, and others. The degree, type, and range of uncertainty associated with estimating these impacts is significantly greater than that associated with estimating manufacturing costs.

Design for sustainability needs everything that industrial engineering tools can provide. In this chapter, we provide a summary and overview of work we have done to date towards these problems. The next section describes our general approach, which is decompositional in nature; breaking a difficult, unsolvable problem into smaller, solvable pieces and then reassembling those pieces into a whole.

What follows is a description of the mathematical modeling methods we have employed, beginning with those for addressing conflicting objectives. The following section presents methods for addressing the entire life cycle, focusing on disassembly. Then, a method for using new data collection tools is described, followed by more recent work in investigating the role of consumer behavior in design for sustainability.

22.2 Mathematical Modeling Approach to Sustainable Design

There are several key areas of focus for this chapter, as highlighted in Fig. 22.1. These are (1) the need to consider a broader set of conflicting objectives, (2) the need to assess and analyze sustainability-related outcomes across the entire product life span, (3) the need to recognize information-intensive nature of the sustainable design, and employ new data collection tools, and finally (4) the need to consider the complex and understudied role of consumer behavior.

Design for sustainability is difficult for the reasons described above. Work presented in this chapter employs mathematical models created to help predict, control, and improve the outcomes of design decisions. Then, results can then be analyzed to provide insight as to how to improve further. We center our discussion around the ideal of a bi-level optimization formulation to simultaneously consider the objectives of both manufacturers and consumers. Each section of this chapter describes work done in one area of the problem, beginning with identifying which objectives to include (or not) from the manufacturer's perspective, how to best satisfy different customer market segments, employing a designed experiment

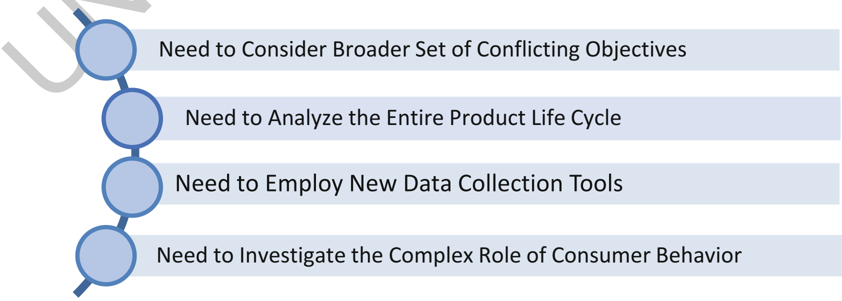

Fig. 22.1 Difficulties in sustainable engineering design

to reveal hidden causes of pollution, and using simulation methods to improve disassembly and reassembly operations.

The focus of optimization models used in the "design for sustainability" context is on identifying an optimal mix of strategies that result in minimum costs and environmental impacts with maximum customer satisfaction. The advantages of bi-level optimization models are that both the manufacturer's and customers' interests are considered. To incorporate the role of uncertainty, we can extend a simple bi-level optimization model to a stochastic optimization framework.

Ideas from probability theory and bi-level optimization can be employed to capture, quantify, and apply imperfect information about consumers' preferences in purchasing, using, and discarding products. The set of optimization models that designers build establishes a framework for evaluating intervention strategies (e.g., design for disassembly, design for longer lasting products) towards both environmental impact prevention and economic gain.

The results of simulation-based data generation techniques can also be integrated with optimization models. The integration of data generation tools within the optimization framework can provide designers with accurate estimates of the uncertainty associated with both consumers' decisions, expected profitability, and environmental impacts.

In our stochastic bi-level optimization models, consumers are the decision-makers in the lower level portion of the model, who make product purchase and usage decisions in response to design decisions made by the manufacturers in the upper level. One distinct feature of these models is their ability to find equilibria in the market system by employing a prospective approach. Manufacturers can make decisions about the types of design features that should influence both purchasing and consumer-use behavior.

The standard stochastic bi-level optimization is in the following form:

$$\min_{x \in X} f(x) + \mathbb{E}\left[g\left(y\left(x, \omega\right)\right)\right] \tag{22.1}$$

$$\text{s.t.} \quad y(x, \omega) = \arg\min_{y \in Y(x)} h(x, y, \omega) \tag{22.2}$$

where x is the upper-level decision vector describing the manufacturers design interventions, ω is a random vector affecting probabilistic choices made by consumers, and $y(x, \omega)$ is the lower level decision vector of consumers given x and ω.

To solve the stochastic bi-level optimization problem, a computational approach can be developed that combines a single-level reformulation technique using Karush-Kuhn-Tucker (KKT) conditions for the lower level problems and a Monte Carlo simulation approach with sample average approximation (SAA) for the upper-level problem. The capability of bi-level optimization models has already been demonstrated in the literature and different solution algorithms have been developed. Examples include as reducing a bi-level model to a single-level model (Camacho-Vallejo et al. 2015), two-stage heuristic algorithms (Du and Peeta 2014), using meta-heuristic techniques such as progressive hedging (Yi et al. 2017), genetic algorithms (Mahmoodjanloo et al. 2016), simulated annealing algorithms (Starita and Scaparra 2018), and stochastic equilibrium constraints algorithms (Faturechi and Miller-Hooks 2014).

A look at the above-mentioned mathematical models reveals the importance of considering several points as highlighted in Fig. 22.1: (1) the importance of considering multiple objectives, (2) the need to consider sustainability effects of the entire product life span, (3) the need for collection and utilization of accurate and timely data for mathematical models, and (4) the role of consumer behavior as one of the main stakeholders. In the next several sections, we describe several studies conducted by the authors towards meeting these needs.

22.3 The Need to Consider Conflicting Objectives

This section presents the progression of our work in developing these models, beginning with simply broadening the set of objectives considered to evaluate a set of discrete options and formulating a multiattribute evaluation function, then: (1) using that function as the basis of the objective function in a constrained optimization formulation to (2) identify the best possible option subject to unavoidable cause and effect relations between decisions and attribute outcomes, and (3) finally using statistical manufacturing process control to discover opportunities for pollution prevention that can then be woven into the optimization formulation.

