The Effect of Uncertain End-of-Life Product Quality and Consumer Incentives on Partial Disassembly Sequencing in Value Recovery Operations

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ABSTRACT

This dissertation addresses gaps in the interaction between End-of-Life (EoL) product acquisition systems and disassembly sequencing. The research focuses on two remanufacturing research problems; 1) modeling uncertain EoL product quality, quantity, and timing in regards to EoL product acquisition and disassembly sequencing and 2) designing EoL product acquisition schemes considering EoL product uncertainty. The main research objectives within these areas are; analyzing, predicting, and controlling EoL product uncertainty, and incorporating EoL product uncertainty into operational and strategic level decisions. This research addresses these objectives by researching a methodology to determine optimal or near-optimal partial disassembly sequences using infeasible sequences while considering EoL product quality uncertainty. EoL product age distributions are key to integrating the disassembly sequence method with EoL product acquisition management, acting both as an indicator of quality and as a basis for determining return quantity when considering incentives. This research is motivated by the rising importance of value recovery and sustainability to manufacturers. Extended Producer Responsibility (EPR) and Product Stewardship (PS) policies are, globally, changing the way products are treated during their use-life and EoL. Each new policy places a greater responsibility on consumers and manufacturers to address the EoL of a product.

A partial disassembly sequence, multi-objective genetic algorithm (GA) is used a solution procedure to address the problem of determining the optimal or near-optimal partial disassembly sequence considering a continuous age distribution of EoL or available consumer products, with and without a consumer take-back incentive. The research presented here within provides three contributions to disassembly and EoL product acquisition research: 1) integrating EoL product age distributions into partial disassembly sequencing objective functions, 2) accounting for partial disassembly sequence expected profit, profit variation, and profit probability as compared to disassembly sequencing methods that have, historically, only considered expected profit, and 3) studying the impact of EoL product age distributions and consumer take-back incentives on optimal or near-optimal partial disassembly sequences. Overall, this doctoral research contributes to the body of knowledge in value recovery, reverse logistics, and disassembly research fields, and is intended to be used, in the future, to develop and design efficient EoL product acquisition systems and disassembly operations.

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EXECUTIVE SUMMARY

This dissertation addresses gaps in the interaction between End-of-Life (EoL) product acquisition systems and disassembly sequencing. The research focuses on two remanufacturing research problems; 1) modeling uncertain EoL product quality, quantity, and timing in regards to EoL product acquisition and disassembly sequencing and 2) designing EoL product acquisition schemes considering EoL product uncertainty. The main research objectives within these areas are; analyzing, predicting, and controlling EoL product uncertainty, and incorporating EoL product uncertainty into operational and strategic level decisions. This research addresses these objectives by researching a methodology to determine optimal or near-optimal partial disassembly sequences using infeasible sequences while considering EoL product quality uncertainty. Consumer incentives are integrated into the methodology to study the effect of EoL product take-back incentives, but it also allows for the study of EoL product quantity uncertainty. EoL product age distributions are key to integrating the disassembly sequence method with EoL product acquisition management, acting both as an indicator of quality and as a basis for determining return quantity when considering incentives. At a broader level, this research makes it possible to study the impact of EoL product quality, and to an extent quantity, uncertainty resulting from strategic level (acquisition scheme) decisions, on operational (disassembly sequencing) decisions.

This research is motivated by the rising importance of value recovery and sustainability to manufacturers. Extended Producer Responsibility (EPR) and Product Stewardship (PS) policies are, globally, changing the way products are treated during their use-life and EoL. Each new policy places a greater responsibility on consumers and manufacturers to address the EoL of a product. Manufacturers, in particular, may have to fulfill these obligations by such means as contracting 3rd parties for EoL recovery or performing recovery in-house. The significance of this research is linked to the growing presence of remanufacturing and recovery in the US and global economy, either via profitable ventures or environmental regulations. Remanufacturing, in particular, was surveyed by the US International Trade Commission in 2011-2012, where it was determined that remanufacturing grew by 15% to $43 billion, supported 180,000 full-time jobs from 2009-2011, and is continuing to grow.

A partial disassembly sequence, multi-objective genetic algorithm (GA) is used a solution procedure to address the problem of determining the optimal or near-optimal partial disassembly sequence considering a continuous age distribution of EoL or available consumer products, with and without a consumer take-back incentive. The multi-objective GA, novel to the presented approach, relies on infeasible sequences to converge to optimal or near-optimal disassembly sequences. It is verified with a discrete economic and environmental impact case prior to incorporating EoL product age distributions. Considering the age distribution of acquired EoL products allows for decisions to be made based not only on expected profit, but also on profit variance and profit probability per EoL product, which was not observed in previous literature. As such, the research presented here within provides three contributions to disassembly and EoL product acquisition research: 1) integrating EoL product age distributions into partial disassembly sequencing objective functions, 2) accounting for partial disassembly sequence expected profit, profit variation, and profit probability as compared to disassembly sequencing methods that have, historically, only considered expected profit, and 3) studying the impact of EoL product age distributions and consumer take-back incentives on optimal or near-optimal partial disassembly sequences. Overall, this doctoral research contributes to the body of knowledge in value recovery, reverse logistics, and disassembly research fields, and is intended to be used, in the future, to develop and design efficient EoL product acquisition systems and disassembly operations.

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1. INTRODUCTION

Sustainability emphasizes holistic decision making across many fields; including but not limited to industry, business, society, and government. The sustainability philosophy emerged from meetings and reports in the 1970’s and 1980’s that aimed to address societal concerns regarding environmental incidents, chemical contaminations, and resource depletion. One of these reports, entitled *Our Common Future* (World Commission on Environment and Development 1987), pointedly stated that we were and may still be near the Earth’s natural limits, and introduced the widely adopted definition of sustainable development as *“meeting the needs of the present without compromising the ability of future generations to meet their own needs.”* Sustainability and sustainable development are distinctly different. Sustainability, as the term implies, suggests a system that does not change, but maintains a desired level of performance whereas development is often synonymous with expansion and growth in industry, standard of living, Gross National Product (GNP), Gross Domestic Product (GDP), etc. Within the sustainable development framework, development is interpreted as qualitative improvement within the Earth’s natural limits, which may or may not be known (Daly 1996). In either case (sustainability or sustainable development) three mutually reinforcing pillars (economy, environment, and society) characterize any given system. These three interdependent pillars have been referred to as the triple bottom line (*i.e.*, people, profit, and planet) and other related terms that evoke a holistic world view, Figure 1.

The economic pillar has been the primary barometer of national and societal development. As such, it has received the most attention from policy makers and has been the focus of many societal demands. GNP and GDP per capita are common measures of the economic pillar. A particular complication with GNP is that aggregating the micro-level of an economy (which has an optimal scale) to the macro-level removes limiting constraints (*i.e.* infinite growth is possible). This results from the notion that the macro-level is the whole of the system and is not a sub-system of something greater (Daly 1996), akin to removing the environmental and societal aspects. Sustainable development has

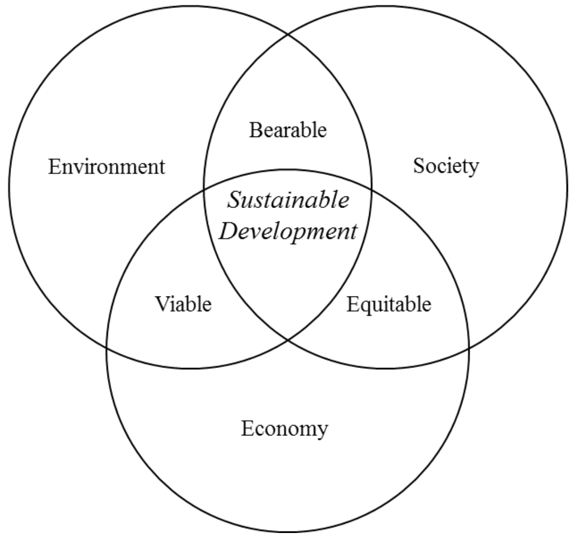

Figure 1 Three pillars of sustainable development: environment, economy, and society

altered this viewpoint, *i.e.* the economic pillar is not considered independent of the environmental or societal pillar and is constrained by available natural resources, which limit commodity production (Daly 1996). Policies adopted in the EU (End-of-Life Vehicle Recovery - ELV (EU Directive 2000), and Waste Electronics and Electronic Equipment - WEEE (EU Directive 2002)), the US (assorted EPA regulations), and other developed nations are indications that this viewpoint is gaining momentum, at least in developed nations.