In our work, we have most often employed a multiattribute utility function as shown below in Eq. 22.3, where K and k_i are scaling constants and y_{ij} refers to the level of attribute i for decision j. The constraint functions (not shown) define the correlation between design decisions and each resulting attribute.

Despite misconceptions to the contrary, this functional form can be very useful during the design process (Thurston 2001). When properly assessed, it can accurately reflect whether utility is linear or nonlinear with respect to performance in any one attribute, the effect of uncertainty, and whether the designers' willingness to trade off one attribute against another remains constant or varies over the feasible design region.

Unlike other multi-objective evaluation methods (such as the weighted average method), this approach requires a rigorous, systematic process for defining the set of attributes that are both relevant and negotiable, their range of negotiability, the decision-maker's willingness to make tradeoffs (Thurston 1991), and the effect of uncertainty on the utility of design alternatives. This process requires some expertise in decision analysis, but is no more arduous than other analytic tools routinely employed by design engineers. We have also found that going through this process itself focuses the designer's effort where the payoff is greatest. In addition, defining the attributes and their ranges of negotiability in such a way that the preferential and utility independence conditions required so the Eq. 22.3 is valid has been especially useful.

$$1 + KU(y_1, y_2, \ldots, y_n) = \prod_{i=1}^{n} \left[K k_i U_{ij} \left(y_{ij} \right) + 1 \right] \tag{22.3}$$

22.3.1 Broadening the Set of Conflicting Objectives

Consideration of sustainability requires the designer to consider outcomes of the design decisions that were previously "outside the box" bounding their analytic frame. A formal method for design evaluation of multiple conflicting attributes was presented in (Thurston 1991). Material substitution in the automotive industry was investigated. Part of the motivation for this work was that collaborators (designer at several automotive companies) indicated that they wished to compare steel, aluminum, and polymer composite materials, and in particular wished to explicitly consider (and value) the sustainability of their material choices. A normative multiattribute utility function was formulated to help the designers make decisions that reflected their unique willingness to make tradeoffs. The assessment methodology employs a decompositional, "lottery" question and answer approach that measures the extent of decreasing marginal value as one attribute is improved, the subject's willingness to sacrifice performance in one attribute in order to gain in another, and the effect of uncertainty on their valuation of a design alternative. One interesting outcome of the analysis was that although the subjects all said that they were concerned about the environment and wished to consider sustainable options, their responses to the lottery questions revealed that they, in fact, were not willing to make any tradeoffs to achieve sustainability, and as a result compliance with environmental regulations was then treated as a binary "must comply" constraint in the analysis.

22.3.2 Constrained Multiattribute Utility Optimization

In Mangun and Thurston (2002), the customer's willingness to make tradeoffs for sustainability in personal computers was explored. A constrained optimization problem was formulated, maximizing multiattribute utility (cost, reliability, and environmental impact), the structure of which is shown in Fig. 22.2. The binary decision variables reflected whether or not each of 88 components were to be new, reused, remanufactured, or recycled in a second product life cycle. It was determined that the customer was willing the make tradeoffs, and that, compared with all-new components, remanufacturing and recycling certain components for a second life cycle did increase customer utility. Further, the magnitude of this willingness to pay depended on which market segment a customer belonged to; technophile, utilitarian, or "green." The model structure enabled the identification of an optimal portfolio of products (a distinct product for each market segment) that presented each segment

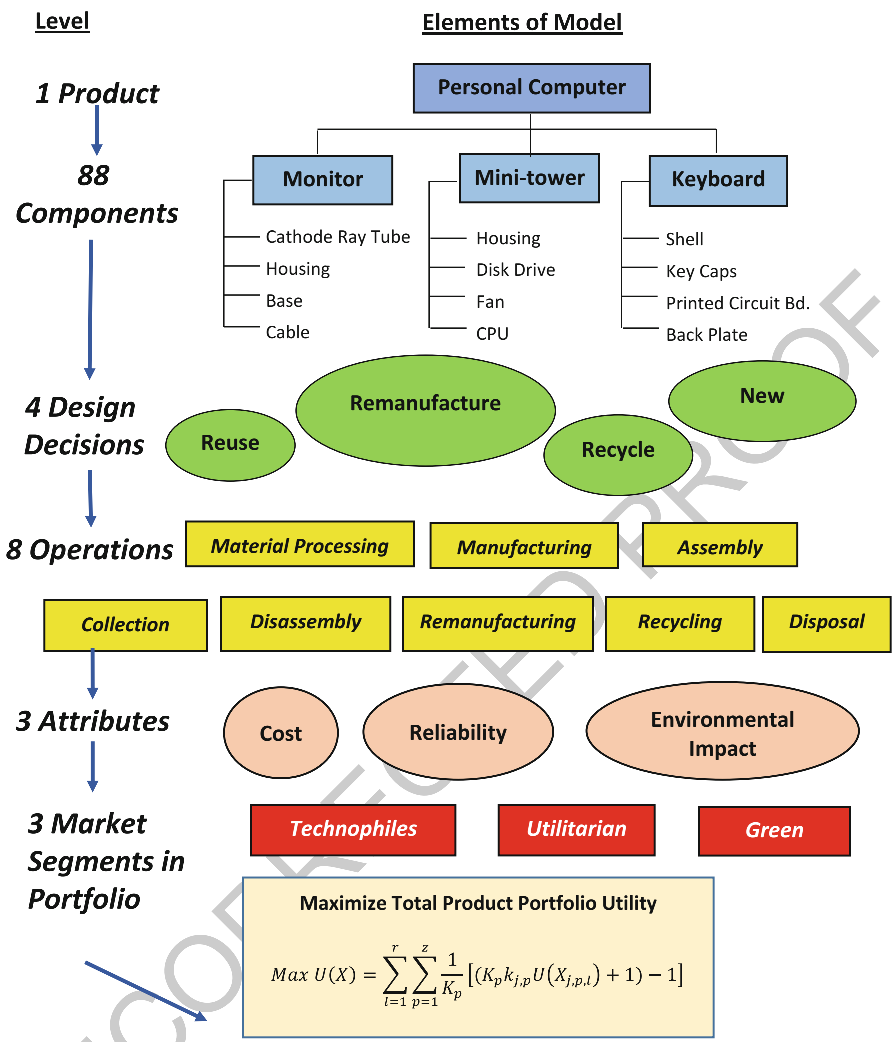

Fig. 22.2 Major elements of constrained optimization model for PC component reuse, remanufacturing, or recycling decisions

with the combination of remanufactured or recycled components that resulted in the set of tradeoffs that were best for them. Post-optimality analysis then revealed that if the manufacturer adopted a service-selling (rather than product-selling) approach, further efficiencies could be realized by controlling and fine-tuning the take-back period to each specific market segment. This was explored in (Thurston and De La Torre 2007), which determined that through a leasing program the specified the length of time of consumer-use, both profitability and consumer satisfaction could be improved.

22.3.3 Statistical Manufacturing Process Control to Identify Pollution Prevention Opportunities

In Carnahan and Thurston (1998)), concurrent design for sustainability of both the product and the manufacturing process was considered. This work was motivated by a floor tile manufacturing plant that was seeking to expand production. At current production levels, they were in full compliance with air pollution control regulations although they sometimes observed unexplained spikes in emissions. If these spikes continued along with increased production levels, unacceptable levels of air pollution would be emitted.

Again, the industrial engineering approach of mathematical modeling was employed to understand, predict, and control this situation. The tradeoffs here were between manufacturing cost, air pollution, and product quality. A constrained multiattribute utility function was employed, and the constraint functions reflected the cause and effect relationships between design decisions (13 raw material choices and 17 manufacturing process parameters) and resulting attributes of cost, pollution, and product quality. The variation in air pollution levels was seen as an opportunity to identify manufacturing process parameters that might be correlated with the variations, and perhaps be controllable. A statistical manufacturing process control experiment was conducted, which identified these correlated parameters, a selected subset of which are shown in Fig. 22.3. Information obtained from the experiment

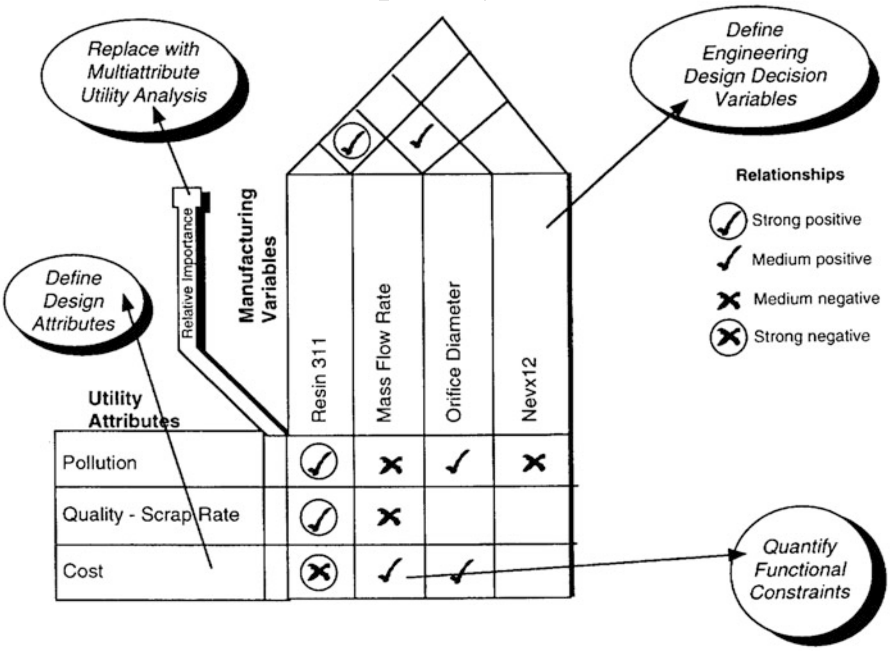

Fig. 22.3 House of quality, DOE and constrained optimization integrated to revealing raw material and manufacturing process parameters correlated to pollution, quality, and cost

also helped to fine-tune the ranges over which the designer was truly able and willing to make tradeoffs. An ironic finding was that one of the raw materials that was correlated with higher air pollution levels had been a scrap material that the manufacturer was recycling on-site in order to reduce solid waste.

22.4 The Need to Analyze the Entire Product Life Span

22.4.1 Maintenance, Repair, Replacement

One possible strategy for reducing waste is to increase the product usage life span and promote repair and reuse practices among individual consumers. However, manufacturers currently do not view "design for longer lasting products" as a profitable strategy. In fact, cost-effective assembly processes are often irreversible (replacing screws with snap-fits, for example), and manufacturers' present strategies are sometimes focused on making products difficult and expensive to repair and reuse (Cooper 2012).

However, there are several economic reasons why manufacturers may be interested in design policies that facilitate repairs: (1) design for repairable products reduces the cost of after-sales services and warranty offers (Saccani et al. 2007; Fang and Hsu 2009), (2) repairability might be regarded as marketing and sales strategies (e.g., rated repairability attributes in online product reviews) (Gaiardelli et al. 2008; Stevels 2002), (3) new business models adopted by enterprises based on the concept of a sharing economy, the peer economy (e.g., renting, sharing, exchange) and service-based business models require durable products (Preston 2012), (4) design for repairable products is a strategy to secure the future supply of critical materials and rare earth elements (Peck et al. 2015), (5) repairability influences the future reusability of devices, the cost of remanufacturing, and the profitability of remarketing in the second-hand market (Cuthbert et al. 2016), and finally (6) the independent repair businesses and initiatives, e.g., the Digital Right to Repair Coalition, have been forming worldwide campaigns against the short-term profit-driven policies of manufacturers and urging them to produce more repairable electronics, to share the repair guides, and to supply the spare parts to the market (Rosner and Ames 2014). A product's repairability not only influences its first life cycle, but also it increases its future reusability and the opportunity to generate a new market for used devices.