The environmental pillar was initially evaluated with cost-benefit analysis that transformed environmental impacts into monetary costs (OECD 2006). Environmental impacts are now evaluated with Life Cycle Assessment (LCA) tools, which are guided by ISO 14000 standards (Tukker 2000). A typical output of LCA provides estimates regarding global warming (kg CO2-eq), waste heat (MJ), human toxicity (kg b.w.4), etc. Each output has different units and scales that transform traditionally single objective decision problems (cost) into multi-objective problems.

The societal pillar encompasses the impact of a system, technology, or policy on society in terms quality of life, health, or happiness metrics, many of which are difficult to quantify. A question that is inherent to this pillar is: what is a sustainable society and how can it be evaluated? One viewpoint is that a sustainable society is one that does not generate waste at a rate greater than the ecosystem can efficiently process. However, this is difficult to accomplish due to population growth, rising consumption levels, and developing nations transitioning to developed nations (Beinhocker et al. 2009). Attempts to mitigate these affects have generally focused on technology (*e.g.* advanced recycling methods, renewable energy, dry machining) but advancements in public policy have also been made (*e.g.* EU WEEE, ELV, and packaging waste policies) (Rickli et al. 2008). These policies are being adopted in nations beyond the EU (US, Korea, Japan) (Rickli et al. 2008) and have led to movements, such as the Basel Action Network (BAN), which focus on reducing the trade of toxic waste from developed to developing nations. BAN is especially critical in the case of electronics since these devices are often in high demand in developing nations. The demand can fulfilled by exporting End-of-Life (EoL) devices, but developing nations are rarely equipped to properly dispose of the imported electronics (Rickli et al. 2008). The societal pillar is an active research area that focuses, from an engineering perspective, on exploring new evaluation metrics and integrating societal metrics into current decision models, optimization routines, and analysis methods (Haapala et al. 2013).

The breadth of research, industry, and policymaking areas addressed by the three pillars of sustainable development is comprehensive. Consider Figure 2, which depicts a simplified flow of raw materials, products/services, and waste in a generic product stream. Each aspect of the product stream can be analyzed from a sustainable development viewpoint. Take environmental capital, representing an ecosystem's natural resources, as an example. Environmental capital estimates may change based on energy research because new renewable resource technologies may increase available capital. However, energy research must also be accompanied by new government policies and forecasts that predict the impact the technologies will have on society.

An interesting case to consider is bio-fuel. The advantage of bio-fuels is that the replenishment time is drastically less than fossil fuels (a single year compared to thousands). However, if policies are put in place requiring a higher use of biofuel in automotive fuel, then the effect on the US food supply must be predicted. Swapping farmland previously used to produce food to produce biofuel could lower the available food supply, raise food prices, or lead to new food production technologies. Similar cases exist at each stage of Figure 2; industrial systems, society, the waste stream, and natural system decomposition.

Manufacturing, an aspect of industrial systems, plays a critical role in the overall system flow in Figure 2 because it uses energy to transform raw materials into consumer products that are marketed and sold based on demand. In general, global consumption levels have risen (Beinhocker et al. 2009), increasing manufacturer demands and the energy, waste, and raw materials used in manufacturing processes. As a result, manufacturing represents a significant burden on the environment as well as a common method of wealth generation and job creation, *i.e.* development (Haapala et al. 2013). For example, in 2002, the US manufacturing sector accounted for $1.35 trillion (12.8%) of industry gross domestic product (USDOC 2012), but was also responsible for approximately 84% of US energy-related carbon dioxide emissions and 90% of the energy consumption within the US (USDOC 2010).

Manufacturing is also a key stakeholder in past, current, and future environmental policies introduced in the EU, which have attracted attention from other nations. The policies promote Extended Producer Responsibility (EPR) and/or Product Stewardship (PS). EPR calls for producers to take the majority of the responsibility for the life cycle of a product, particularly EoL, and PS calls for a shared

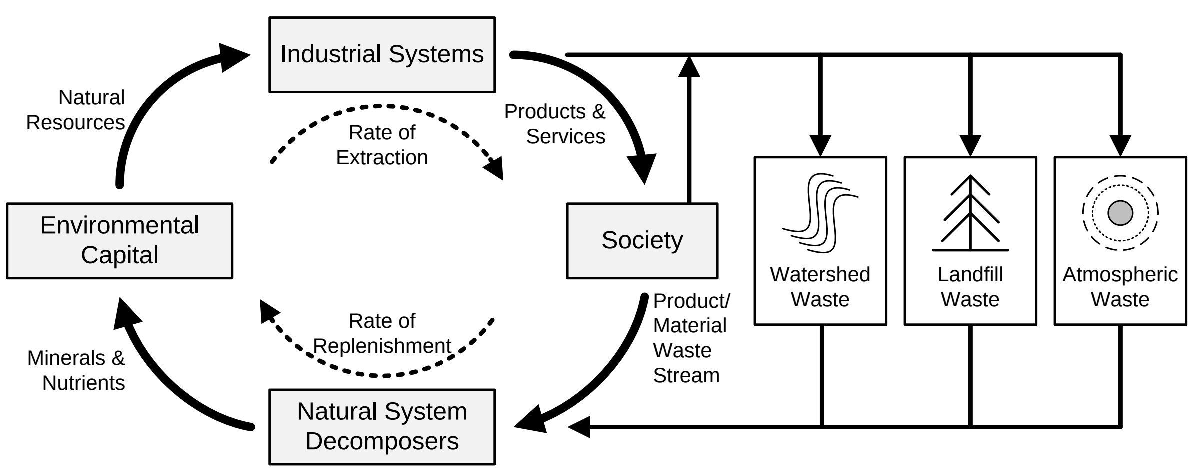

Figure 2 Flow in a generic product stream

responsibility between all product stakeholders, including consumers. Both policy initiatives extend the role of manufacturing to the interaction between society, waste streams, and value recovery operations; thus increasing manufacturing's potential impact on the sustainable development pillars; economy, environment, and society.

Sustainable manufacturing, similar to Environmentally Conscious Design and Manufacturing, ECDM, is divided into two main thrusts, 1) manufacturing processes and 2) manufacturing systems (Haapala et al. 2013). These two thrust areas are aspects of industrial systems (Figure 2), and are shown in relation to other aspects of industrial systems in Figure 3. Manufacturing processes include issues related to planning, development, analysis, and improvement of processes such as milling, turning, casting, etching, etc. On the other hand, manufacturing systems address challenges relating to facility design and operation, production planning and scheduling, supply chain design, and value recovery (Haapala et al. 2013). The research in this dissertation is aligned within the value recovery activities of the manufacturing systems area of sustainable manufacturing.

Value recovery is defined in this dissertation as all activities associated with the EoL of a product. The benefits of performing value recovery include the following: 1) reduction in the amount of EoL products disposed of illegally or in landfills, 2) recovery of raw material that can alleviate natural resource limitations, 3) creation of profitable business ventures for Original Equipment

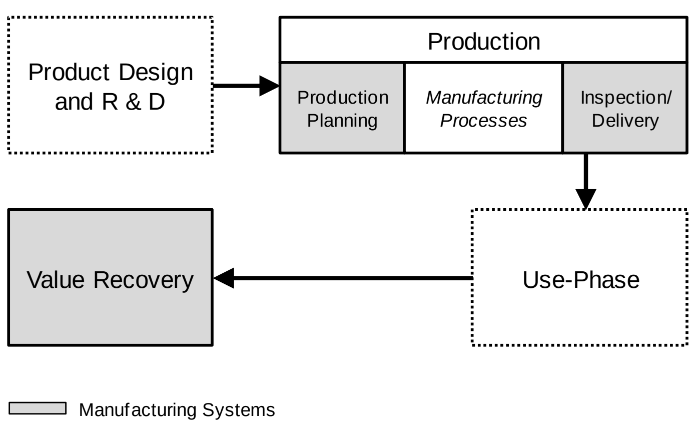

Figure 3 Key thrusts of sustainable manufacturing within industrial systems

Manufacturers (OEMs) or third parties, and 4) development of an outlet for consumers to exchange older products for newer ones (*e.g.* in the case of rapid technology advancements). Each objective is beneficial to developing a waste recovery system that can sustainably counteract high consumption per capita levels that exist in developed nations and are sought after in developing nations. Ilgin and Gupta (Gupta and Ilgin 2012) classify value recovery research into three categories; Design issues, Planning issues, and Processing issues. Design issues are long-term decisions such as product design, facility design, and reverse supply chain design. Planning issues are considered medium-term and include production planning, inventory control, Product Acquisition Management (PrAM), capacity planning, and others as listed in (Gupta and Ilgin 2012). Processing issues are short-term/day-to-day issues such as disassembly, cleaning, sorting, inspecting, and reassembly. Figure 4 illustrates an example value recovery system flow between the aforementioned areas, which are discussed in more detail.