Design for sustainability via facilitating cost-effective maintenance, repair or component replacement, can increase the length of product life cycles, decrease waste, and increase profitability. However, disassembly, repair, and reassembly processes incur costs and sometimes result in damage to one or more components. In Behdad and Thurston (2012), a graph-based integer linear programming and multiattribute utility analysis model is formulated to find the optimal sequence of disassembly operations. Conflicting attributes considered are disassembly time (and cost) under uncertainty, the probability of not incurring damage during disassembly, reassembly time (and cost), and the probability of not incurring damage during reassembly. A solar heating system example is presented. Analysis of the model and results revealed the auxiliary heater as a target for redesign to improve accessibility and/or longevity due to its need for frequent replacement.

22.4.2 Selective Disassembly, Value-Mining, and Sharing Disassembly Operations for Multiple Products

Returned end-of-life products arrive at the take-back facility with a great degree of variability and uncertainty in terms of quantity, age, and quality. The value of individual components is sometimes not worth the cost of full disassembly. Towards a solution to this problem, a stochastic chance constrained programming model converted to a mixed integer linear program for waste stream acquisition (as opposed to market-driven systems) is presented in (Behdad et al. 2012). The model treats returned product quantity as an uncertain parameter and determines the optimal degree to which disassembly processes should be performed, as well as the optimal EOL option for each resulting subassembly. A stream of PCs received at a refurbishing company located in Chicago serves as an illustrative example.

In addition to uncertainty and variability in returned product quantity, age, and quality, incoming feedstock is often varies widely and includes several different product. This further hampers the profitability of product take-back operations. Two types of decisions are considered for multiple returned product streams in Behdad et al. (2010); how to efficiently perform selective disassembly operations, and how best to "mine" the value still embedded in components. An example using two cell phones illustrates the integration of a transition matrix with a mixed integer linear programming model for disassembly operations for multiple products. The solution simultaneously identifies the degree to which each product should be disassembled, and also the optimal end-of-life decision (disposal, reuse, recycle) for each component or subassembly. The example results indicated that sharing disassembly operations between different products can increase the cost-effectiveness of disassembly operations.

22.5 The Need to Use New Data Collection Tools

So far, we have discussed mathematical models for including new, conflicting objectives and for the considering sustainability issues throughout the entire life span of a product. This section discusses the role of data collection tools in gathering the information that these expanded models require. The focus of our discussion is on the role of Immersive Computing Technology (ICT) and virtual reality environments employed during the design process. ICT provides a relatively inexpensive technology (compared with multiple iterations of physical prototype testing) that allows designers to create virtual prototypes of design concepts, generate new ideas, test design concepts, evaluate them, and collect data. ICT has also has been used as a means of sharing information and experience among users. Research on ICT first was mainly focused on developing the technology, but more recently applications of the technology have also generated interest (Ong and Nee 2013), broadly ranging from engineering design through education, gaming, and other entertainments.

While the technology has advanced to the point that it offers many capabilities for data collection, product-user experiences, and visualization of artifacts, there is still much to be done towards improvements in the cognitive aspects of knowledge representation and processing. Advances in ICT need to be expanded to include mental models that designers employ, including how information provided by the ICT is perceived, processed, and acted upon.

Considering the example of design for disassembly, often the collection of the required information about the disassembly process is very challenging and time-consuming. Disassembly is an integral part of remanufacturing, repair and reuse activities, and disassembly times, cost and possible damage can vary from one operation to another based on component and subassembly geometry, fastening methods, component condition, operator motions required, operator experience, and other factors. Designers most often do not have data on the probability distributions of disassembly times, costs, and possible damage to components during the disassembly process. Having access to such information during the early stages of product design can help designers create alternatives (e.g., the type of fasters, the number of joint parts) that facilitate particular disassembly sequences. To identify the best disassembly sequence (e.g., minimizing disassembly time and/or component damage), designers need to know the probability distribution of disassembly time and/or component damage during disassembly as a function of design and disassembly specifications.

Such data can be made available through the use of an ICT system, in which designers have the opportunity to create a virtual prototype of the product, disassemble the prototype, and collect the required data. In one study (Behdad et al. 2014a), we formulated a mixed integer nonlinear program equipped with data collected using ICT to determine an optimum disassembly sequence for a burr puzzle.

The six-component burr puzzle employed is shown in Fig. 22.4 has properties making it ideal for analyzing assembly and disassembly processes. Not all components can be moved at all times, and there are precedence relationships. Also, many movements are orthogonal to others. Each component is labelled according to its color in the ICT: (T)eal, (B)lue, (G)reen, (Y)ellow, (P)urple, and (R)ed.

The first step was to determine all feasible disassembly sequences and present them in the form of a disassembly graph. The next step was to supplement the disassembly graph with some sort of cost structure (e.g., disassembly time, component damage for each disassembly operation). The third step was to obtain the data required by simulating the disassembly operations in the ICT environment,

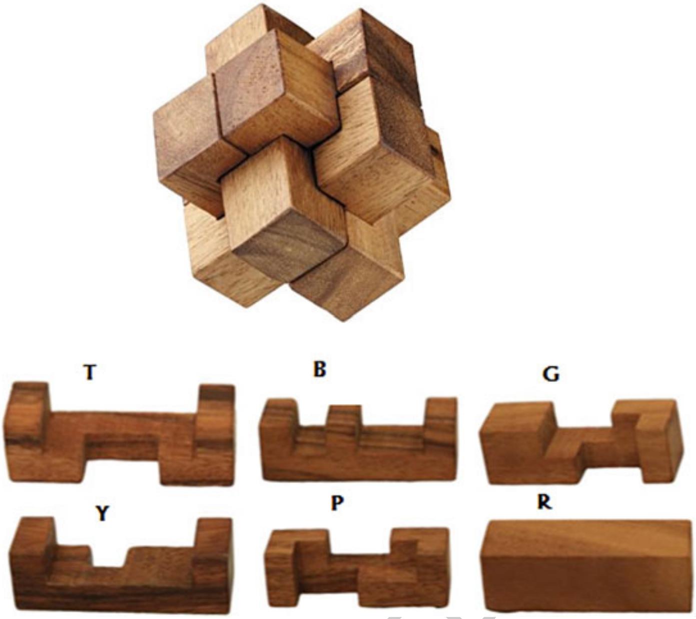

Fig. 22.4 A burr puzzle with six interlocking pieces

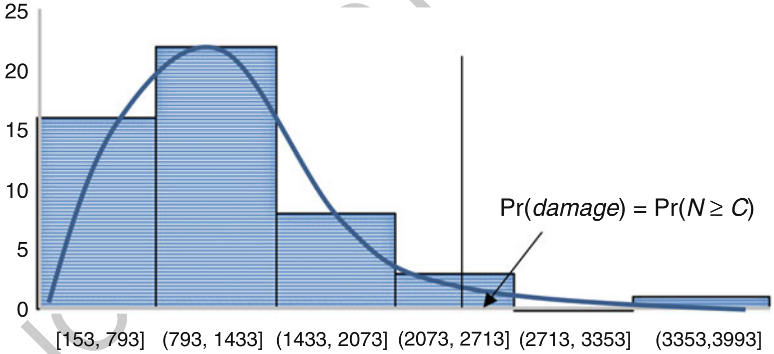

Fig. 22.5 The distribution of the number of collisions between parts

and the final stage was to use the data collected in a mathematical model in order to determine the optimum disassembly sequence.

We simulated feasible disassembly operations for the burr puzzle and conducted 30 trials of each feasible disassembly transition manually to collect 30 data points for each disassembly operation. The number of collisions between components was recorded, as a representative of component damage. This data enabled us to draw statistical distributions of the number of collisions between parts (N) for each disassembly operation, shown in Fig. 22.5.

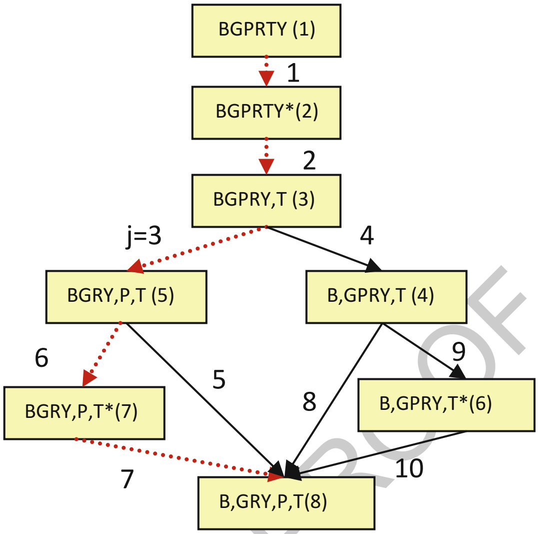

Fig. 22.6 The disassembly graph and the optimum sequence derived from the mathematical model (from Behdad et al. (2014a))

The mathematical model developed in this study was a chance constrained program with the single objective of minimizing the number of collisions between different components during disassembly. The mean and standard deviation of the distribution of the number of collisions collected in the ICT was used to estimate the probability of damage. The distribution of the number of collisions was used to estimate the probability of damage directly. For example, if a threshold (C) is defined for the acceptable number of collisions between parts, using the distribution of the number of collisions and the defined threshold, the probability of components damage can be quantified as follows:

$$\Pr(\text{damage}) = \Pr(N \geq C)$$

Figure 22.6 shows the optimum sequence (1–2–3–5–7–8) derived from the mathematical model for the example of burr puzzle.

In addition to data collection, we also employed ICT capabilities to explore intuitive disassembly sequences and compare the results with the optimum disassembly sequence obtained above. The goal was to determine if there could be some synergy between the mathematical model and intuitive human expertise.

An experiment was conducted in the ICT environment as shown in Fig. 22.7 to determine what disassembly process a human might employ while "seeing" both the burr puzzle and its disassembly graph. The result of the experiment indicated that the user intuitively followed a disassembly path (1–2–3–5–8) that was different from the optimal path identified by the model.

For example, considering State 3 in the disassembly graph presented in Fig. 22.5. There are two options: remove Part B or remove Part P. In practice, the disassembly processes for these two parts are not the same. While Part P can be removed using one single horizontal manipulation, Part B requires manipulation across two axes,

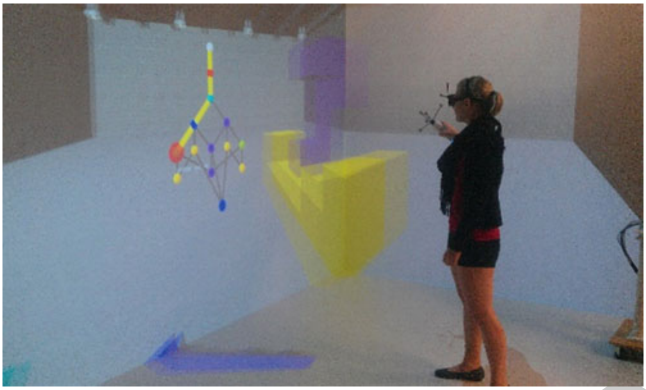

Fig. 22.7 An ICR experiment where a user disassembles a burr puzzle. The experiment has been simulated using the VR facility in Mechanical Engineering department at Iowa State University (courtesy of Dr. Judy Vance and Leif Berg)

however, this is not visible to the operator. If the optimum path is followed, then Part P is separated. From State 5, removing Part B appears to be a simple and intuitive one-piece removal operation; however, the optimal sequence suggests an intermediate operation in which Part P is reoriented to be visible to the operator and reveals the physical constraint for removing Part B to the operator. Thus, the fact that the intuitive path differs from the optimal path provides insights for redesign. Realigning the R component could provide a better operator perspective of B's interconnectedness. When the operator then removes B and is aware of the interconnectedness, greater care may be taken and damage minimized.