PrAM (Guide Jr and Jayaraman 2000) is the design and planning of EoL product collection systems, mechanisms, and policies that facilitate efficient and profitable EoL product recovery operations. Its primary goal is to interface the reverse supply chain with production planning and control. One of the most common types of PrAM practices is to offer an incentive in exchange for an EoL product. Incentives can vary in form, such as deposit/refund, governmental policies, or a buy-back

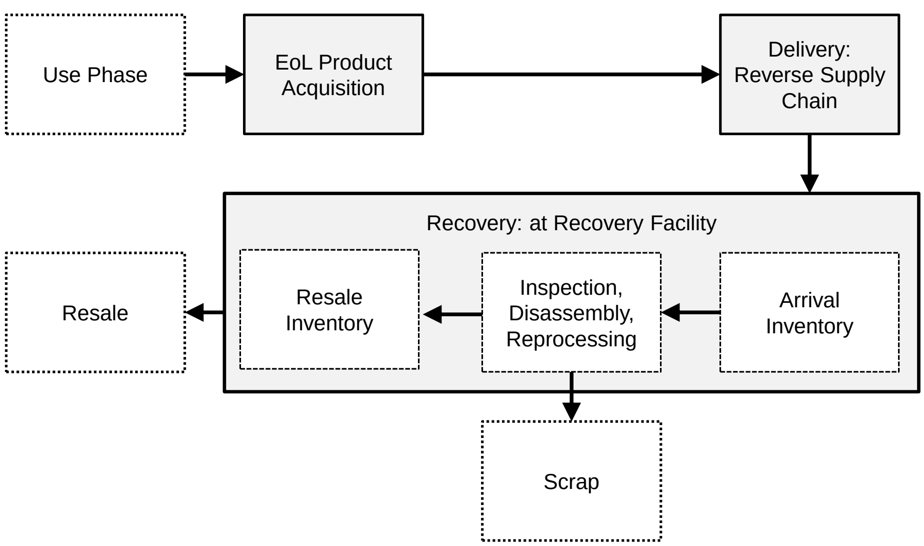

Figure 4 Value recovery encompasses all activities after the use-phase of a product

program. Retail industries have implemented incentive schemes to reduce early customer returns and unsold goods (Guide Jr and Wassenhove 2006; Janse et al. 2010; Ketzenberg and Zuidwijk 2009). Their pricing and return policies created a communication network between suppliers, retailers, and customers and information pertaining to products that were not sold or returned early could be easily exchanged. The newsvendor problem is a well-known example of an incentivized PrAM scheme where unsold newspapers are purchased for a salvage price (incentive). Guide et al. (Guide Jr et al. 2003) introduced the concept of PrAM as a way to influence EoL product quality, and optimize the selling price of remanufactured products in order to provide a frame of reference for determining an incentive value. Key questions within the area of PrAM include; how incentives impact consumer decisions to return an EoL product, and how incentives influence returned product quality, quantity, and timing.

The reverse supply chain encompasses all methods and activities required to transport acquired EoL products from a collection center to recovery facilities. It is the conduit between EoL product acquisition and the recovery facility. Significant research has been done in developing and optimizing mathematical models of reverse supply chains (Gupta and Ilgin 2012). Major thrust areas include flow optimization, determining the size and location of collection and recovery facilities, simultaneously considering the forward supply chain and reverse supply chain, evaluation metrics for collection centers, and simultaneously considering reverse supply chain and product design. Stochastic reverse supply chain models have also been introduced in order to account for EoL product uncertainty (Gupta and Ilgin 2012).

The final value recovery stage discussed here is the recovery facility. Activities within the recovery facility include but are not limited to arrival inventory, inspection, disassembly, reprocessing, final inspection, and resale inventory. The interaction between arrival inventory and uncertain product acquisition quantities is critical to production planning and control decisions. Additionally, uncertain quality adds to planning complexity since storing low quality products in the arrival inventory may be more costly than immediate disposal. Disassembly and reprocessing are essential operations that restore the value of an EoL product. Disassembly separates an EoL product into its components or subassemblies, and reprocessing operations restore an EoL component or subassembly to or nearly to OEM standards. Major research areas within disassembly include scheduling, sequencing, line balancing, disassembly-to-order systems, ergonomics, and automation (Gupta and Ilgin 2012). Embedded disassembly mechanisms (Design for Active Disassembly – DfAD) have also been an active area of disassembly research. DfAD mechanisms use smart materials to quickly and easily disassemble EoL products (Chiodo and Jones 2012). Disassembly is a key aspect of value recovery as almost all EoL treatments (*e.g.* remanufacturing, recycling, component/subassembly disposal, reuse) require disassembly operations, save for direct shredding/disposal (Gupta and Ilgin 2012).

1.1. Motivation and Significance

This research is motivated by the rising importance of value recovery and sustainability to manufacturers. Environmental policies that prohibit uncontrolled product EoL have resulted from rising sustainability awareness and rising consumption levels (Beinhocker et al. 2009) that demand higher production levels and generate more waste. Of particular concern to manufacturers is the increased responsibility of product EoL from EPR and PS policies. These obligations can be fulfilled in multiple ways, two of which are contracting 3rd parties for EoL recovery or performing recovery in-house. In the case of high value components, companies may already be performing remanufacturing and recovery, however, components with less value (*e.g.* cell phones, computers) that are less controlled are riskier due to tighter profit margins.

The risk of remanufacturing and recovering EoL products can be attributed to two sources 1) uncertainty in demand for recovered products, affecting associated market prices and 2) uncertain quality, quantity, and timing of EoL product returns (Guide Jr and Jayaraman 2000; Guide Jr and Wassenhove 2006; Gupta and Ilgin 2012). In 2000 it was reported that the majority of remanufacturing firms, 61.5% of those surveyed, had little to no control over the timing of returns (for remanufactured cores with an average value equal to $141,325). The survey also identified seven target concerns for remanufacturing: 1) uncertain timing and quantity of returns, 2) the need to balance demand with returns, 3) the need to disassemble returned products, 4) uncertainty in materials recovered, 5) requirements for a reverse logistics network, 6) complication of material matching restrictions, and 7) problems with stochastic routings of materials for repair/remanufacturing operations and highly variable processing times (Guide Jr and Jayaraman 2000). In 2006, these targets were updated to include: 1) development of formal models to understand cascade reuse opportunities, 2) reverse supply chain coordination and incentive alignment, 3) use of information technology to facilitate closed loop supply chain development and control, 4) a clear understanding of market cannibalization issues, 5) a life-cycle approach to product returns that integrates all the types of returns, 6) interdisciplinary research, including improved integration with industrial ecology methods and models, and 7) industry driven research (Guide Jr and Wassenhove 2006). Most recently, it was identified that the limiting agent in remanufacturing enterprises is not technical knowledge but is the lack of EoL products that can achieve a certain level of quality for a reasonable price (Guide Jr and Van Wassenhove 2009).

The significance of this research is linked to the growing presence of remanufacturing and recovery in the US and global economy, either via profitable ventures or environmental regulations. Remanufacturing, in particular, was surveyed by the US International Trade Commission in 2011-2012 (USITC 2012). They determined that from 2009-2011 remanufacturing grew by 15% to $43 billion, supported 180,000 full-time jobs, and that it is continuing to grow. In addition, the expanded role manufacturers may have (total or partial life-cycle responsibility) under new EPR and PS type policies make value recovery research significant to both industry, policy-makers, and society in general.

1.2. Research Problem

This dissertation addresses research gaps in the interaction between EoL product acquisition systems and disassembly sequencing. The basic research problem is formally defined as follows:

"Exploring the impact of uncertain EoL product quality, quantity, and timing on optimal partial disassembly sequences by linking product acquisition management and disassembly planning". EoL product uncertainty can be addressed in two ways; 1) controlling EoL production return via enhanced product acquisition schemes/policies (Guide Jr and Jayaraman 2000; Guide Jr et al. 2003; Gupta and Ilgin 2012) or 2) developing inventory control methods, disassembly operations, and product designs that are robust to EoL product uncertainty. EoL product uncertainty is caused, in part, by the large variety of users and uses for products as wells as, in some cases, consumer dependent return time. Figure 5 and Figure 6 illustrate this difference by comparing the supply network of traditional, forward manufacturing and value recovery, respectively. Forward manufacturing operations retain a set of suppliers that deliver products on-time and to specifications, thus reducing part uncertainty. However,

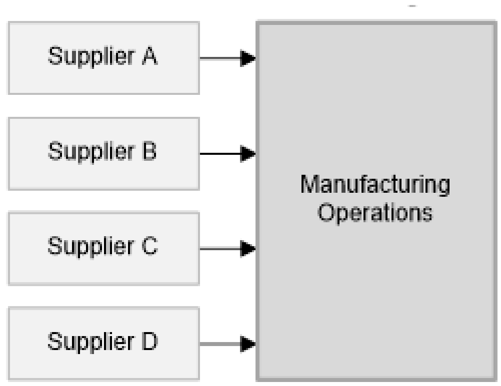

Figure 5 Structured supplier flow in forward manufacturing

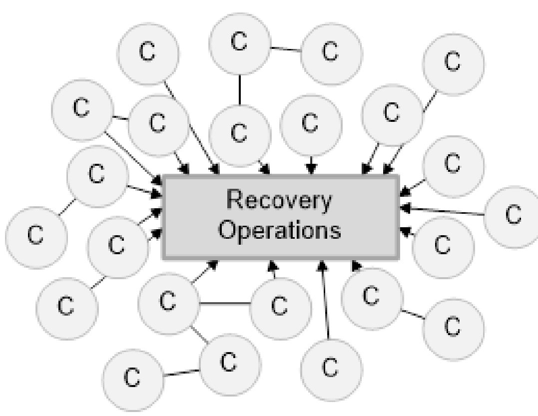

Figure 6 Chaotic consumers supply network in value recovery

in value recovery operations, consumers, *C*, are individual suppliers and, in some product acquisition schemes, decide when, or if, to return an EoL product and at what quality level.

The degree of acquired EoL product uncertainty is dependent on multiple factors, one being the PrAM scheme. PrAM works to control the flow of EoL products into a value recovery network. Incentivized product acquisition schemes have been investigated as a means to influence EoL product return in consumer controlled systems (Guide Jr et al. 2003). These schemes encourage consumers to return EoL products at a specific quality level, at a desired quantity, and at a specific time with an incentive. An emphasis has been placed on uncertain quality, quantity, and timing of EoL products because low quality EoL products require a higher degree of reprocessing than higher quality EoL products, thus low quality EoL products incur higher recovery costs and, potentially, more harmful environmental impacts. Three example recovery scenarios from three industries are presented below to showcase the affect the consumer use-phase, the PrAM scheme, and the EoL product type can have on EoL product uncertainty in the form of product age distributions and EoL treatment methods.

Example #1, Fuji Xerox: Printer cartridge recovery from Xerox photocopiers is a well-studied value recovery system. One example of Fuji Xerox's recovery operations is the installation of reused or remanufactured components in new photocopiers (Matsumoto and Umeda 2011). Factors that contribute to the success of Xerox value recovery are their leasing/service contract system and photocopier maintenance program, provided by Xerox. The leasing contracts give Xerox total control over the collection of photocopiers and the maintenance program provides a detailed history and evaluation of the remaining life of the photocopier components. The leasing contracts and maintenance program make Xerox photocopiers a service system (Matsumoto and Umeda 2011), which exhibits more control over EoL product recovery and, thus, reduces the amount of uncertainty in EoL product age distributions. Consequently, the remaining life and quality of the photocopier and its components is more easily predicted.

Example #2, Chicago E-Waste Collection: Electronic waste collection in the Chicago area employs a very different type of PrAM scheme. Electronic waste, in this scenario, is owned by consumers who have full control over when the product is returned to a recovery enterprise and in what condition. For example, a one year old and twenty year old television could be deposited at the collection center in a single batch. The recovery center would then be responsible for properly treating each EoL television even though the remaining value and reprocessing requirements of each television are vastly different. E-waste recovery is more volatile due to rapid technology advancements that make young products with high levels of quality obsolete. The remaining life of a technologically obsolete electronic device may still be relatively high, however, the remaining value is extremely low. Kwak et al. (2011) studied the age distributions of EoL products voluntarily returned by consumers to a Chicago area e-waste recovery facility. Products were categorized as CPUs, laptops, monitors, printers, and televisions, and the age distributions for each had an approximated range of one to twenty years. The glaring difference between Xerox and the Chicago e-waste collection systems is the lack of control over EoL product recovery by the Chicago e-waste system.

Example #3, Heavy Duty Truck Recovery: Heavy Duty Trucks (HDTs) are numerous throughout the US and are used by many small, medium, and large businesses to transport goods. HDTs inherently have a significant amount of material value in the truck (engine block, transmission, side rails) but also have value in secondary markets that trade in reused or remanufactured parts. The recovery system for HDTs differs from the Xerox photocopier and the Chicago e-waste recovery systems because of its competition. Demand for used HDTs is significant, so much so that salvage auctions are common and attended by a variety salvagers looking to purchase low priced whole trucks in order to sell the HDT parts and material for a profit. The estimated value retained in a HDT (a function of age/miles and use) is critical to a salvager's bid. Costs included in the decision to buy or ignore include the cost of reprocessing, disassembly, and transport. These costs are offset by the selling price of scrap material, reused/aftermarket parts, and remanufactured components. The age distribution of HDTs, thus, can affect the expected profit of an HDT, but the variation of the age distribution may be more critical as it could reduce the confidence of achieving a profit from a salvaged HDT.

1.3. Research Objectives

The research objectives of this dissertation focus on two target remanufacturing research areas (Guide Jr and Jayaraman 2000; Guide Jr and Van Wassenhove 2009; Guide Jr and Wassenhove 2006); 1) modeling EoL product quality, quantity, and timing uncertainty in regards to EoL product acquisition and disassembly sequencing and 2) designing return incentive schemes considering EoL product uncertainty and operational disassembly decisions. Addressing these research areas requires investigations into methods that can analyze, predict, and control EoL product uncertainty, and into models that incorporate and optimize return incentives based on remanufacturer needs and demand forecasts. PrAM can influence EoL product uncertainty, which, in turn, influences inventory and operational decisions at a recovery facility. Thus, supply chain operations, product acquisition management, and reprocessing operations are dependent on each other, and their interactions must be modeled, analyzed, and studied in order to determine optimal product acquisition parameters and the cost/benefit tradeoffs (monetarily, environmentally, and socially). Three research objectives, described in the following sections, are addressed in this dissertation.

1.3.1. Research Objective #1

The first research objective focuses on developing a method to determine optimal partial disassembly sequences considering multiple objective functions. Partial disassembly sequencing is the process of determining the optimal disassembly sequence and the optimal disassembly level. Disassembling past this optimal level may reduce the return on EoL products due to intensive inspection, cleaning, or reprocessing. A multi-objective approach to partial disassembly allows for advanced analyses to be completed, yet is challenging due to differences of units and an increase in problem complexity. This research objective is addressed by the creation of a multi-objective heuristic method that is used to converge to the optimal or near-optimal partial disassembly sequence. Objective functions such as expected value, profit variance, profit probability, and environmental impact are optimized via a multi-objective fitness function.

1.3.2. Research Objective #2

The second research objective focuses on formulating the partial disassembly sequence optimization problem considering acquired EoL product age distributions. Uncertain EoL product quality influences the disassembly level, *i.e.* as component quality decreases it may no longer warrant disassembly and reprocessing, but the impact is difficult to assess without access to the profit variance and profit probability of an EoL product. Additionally, considering acquired age distributions transforms the partial disassembly problem from a single product level to a level that considers an entire population of EoL products. Analyzing disassembly sequencing from an EoL product population perspective is difficult because a population of EoL products with a quality distribution must be considered rather than a single product with a known quality level. As such, the research objective is to mathematically formulate the expected profit, profit variance, and profit probability of an EoL product given an acquired EoL product age distribution and partial disassembly sequence.

1.3.3. Research Objective #3

The third research objective focuses on merging the partial disassembly optimization heuristic method and PrAM. PrAM schemes (such as incentivized take-back) have the ability to influence; 1) EoL product uncertainty and 2) consumer EoL product return decisions by altering the acquired EoL product age distribution. Addressing this research objective requires methods that merge long-term, strategic level PrAM formulations with short-term, disassembly sequence optimization. These formulations create the link between PrAM and disassembly models and create the theory that allow the two to interact. This research objective is identified because there is a gap between operational level and strategic level value recovery research, as will be discussed in Section 2.

The remainder of this dissertation is organized as follows. Section 2 is a comprehensive literature review of disassembly sequence optimization and PrAM. Section 3 outlines the partial disassembly problem formulation with and without considering an incentivized take-back acquisition scheme. Section 4 describes the genetic algorithm (GA) solution procedure and its capability to use infeasible disassembly sequences to reach optimal or near-optimal solutions, and Section 5 presents the results for each partial disassembly problem. Lastly, Section 6 discusses the conclusions and contributions of this dissertation.