In a related study (Behdad et al. 2014b), we extended our data collection efforts in the ICT environment to collect not only the number of collisions as a representative of the probability of damage, but also the distance movement of parts to estimate the disassembly cost. We also developed a new multi-objective mathematical model using a multiattribute utility function as the objective function of a dynamic programming model. The probability of damage vs. disassembly time (or cost) are the two conflicting objectives. The faster is the pace of disassembly, the lower is the disassembly time (or cost) but the higher is the probability of damage and vice versa.

22.6 The Need to Investigate the Complex Role of Consumer Behavior

Consumer behavior plays a critical but understudied role in design for sustainability. Traditional views of the sustainable design, including many of those in the design for X domain, largely focus on improvement of end-of-life remanufacturing activities such as disassembly (Harjula et al. 1996) refurbishment (Nee 2015) and recycling

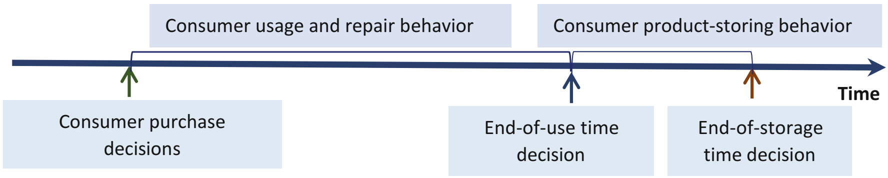

Fig. 22.8 The consumer decisions during the product life span (e.g., purchase, usage, repair, disposal)

(Gaustad et al. 2010), but fail to comprehensively consider the role of consumer behavior during product usage and end-of-use. The effectiveness of sustainable design policies depends on consumers' attitude and behavior, which are critical and are uncertain in nature.

Overall, there is a linkage between the product life cycle, design features, and consumer decisions to repair, reuse, or disposed of a product. Figure 22.8 illustrates the overall process of consumer decision-making during the product life span and the impact of consumers' behavior on usage and storage times.

It is important to develop analytical models that quantify the heterogeneity of consumer behavior and the deterioration of product-critical components, as well as integrate consumers' usage and disposal behaviors into design decisions.

Despite recent efforts to consider consumer marketing preferences, less attention has been paid to modeling the usage behavior of the consumers. Most of the previous studies have strived to address purchase or adoption behavior (Ma and Nakamori 2009; Miller et al. 2013; Davis et al. 2009; Haghnevis et al. 2016). Therefore, one research gap in the current engineering design literature is the lack of scientific methods for considering the heterogeneity and variability of consumers' usage behavior during product design, or accurately quantifying the resulting environmental impacts. Future methods should make designers capable of calculating the total emissions of a system based on the aggregation of the micro-decisions made by individual consumers for individual products.

In this section, we discuss the importance of consumer behavior in reducing the sustainability-related issues during the entire product life cycle. The focus will be on four types of behavior based on several previous studies conducted by the authors: (1) consumer's product storing behavior at the end-of-use phase of the products, (2) usage behavior, (3) repair behavior and consumers decisions in extending product life cycle, and (4) return behavior and consumers decisions about timing, disposal, and waste removal channel for used products.

22.6.1 Consumer's Product Storing Behavior

Consumers often have a tendency to keep old products in storage before returning them back to waste removal chains. This behavior results to further technological obsolescence of used products where in many cases products that are finally returned are not resaleable in the second-hand market and must be shredded and sent to recycling and material recovery operations.

In one study (Sabbaghi et al. 2015a), data from about 10,000 used computers and laptops returned during 2011 and 2013 to an e-waste collection site located in Chicago, IL have been analyzed to determine the average storage times for used products and whether there are any connections between different design features and how long consumers kept their used electronics in storage. With the help of SMART software, we were able to retrieve data identifying the last time the operating system was used on each device, and since we also had information on the manufacturing date and return date, we were able to calculate the storage time (Storage time = Return date − Last time the OS was used), the upper bound of usage time (Usage time = Last time the OS was used − Manufacturing date), and the product age (Age = Return date − Manufacturing date). We also had information about the size of the hard disk drive, the brand, and the consumer type. We had information about two groups of consumers: individual households and commercial consumers (corporate) organizations who returned their used computers for recycling. Various statistical analyses were performed on the dataset and various insights have been derived.

It was found that the average product age and the average storage time was 6.9 years and 1.1 years, respectively. There was no statistically significant difference between different brands and sizes of the hard disk drives, but commercial users stored used electronics longer than households. Data security concerns and administrative processes might be the cause of this. Figure 22.9 shows the histograms of storage time, usage time, and product age for two groups of consumers.