2. LITERATURE REVIEW

Literature relevant to this dissertation is divided into two categories; 1) disassembly sequencing research and 2) product acquisition management (PrAM) research. In general, optimization methods have been prevalent in both areas to either optimize the disassembly sequence or optimize the incentive/selling price of EoL products. The following two sections review the state-of-the-art research for disassembly sequencing (also known as disassembly planning) and PrAM.

2.1. Disassembly Sequencing

Three primary types of disassembly sequencing exist; 1) complete, which disassembles an EoL product to each individual component, 2) selective, which targets a specific, high value component(s) and disregards the remaining components, and 3) partial, which disassembles an EoL product only to the point where returns on components diminish. Complete and selective disassembly can be considered shortest path problems. The goal of complete disassembly problems is to find the optimal disassembly sequence to a known level (all components disassembled). On the other hand, selective disassembly chooses a specific component and then aims to find the optimal disassembly sequence to extract that component, or, in other words, obtaining the highest value component(s) at the lowest cost (Wang et al. 2003). Disassembling to a selected component may require full disassembly or disassembly to a specific point, but in either case, selective disassembly has a known level. Various methods have been developed for selective disassembly including: an ant colony algorithm (Wang et al. 2003), modified Nevins and Whitney method (Kara et al. 2005), and disassembly wave propagation (Mascle and Balasoiu 2003; Srinivasan H. et al. 1999; Yi et al. 2007).

Contrary to complete and selective disassembly, partial disassembly searches for the optimal disassembly level and the optimal sequence to reach this disassembly level. The disassembly level is unknown, and may include a group of disassembled components that are more valuable separated from the EoL product and a subassembly that has minimal value. Disassembling past this optimal level may reduce the return on the EoL product due to expensive inspection, cleaning, or reprocessing. Constraining the disassembly level of the partial disassembly problem transforms it into a complete or selective disassembly problem. Harjula et al. (1996), Zussman and Zhou (1999), Sarin et al. (2006), Lambert (2003), Tripathi et al. (2009), Behdad et al. (2010), and Edmunds et al. (2011) have addressed the single objective partial disassembly problem to varying degrees using various methods.

Harjula et al. (1996) studied partial disassembly assuming that the disassembly sequence is the reverse of the assembly sequence, and Zussman and Zhou (1999) determined the optimal disassembly sequence using a disassembly Petri-net that incorporates the success rate of disassembly operations as probabilities. Sarin et al. (2006) used a precedence constrained traveling salesman problem to achieve optimal or near-optimal solutions, and Lambert (2003) developed an exact method that relies on a detailed Bourjault's tree. Tripathi (2009) used a self-guided ants method to determine the optimal level of disassembly based on warranty and field service data, and Behdad (2010) developed a mixed integer linear program that was based on determining feasible subassemblies first and then using the program to optimize the disassembly level. Edmunds et al. (2011) partnered a hierarchical GA with an AND/OR graph. The AND operations were first identified and removed so that the hierarchical GA could optimize the OR operations. A dynamic programming (DP) approach was adopted by Teunter (2006) and Kang and Brissaud (2007). Teunter focused on extending a DP that accounted for uncertainty in EoL product quality from complete disassembly to partial disassembly. Kang and Brissaud developed a life cycle costing system to accompany a partial disassembly DP. Single objective partial disassembly optimization methods analyze disassembly from either a net profit or environmental aspect, but not both. Including environmental impact and net profits in a multi-objective method is a natural extension of the partial disassembly problem due to value recovery's link with sustainability.

Disassembly research surveys have concluded that the inclusion of environmental impacts expands the problem to the point where extended models are necessary (Lambert, A.J.D. 2003; Tang et al. 2000). The environmental impact of disassembly sequence problems comes from EoL component reprocessing and disassembly operations. EoL component treatments are generally categorized into recycling, reuse, remanufacturing, and disposal/landfill (Kumar et al. 2007). Recycling extracts material value from products but discards any remaining functional value. Reuse reconditions, repairs, or refurbishes an EoL product or component for a second or third life without reprocessing to original equipment manufacturer (OEM) standards. Remanufacturing adds functional value to an EoL component or product, ideally reaching OEM standards. Remanufacturing is optimal for products with extended lives (heavy machinery) but has been applied to technology based products (*e.g.* cell phones) (Franke et al. 2006). Disposal terminates all remaining functional and material value via landfilling or incineration, but can recover some energy value.

Disassembly operations create environmental impacts by way of energy usage or cleaning fluid waste. The degree to which EoL treatment and disassembly operation environmental impacts have been included in disassembly sequence problems has varied. Zussman et al. (1994) transformed environmental impacts into a net profit. Only recycling and disposal were considered, and the objective of the program was to maximize overall profit, maximize the number of reused parts, and minimize landfill waste. LCA provides an alternative way to Zussman et al. (1994) to represent environmental impacts, but requires more advanced multi-objective approaches since impacts may be in units of energy, heavy metals, or points. Lee et al. (2001) accounts for LCA environmental impacts (recycling and disposal) and cost of disassembly with two independent charts. These charts illustrate any increase or decrease in cost or environmental impacts during the progression of a known disassembly sequence. The construction of the charts requires that an optimal disassembly sequence first be chosen using a shortest path based algorithm and a specified end-node (Lee et al. 2001). Seo et al. (2001) paired LCA with a total cost assessment in order to translate LCA environmental impacts into costs to reduce the optimization to a single objective. These three methods account for environmental impact in ways that make it difficult to analyze the tradeoffs in revenue/cost and environmental impact as a function of the disassembly sequence.

In order to analyze the effect of tradeoffs in multi-objective disassembly problems, Hula et al. (2011) used a genetic algorithm (GA) for partial disassembly sequence optimization of a coffee maker liaison graph. Disassembly results between a recovery scenario in Ann Arbor, MI and in Aachen, Germany were compared. Net profits; recycling profits, transportation costs, landfill costs, shredding costs, and disassembly costs were considered. For environmental impacts; transportation energy, shredding energy, recycling energy, and landfill energy were included. Apart from energy, other environmental impacts attributed to disassembly operations and EoL treatment processes were not considered. A GA was used because of its ability to handle multi-objective problems and its robustness for discrete problems. The initial GA population was not randomly generated but was seeded with the maximum profit and maximum energy recovered sequences. Infeasible chromosomes were repaired during the GA to ensure valid, feasible sequences. The GA chromosome contained information regarding the sequence length, remaining subassembly, EoL treatment, disassembly sequence, and component EoL treatment.

Giudice and Fargione (2007) developed a GA for the multi-objective selective disassembly problem and one for the partial disassembly problem. The selective disassembly GA optimizes only for the disassembly time, but the partial disassembly GA takes into account environmental impact and costs. The environmental impacts considered come from part production, disposal, and recycling. Impacts from disassembly operations and EoL treatments, apart from recycling, were not considered. The costs included were; recycling costs, disposal costs, disassembly costs, and the revenue of component recycling. Initial populations of the GA required that at least one feasible sequence be present. If this was not the case, then a feasible sequence was inserted into the initial population. A weighted sum of disassembly time, cost, and environmental impact was used for the multi-objective optimization function. Each single objective function was normalized to its global maximum value, and fitness function values, used for parent selection in the GA, were calculated for feasible sequences.

Chromosomes contained information regarding the component to be disassembled, disassembly direction, and the EoL treatment option.

An aspect consistent between Hula et al. (2011) and Giudice and Fargione (2007) is sequence feasibility. Disassembly sequence research surveys, Tang et al. (2000) and Lambert A.J.D. (2003), concluded that reducing the disassembly sequence search space using the feasibility constraint was critical. Generally, approaches to accomplish search space reduction have focused on ensuring feasibility, such as repairing infeasible sequences, seeding the initial population with feasible sequences (Hula et al. 2011), or evaluating fitness functions only for feasible sequences (Giudice and Fargione 2007). Other GA formulations developed for disassembly sequencing problems have treated feasibility in similar manners (Caccia and Pozzetti 2001; Hao and Hongfu 2009; Hui et al. 2008; Imtanavanich and Gupta n.d.; Kongar and Gupta 2005; Liu et al. 2010). Constraining feasibility in dynamic, linear, non-linear, or integer programming is essential, but in a GA, it can filter infeasible chromosome solutions that may evolve to optimal or near-optimal solutions.

Dini et al. (1999) took a different approach by included feasibility in objective function selection and evaluation. The objective function value of an infeasible sequence was limited to a feasibility score until the disassembly sequence and its gripper changes were feasible. As a result, the method repaired the infeasible sequence with objective functions rather than direct chromosome manipulation. The number of gripper changes, assembly direction, and number of similar/consecutive disassembly operations were considered once a sequence was deemed feasible.

Disassembly sequence optimization research has primarily focused on determining the optimal disassembly sequence in terms of deterministic or expected disassembly costs, processing times, market value, and environmental impact (Ilgin and Gupta 2010; Lambert, A.J.D. 2003; Tang et al. 2000) even though uncertainty in product quality, quantity, and timing have been deemed significant factors in recovery systems (Guide Jr and Jayaraman 2000). Uncertainty in disassembly sequencing has been included in prior research by Reveliotis (2007), Tian et al. (2011), and Gao et al. (2004).

Reveliotis (2007) extended disassembly petri nets to develop a dynamic programming algorithm that was able to study uncertainty in disassembly sequencing. Uncertainty was included as classification probabilities, which characterize the probability that a component was in a specific type of condition given that the prior component had a known condition. Tian et al. (2011) used a stochastic disassembly network graph with uncertain processing times. Uncertain processing times can lead to the premature halting of disassembly operations because the variability of a specific disassembly operation/processing time may be too great to warrant disassembly.

Gao et al. (2004) took a different approach to uncertainty in disassembly sequencing. A fuzzy logic approach was created that made disassembly decisions after each physical disassembly step rather than developing a complete sequence prior to disassembly. Disassembly was halted if the fuzzy logic deemed that further disassembly was detrimental. The approach of Gao et al. (2004) relied on accurate EoL product inspection to make informed disassembly decisions.

2.2. Product Acquisition Management (PrAM)

Product Acquisition Management (PrAM) was first introduced by Guide and Jayaraman in 2000 (Guide Jr and Jayaraman 2000), and is strategically positioned in value recovery enterprises at the intersection of purchasing, marketing, and production as shown in Figure 7. They proposed a formal PrAM framework that highlighted six critical activities; 1) core acquisition, 2) forecasting core availability, 3) synchronizing returns with demands, 4) coordinating materials replacements, 5) resource planning, and 6) reducing uncertainty in EoL product returns. It was predicted that the potential impacts of successfully implementing these activities included but was not limited to; reliable sources of cores, lower cost of cores, improved customer service, simplified inventory and production control, and improved planning. Research regarding PrAM has largely focused on these six activities, particularly due to the perceived impact of uncertain quality, quantity, and timing of acquired EoL products on value recovery profitability.

Commonly, PrAM is summarized as a return ratio, which is a percentage of the total available EoL product that is returned to a value recovery enterprise. This is an essential parameter in value recovery models, spanning production planning, inventory control, and reverse supply chain design. It is also an essential parameter to estimating processing decisions; *e.g.* line balancing, job sequencing, process control mechanisms. For an overview of value recovery inventory management, production planning, and reverse/closed loop supply chain models, see Ilgin and Gupta (2012). Two specific examples in (2012) worth a brief discussion are Zanoni et al. (2006) and Xanthopoulos and Iakovou (2009). Zanoni et al. (2006) specified a return ratio of 0.8, but allowed the return ratio to follow a Poisson distribution with 0.8 as the distribution parameter. This adds a level of EoL quantity uncertainty, although, acquired EoL product quality and timing uncertainty are not included. Xanthopoulos and Iakovou (2009) incorporate the EoL product return quantity as a decision variable

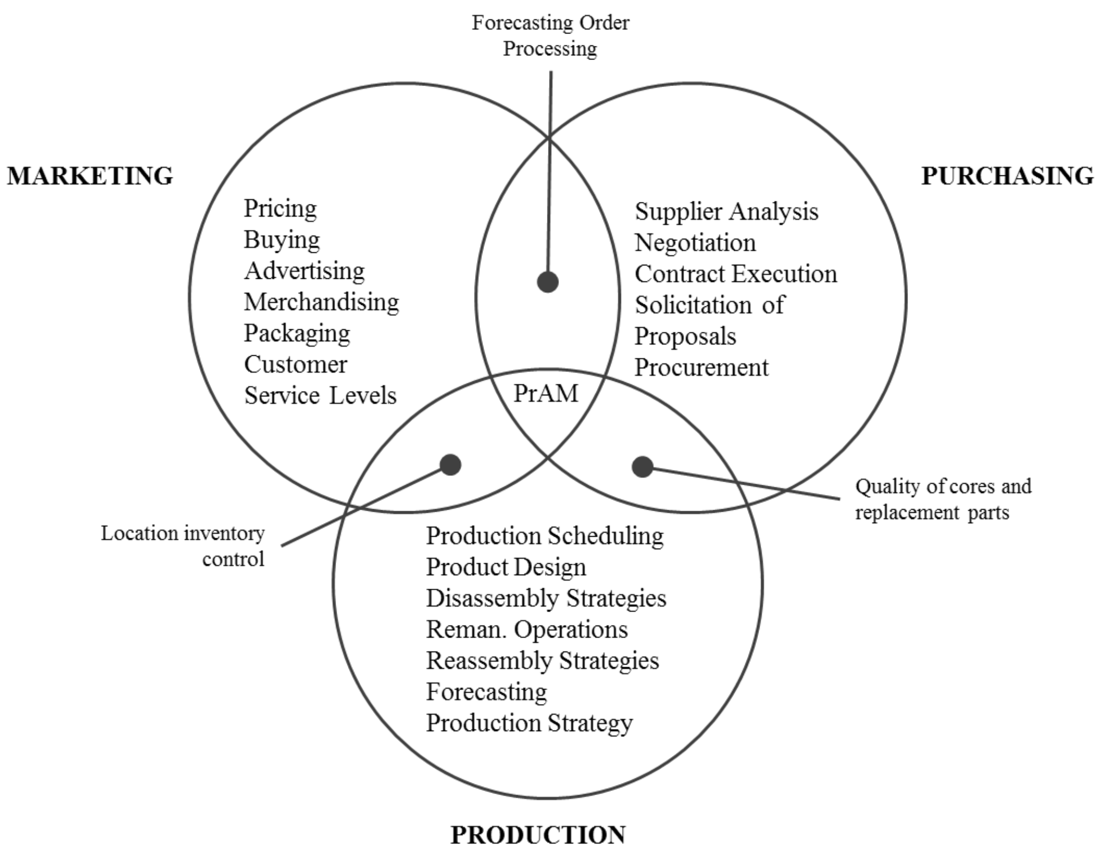

Figure 7 PrAM's position within value recovery (Guide Jr and Jayaraman 2000)

and determined how many EoL products should be collected in a given period. This approach manages uncertainty by balancing EoL product supply and demand.

Inderfurth and Langella (2006) and Teunter and Flapper (2011) are two other examples of balancing methods that determine the optimal number of EoL products to acquire and remanufacture based on stochastic yield from EoL products and consumer demand. Each method focuses on the yield from remanufacturing operations, which was assumed known. Uncertainty management in remanufacturing extends even further to disassembly operations, such as in Meacham et al. (1999), which focuses on optimizing how many products to disassemble based on the yield from the optimal disassembly level (disassembly degree) of an EoL product. Similar approaches to modeling EoL product return and managing uncertainty are surveyed in (Gupta and Ilgin 2012), however, these types of approaches do not thoroughly account for the interaction between consumers, value recovery enterprises, and the product acquisition scheme.

Alternatively, forecasting methods can be used to model EoL product return from historical data. Ilgin and Gupta (2012) present multiple forecasting models such as moving average and exponential smoothing. One forecasting method of note is the transfer function model developed by Goh and Varaprasad (1986) and later modified by Toktay et al. (2000). Goh and Varaprasad (1986) used a transfer function to estimate the returns of Coca-Cola bottles and Toktay (2000) extended the model for application to Kodak single use cameras. The transfer function, essential, captured the interaction between the consumers and EoL product return. The major advantage of forecasting is that it can be independent of consumers and acquisition schemes, allowing for methods to be applied to any type of acquisition system. However, it generally lacks the ability to interact with acquired EoL products, in other words, the ability to influence or reduce EoL product uncertainty. This distinction is critical because uncertainty in EoL products may limit the ability to make accurate return forecasts.

Recent PrAM literature has explored ways to provide more control to EoL product acquisition to not only reduce EoL product uncertainty but also to prevent volatile inventory levels and, potentially, low customer satisfaction (Gupta and Ilgin 2012). Guide and Van Wassenhove (2001) formally outline a value recovery approach that stresses the proper management of product returns through the use of an Economic Value Added (EVA) approach and present a case study discussion regarding the cell phone remanufacturer, Recellular. Their discussion identified future research in EoL product acquisition as mathematically defining the objective functions that characterize PrAM in order to take advantage of optimization models. A key aspect pointed out in Guide and Van Wassenhove (2001) was that the relationship between EoL product return incentives and returned products is necessary as this would provide a mathematical relationship between acquisition price and EoL product quality (and potentially EoL product quantity and timing as well). Incentives are defined as any type of motivation for a consumer to return an EoL product, including monetary, refunds, penalties, or discounts. Incentives have been shown to effectively influence consumer preference in other cases such as for at home meal delivery timing (Campbell and Savelsbergh 2006). Initial approaches to mathematically analyzing PrAM decisions have sought to determine the optimal buy-back and selling/reprocessing cost (Guide Jr et al. 2003; Klausner and Hendrickson 2000). In each case the relationship between the acquisition incentive (buy-back price) and the remanufacturing yield (high EoL product quality correlating to a higher yield) was linear and the optimization models were based on expected value, lacking sufficient analysis regarding the impact of EoL product uncertainty.