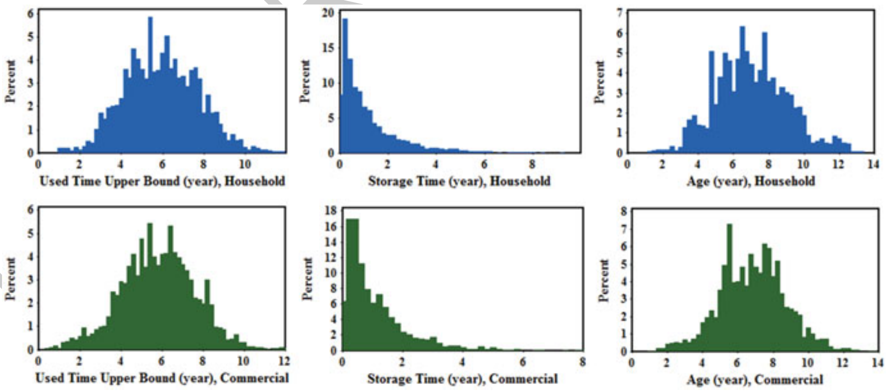

Fig. 22.9 The statistical distributions of the upper bound of usage time, storage time, and product age for two different groups of consumers (data from Sabbaghi et al. (2015a))

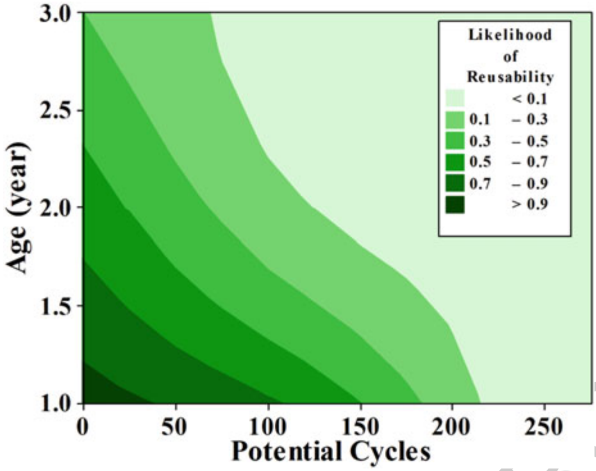

Fig. 22.10 The reusability of batteries based on their age and the number of potential used cycled (data from Sabbaghi et al. (2015b))

22.6.2 Consumer's Product Usage Behavior

Another important consumer behavior is their usage behavior. The way that consumers use their products can influence sustainability outcomes such as energy consumption and future reusability. For example, the way that consumers charge and discharge their laptop batteries impacts the future reusability of used laptops, and this behavior varies significantly from customer to customer. This uncertainty must be considered. To shed light on the impact of consumer usage behavior, in one study (Sabbaghi et al. 2015b), about 500 same-brand laptop batteries used by students in a high school in Burbank, IL were studied over 3 years of usage to monitor the number of used cycles for each battery. The purpose of the study was to predict the future reusability of batteries based on age, battery type, number of used cycles, and consumer groups (e.g., students of the class of 2012, 2014, 2015, and 2016). For example, Fig. 22.10 illustrates the future reusability of batteries based on their age and the number of used cycles. Finally, we have determined what would be the most profitable end-of-use option (e.g., reuse, recycle, refurbish) for each battery based on their profile of usage.

22.6.3 Consumer's Repair Behavior

The shortcomings of traditional design policies adopted by manufacturers are especially acute in the design for repairability domain (Cairns 2005). While different design concepts ranging from design for disassembly (Boothroyd and Alting 1992), reliability (Crowe and Feinberg 2001), reuse (Cowan and Lucena 1995), and recycling (Kriwet et al. 1995) have recently become better integrated with design efforts, the concept of "design for repair" has been overlooked. Manufactures in general do not consider "design for longer lasting products" a profitable strategy. In fact, manufacturers' policies are sometimes focused on making products difficult and expensive to repair and reuse with the aim of creating more market share for newly developed products (Cooper 2012).

In one study (Sabbaghi et al. 2016), an industry dataset was analyzed to extract consumer viewpoints towards product repairability, and the factors that make it difficult for consumers to repair products themselves under three main categories of product, economic, and consumer-related factors. The final objective was to test whether and how product repairability might influence consumers' future purchase choices and recommendations to family and friends. An online survey was conducted in collaboration with iFixit.com. iFixit has provided an initial dataset of around 11,500 respondents being surveyed from three different subject groups, including individual consumers (about 8000 respondents), employees of repair shops, and employers of repair businesses. This comprehensive iFixit survey includes a total 27 questions.

Among all 27 questions included in the iFixit survey, two directly inquire about the importance of product repairability, its associated cost, and the effect on future purchase decisions. Measured in an ordinal scale, two questions were asked of iFixit survey respondents: "If you successfully repaired a product, are you more likely to buy new products from the same company in the future?" (CLL: Consumer Loyalty Level: low, medium, high), "Have your experiences fixing your own products impacted the purchasing recommendations you give to your friends? (PRL: Product Recommendation Level)". Assuming there is a significant correlation between these two questions, a bivariate ordered probit model was employed to estimate the probability that an observation (a consumer) with specific characteristics (repair experience) will come under one of the ordered categories (low, medium, and high loyalty and recommendation levels). Table 22.1 shows the relation between consumer loyalty and recommendation level for consumers with prior repair experiences.

Access to repair information, positive attitudes towards repairing electronics, product type, availability of spare parts, and unsuccessful repair experience (time-

Table 22.1 The relation between CLL and PRL given the prior repair experiences (data gotten from Sabbaghi et al. (2016))

		CLL: Consumer Loyalty Level		
		Low 379 (5%)	Medium 4039 (48%)	High 3985 (47%)
PRL: Purchase recommendation level	Low1086 (13%)	163(2%)	613(7.3%)	310(3.7%)
	Medium4874 (58%)	179(2.1%)	2688(32%)	2007(23.9%)
	High2418 (29%)	37(0.4%)	738(8.8%)	1668(19.8%)

consuming repair and broken parts during repair) have been identified as important factors that influence future product choice and recommendation.

22.6.4 Consumer's Product Return Behavior

Another important consumer behavior is their decision about the type of disposal channel to employ, including storage, reselling, the trash bin, a formal collection site, trade-in programs, recycling centers, etc. It is important to estimate which portion of used products are returned back to each of these channels. Thus, in one study (Mashhadi et al. 2016), we developed a simulation framework to model consumer's behavior in returning used products in which consumers have four options: storage, resell, recycle, or discard. An agent-based simulation (ABS) framework integrated with a Discrete Choice Analysis (DCA) method was developed to predict consumer's disposal decisions. Consumers socio-demographic information and product design features were included in the model as possible predictive factors.

To identify the role of product design features on the consumer participation, an agent-based simulation model was created. The diverse set of decision-makers in the take-back systems (consumers, products, OEMs) were represented as "agents." There is a mathematical model behind each agent. All agents have their own set of features, objectives, behavioral patterns, and decision-making rules.

The main objective of the simulation was to evaluate design alternatives in terms of consumers' participation in different take-back channels. Each individual consumer has been modeled as an agent. Consumer decisions on the selection (if any) of take-back systems (trade-in programs, store, trash bin) has been modeled using discrete choice analysis techniques and has been connected with product design strategies controllable by original manufacturers. DCA is commonly employed to study the individual decision-making process. The underlying assumption behind DCA is that individuals seek to maximize their utility considering two sets of attributes, their socio-demographic characteristics, and the features of alternatives available to them (Wassenaar and Chen 2003).

Through the DCA techniques, the choice probability for each decision (e.g., trade-in programs, trash bin, store) was determined based on product design attributes, take-back program features, and consumers' socio-demographic information. The capabilities of agent-based simulation also helped us consider the impact of other dynamic factors such as peer pressure, and consumer awareness of the decision made by each individual consumer. The interaction between agents has been modeled employing the capabilities of agent-based simulation. Figure 22.11 illustrates one example of the simulation results including the number of products stored, returned, sold, and thrown away over time with consideration of interactions between consumers.

Building such simulation tools paves the way for achieving a more comprehensive understanding of consumer behavior and its impact on the used products' return

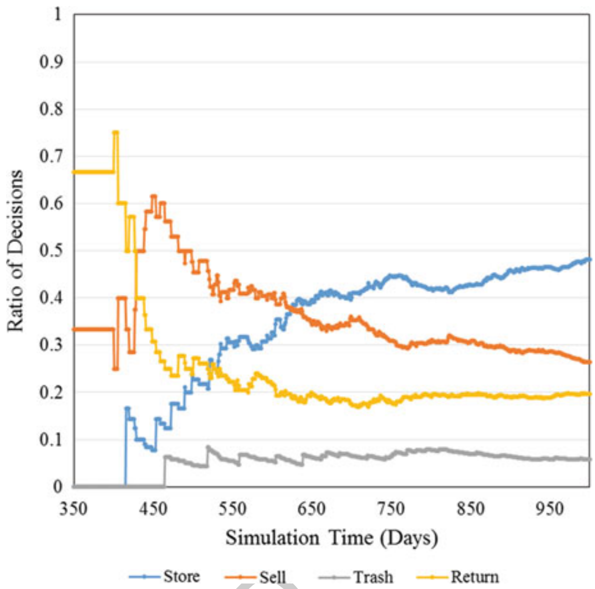

Fig. 22.11 The ratio of products stored, returned, sold, and thrown away over time with consideration of interactions between consumers (data from Mashhadi et al. 2016)

paths. The final outcome of the study was to estimate the number of products stored, returned, sold, and disposed of over time.

22.7 Summary and Closure

This chapter has summarized a body of work that employs industrial engineering approaches to the problem of design for sustainability. These approaches began with normative multiattribute utility analysis to broaden the set of objectives under consideration and evaluate design alternatives, proceeded through constrained optimization to identify the best alternative, statistical process control to create new alternatives and immersive computing technology to gather data required for the optimization model, and conclude with studies of consumer behavior before, during, and after the use phase of the product life cycle.

This mathematical modeling approach requires designers to employ a decompositional strategy, which not only aids in solving previously intractable problems, but also facilitates gaining better insight to the problem as one analyzes the results and the structure of the model in detail. Lessons learned include that facts that although designers might be genuinely concerned about sustainability, their actual willingness to pay for it might be limited, that selling a service (through leasing) rather than selling a product can improve both profitability and customer satisfaction, that statistical manufacturing process control can reveal unexpected opportunities for pollution prevention, that virtual reality design environments can be used to quickly and efficiently gather some of the large amount of data needed to build comprehensive models, and that the customer also plays a significant role.

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Deborah Thurston first learned about engineering as a possible career choice at a seminar for high school senior girls that she signed up for mainly to get out of a day of school. There, she heard from a practicing woman engineer about how fun and satisfying it was to *really* understand something that you wanted to understand, but at first found difficult. She had already been accepted to college with a different major, but switched to engineering. She is now a Gutsgell Professor of Industrial and Enterprise Systems Engineering at the University of Illinois. She serves as design node leader in the Institute for Reducing EMbodied-Energy And Decreasing Emissions (REMADE), Director of the Decision Systems Laboratory, and Co-Director of the Hoeft Technology and Management Program. She earned the M.S. and Ph.D. from MIT. At Illinois, Professor Thurston was instrumental in developing a new interdisciplinary Ph.D. program in Systems and Entrepreneurial Engineering, and also managed the transfer of the Industrial Engineering program during a college reorganization. She has also served as CESUN Chair. As one of the first researchers in engineering design theory and methodology, she brought mathematical rigor to complex design decision problems by formalizing methods for making rational tradeoffs under uncertainty. Her research has been funded by NSF, EPA, and a number of industries. Professor Thurston received the NSF Presidential Young Investigator Award, two Xerox Awards for research excellence, four awards for undergraduate advising, and five best paper awards. She has served as area editor for the *ASME: Journal of Mechanical Design* and *The Engineering Economist*. She is a registered professional engineer and ASME Fellow.

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