Three studies that explicitly account for consumer return decisions do so to determine the optimal location of a collection facility and optimal buy-back incentive (Aksen et al. 2009; Aras and Aksen 2008; Aras et al. 2008). Various scenarios were considered; a product pick-up, voluntary return, and government subsidized acquisition schemes. Each scheme altered the utility of the consumer, the location of the centers, and the perception of the recovery enterprise towards EoL product recovery. Consumer willingness to return was modeled as a uniform distribution, and the relationship between consumer incentive and EoL product return was modeled discretely (Aras and Aksen 2008; Aras et al. 2008) and as a right triangle distribution (Aksen et al. 2009). Wojanowski et al. (2007) also studied a deposit refund acquisition system, with customer preferences incorporated as a discrete choice model. Utility theory was used to model a consumer return decision using a uniform distribution for stochastic utilities. More recently, Galbrath and Blackburn (2010) and Kaya (2010) revisited the optimal incentive/acquisition amount problem for the case where EoL product condition is uncertain, requiring an acquired EoL product amount greater than the demand (Galbreth and Blackburn 2010), and the case where a manufacturer produces new products with virgin and remanufactured components (Kaya 2010). Other types of incentives have been proposed as a means to improve EoL product control through PrAM. A relicensing fee was used as a method to control information technology (IT) server resale, particularly for situations where a higher price was offered by third party dealers (Oraiopoulos et al. 2012). A more direct method applied a non-refundable fee to avoid unwarranted product returns (Hess et al. 1996), while an indirect method that utilized tax systems as incentives was proposed in Shiose et al. (2001).

Two of the overarching influences in PrAM systems from previous literature are consumer decisions and product acquisition schemes. Research has indicated that these two aspects of value recovery have a significant impact on collection center location, reselling price, acquisition quantity, etc. As a product reaches its EoL a consumer analyzes the tradeoffs between available return incentives, potential remaining value, and disposal. Three deciding factors for the consumer are durability, age, and remaining value, which are combined in this dissertation as EoL product quality. Durability is the product's ability to withstand use and maintain an acceptable level of performance. Age is how long a product has been in use and can be quantified in many units, such as hours or years. Age can be related to durability and performance based the assumption that the performance/durability of a product decreases with advancing age. Remaining value, from a consumer perspective, is correlated with both age and durability but is dependent on individual consumer preferences. Value recovery enterprises may have a different perspective of remaining value than a consumer. Secondary factors that do not directly influence product return but have an impact on consumer decisions are new product substitutions, technology advances, and social pressures.

Value curves have been used in previous research to characterize remaining value from both a consumer and value recovery perspective. Kumar et al. (2007) studied product value from a consumer satisfaction perspective. The consumer satisfaction of a product was predicted to increase post-purchase as the product is fully utilized, and decrease thereafter as the product begins to age and wear. Total consumer value was determined as the integral of consumer satisfaction. Brown-West et al. (2010) modeled remaining electronic waste value according to the product, functionality, and material makeup. Product resale value was modeled as a function of the Manufacturer Standard Retail Price (MSRP), initial depreciation value, depreciation rate constant, and the natural logarithm of the product age. Contrary to Kumar et al. (2007), Brown-West et al. (2010) address the perspective of the recovery enterprise rather than the consumer. This distinction is critical because the point at which the consumer deems the product to be "valueless" may not match with the remanufacturer and may be consumer dependent (Kumar et al. 2007).

EoL product return acquisition schemes are intended to improve the collection of EoL products. Incentives have played a major role in acquisition scheme design, and exist in multiple forms. Systems without incentives have been shown to reduce consumer personal investment in a product to the point where product return is not achieved (Morana and Seuring 2007). Seven common acquisition schemes described in Ostlin et al. (2008) include; 1) ownership-based, 2) service-contract, 3) direct-order, 4) deposit-based, 5) credit-based, 6) buy-back, and 7) voluntary-based. In ownership-based schemes a manufacturer owns a product but it is operated by a consumer, such as rental cars. This scheme offers a high degree of control and a low degree of consumer ownership. Service-contract systems are similar to owner-based but offer more ownership to consumers. Contracts ensure product return to a manufacturer at a specific date, *e.g.* Xerox copiers. Direct-order defines a scheme where the consumer returns a product to a remanufacturer and gets the same product back. Deposit-based has two definitions. First, for high value products, consumers may be obligated to return a similar used product in order to purchase a remanufactured product. Alternatively, deposit-based may also require that consumers pay an added fee upon purchase that is refunded if it is returned. Credit-based schemes give consumers credit towards purchasing a remanufactured product when an EoL product is returned.

The final two schemes presented in Ostlin et al. (2008), buy-back and voluntary-based, rely on consumers, and can be combined to form a single acquisition scheme. These types of product acquisition schemes offer a buy-back price for an EoL product but with the stipulation that consumers voluntarily return EoL products to a scrap yard, retail store, manufacturer, or recovery enterprise. Buy-back schemes have been described as schemes that can offer control over the composition of returns (Klausner and Hendrickson 2000), and can be further divided into three sub-schemes: 1) offering a single incentive for all products regardless of quality or age, 2) creating bins (Ferguson et al. 2009; Guide Jr et al. 2003) that "catch" products of specific quality and offer bin unique incentives, and (3) a continuous incentive curve that mirrors the value versus age curve of a product.

In summary, the literature has indicated that it is critical to study the impact of EoL product uncertainty on value recovery, and the interaction between PrAM, consumers, and value recovery operations such as disassembly. These areas have been identified because of their potential ability to reduce uncertainty in EoL product quality, quantity, and timing, which can increase the yield and profits of value recovery operations.

3. PARTIAL DISASSEMBLY PROBLEM FORMULATION

The PrAM and partial disassembly formulation in this dissertation is divided into three sections; 1) a multi-objective formulation to determine the optimal or near-optimal partial disassembly sequence, 2) the extension of the multi-objective formulation to account for uncertain EoL quality, and 3) modeling the relationship between incentivized acquisition schemes, consumer decisions to return EoL products, and the resulting acquired EoL age distribution.

The partial disassembly problem considers an EoL product with K disassembly nodes, designated as $n_1, n_2, \ldots, n_K$, and K^2 potential disassembly arcs, designated as $a_{nk,nk}$, that represent the physical disassembly operations (Figure 8). In this formulation, the network nodes represent the potential disassembly stages of an EoL product. Each stage is unique and can only be visited via a sequence of disassembly arcs, where the set of arcs is designated as *DS* (Disassembly Sequence) and represented as $\{a_{nk,nk}, a_{nk,nk}, \ldots, a_{nk,nk}\}$. The sequence of disassembly arcs, which controls the sequence of nodes visited, determines objective function values. It is assumed that a disassembled component is remanufactured (cleaned, inspected, refurbished, and resold/recycled), and any components not disassembled are recycled via shredding and separating processes, or scraped.

Feasibility is an essential parameter because a *DS* is a valid solution only if it can physically be performed on an EoL product. A feasibility measure, *F*, represents the percentage of arcs in the set *DS* that are physically possible with an EoL product. For example, an *F* score of one indicates that all

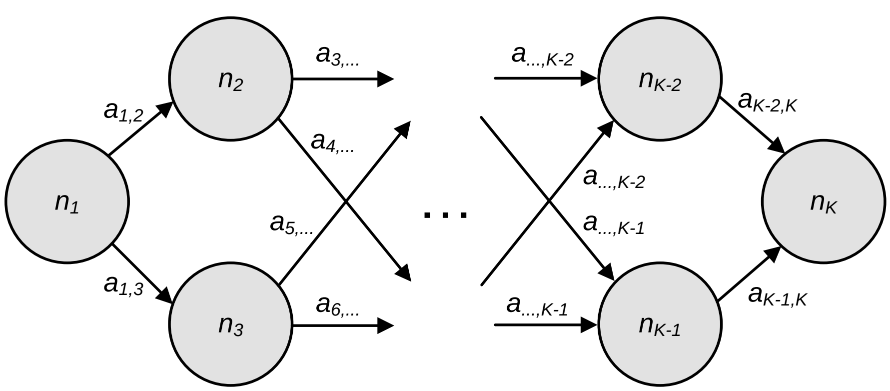

Figure 8 Network architecture for direct disassembly network

the disassembly arcs (and their order) in the *DS* are feasible. Alternatively, an *F* score of zero indicates that none of the disassembly arcs in a *DS* can physically be performed. Intermediate values between zero and one indicate that only subsets of the arcs in *DS* are feasible. As such, *F* is a function of the arcs in a *DS* and must equal to one in order to create a viable solution.

Only a small percentage of the K^2 potential disassembly arcs are feasible. Feasible disassembly arcs are represented by a precedence matrix, *P* in Eq. 1, which is created from the node-to-node interactions of the disassembly network (Giudice and Fargione 2007; Kongar and Gupta 2005; Seo et al. 2001). *P* is derived from a directed flow network, Figure 8, with a single start node (the fully assembled EoL product) and a single end node (fully disassembled EoL product). A disassembly operation, $p_{i,j}$, is depicted as a zero if it is not feasible and as a one if it is feasible.

$$P = \begin{bmatrix} p_{1,1} & \cdots & p_{1,K} \\ \vdots & \ddots & \vdots \\ p_{K,1} & \cdots & p_{K,K} \end{bmatrix} \text{ where } p_{i,j} = \{0,1\} \forall i,j \ \& \ i,j = 1,2,\ldots,K \tag{1}$$

3.1. Multi-Objective GA for Costs, Environmental Impact, and Sequence Feasibility

A formal representation of the multi-objective problem is shown below (Rickli and Camelio 2013). Feasibility is included in the objective function rather than as a constraint, and is calculated as a penalty function that is maximized. This is done in order to use infeasible *DS* to converge to optimal or near-optimal *DS*. Cost, revenue, and environmental impact values of a disassembly sequence are a function of the disassembly arcs and disassembly nodes. Revenue values are strictly a function of the resale or recycling of components from the *DS* terminating node, and are considered because revenues fluctuate between recycling, remanufacturing, and resale EoL treatment decisions.

$$\max_{DS}\left(C(DS)\right), \min_{DS}\left(E(DS)\right), \max_{DS}\left(F(DS)\right)$$
$$\text{where } DS = \left\{a_{k,k}, a_{k,k}, \ldots, a_{k,k}\right\}$$

An extension of the precedence matrix, Eq. 1, is the disassembly operation cost matrix, A_C in Eq. 2, which substitutes the placeholder "1" in the precedence matrix with the cost, $c_{i,j}$, for the arc's associated disassembly operation. In the case that environmental impacts, A_E, are considered, $c_{i,j}$ would be replaced by $e_{i,j}$, Eq. 2. The diagonal and lower triangle of P will always be zero because these positions represent arcs going from and to the same node or arcs going in the reverse direction (*i.e.* from node 4 to node 2). These types of arcs are not permitted in the directed disassembly flow network.

$$A_C = \begin{bmatrix} c_{1,1} & \cdots & c_{1,K} \\ \vdots & \ddots & \vdots \\ c_{K,1} & \cdots & c_{K,K} \end{bmatrix} \qquad A_E = \begin{bmatrix} e_{1,1} & \cdots & e_{1,K} \\ \vdots & \ddots & \vdots \\ e_{K,1} & \cdots & e_{K,K} \end{bmatrix} \tag{2}$$

N_{Ck} denotes the summation of the cost and revenue (net profit) at node n_k, Eq. 3. Node costs and revenues are dependent on the components that have or have not yet been disassembled. cn_m is the cost of remanufacturing, recycling, and scraping the disassembled components, and rn_m is the revenue from reselling used or remanufactured components and the revenue from recycled material. Revenues and costs are summed over all M components/subassemblies that make up the EoL product. The nodal environmental impacts, en_m, are similarly represented as N_{Ek}, Eq. 4.

$$N_{Ck} = \begin{bmatrix} cn_1 \\ cn_m \\ \vdots \\ cn_M \end{bmatrix} + \begin{bmatrix} rn_1 \\ rn_m \\ \vdots \\ rn_M \end{bmatrix} \forall k = 1,2,\ldots,K \tag{3}$$

$$N_{Ek} = \begin{bmatrix} en_1 \\ en_m \\ \vdots \\ en_M \end{bmatrix} \forall k = 1,2,\ldots,K \tag{4}$$

The scope of the environmental impact, cost, and feasibility partial disassembly problem is limited to the disassembly and recovery of an EoL product. This means that disassembly and recovery process environmental impacts are desired over material extraction and original manufacturing environmental impacts. Including material impacts normally attributed to product manufacturing can skew the actual environmental impacts of recovery. As such, the most critical environmental impacts originate from disassembly operations, remanufacturing processes, recycling processes, and scrapping/landfilling.

Unfortunately, assessing the impacts of value recovery processes is difficult due to a lack of dedicated data, and because, generally, LCA software requires the inclusion of material extraction impacts. Process specific environmental impacts are estimated by subtracting the environmental impacts attributed to material extraction from the combined processing and material extraction environmental impacts. Disassembly arc environmental impacts are be calculated using Eq. 5, where $e_{k,k}$ is the environmental impact value of each arc, $DP_{m(i,j)}$ is the environmental impact of disassembling component *m*, and $MI_{m(i,j)}$ is the material extraction impact of component *m*. Likewise, en_k is the impact value of a disassembly node, *MI* is the material extraction impact of all components of the EoL product, and *T* is the total impact of all recovery processes, *l* at node *k*. By using Eq. 5 and 6, environmental impact values are be obtained that estimate the recovery processes. All environmental impacts use the environmental points scale as calculated by the LCA software Simapro.

$$e_{k,k} = DP_{m(i,j)} - MI_{m(i,j)} \tag{5}$$

$$en_k = \sum_{l \in k} T - MI \tag{6}$$

3.1.1 Cost and Environmental Impact Objective Function Value

The net profit and environmental impact objective function values of a *DS* are composed of a disassembly arc and a disassembly node value. The arc value represents the cost and impact of disassembly operations needed to reach a certain disassembly node. Alternatively, node values represent the cost, revenue, and impact resulting from remanufacturing, reusing, recycling, or scrapping components at a given disassembly node. Equation 7 illustrates the process of determining the arc objective function component for cost, $AV_{C,CH}$, and environmental impact, $AV_{E,CH}$. A matrix with ones (which is later defined as a chromosome) indicating the arcs of the disassembly sequence, $ch_{i,j}$, is multiplied by each cell in the cost matrix, $c_{i,j}$, and summed.

Equation 8 shows the node value calculation for net profit and environmental impact, $NV_{C,CH}$ and $NV_{E,CH}$ respectively. It requires that the furthest right column with a one from the CH_F be determined. V_{cmax} is a vector of zeros of length $K+1$ with a one in the cell that corresponds to the furthest right column with a one (corresponding to the DS end-node). A vector multiplication with N_C or N_E from Eq. 3 or 4 results in the DS nodal net profit and environmental impact objective function value. The final objective function value for net profit, C_{CH}, and environmental impact, E_{CH}, for a single chromosome is the sum of the arc value and node value, shown in Eq. 9. The cumulative environmental impact of a disassembly sequence is more dependent on the set of disassembly operations and EoL treatments rather than unique disassembly sequences, whereas costs can be dependent on the sequence of disassembly operations.

$$\begin{aligned} AV_{C,CH}(DS) &= \sum_{i=1}^{K+1}\sum_{j=1}^{K+1} ch_{i,j}c_{i,j} \\ AV_{E,CH}(DS) &= \sum_{i=1}^{K+1}\sum_{j=1}^{K+1} ch_{i,j}e_{i,j} \end{aligned} \tag{7}$$

$$\begin{aligned} NV_{C,CH}(DS) &= N_C V_{cmas}(DS) \\ NV_{E,CH}(DS) &= N_E V_{cmas}(DS) \end{aligned} \tag{8}$$

$$\begin{aligned} C_{CH}(DS) &= AV_{C,CH} + NV_{C,CH} \\ E_{CH}(DS) &= AV_{E,CH} + NV_{E,CH} \end{aligned} \tag{9}$$

3.1.2 Feasibility Objective Function Value

The feasibility objective function value is a ratio of feasible disassembly arcs to the total number of disassembly arcs specified by a *DS* (feasible and infeasible), where s_f is the number of feasible disassembly arcs, s_p is the set of all disassembly arcs, and F_{CH} is the chromosome feasibility value. For example, consider a chromosome that activates arcs *1-2* and *1-3*, where both arcs, individually, are feasibly disassembly processes. However, let's consider that only *1-2* or *1-3*, not both, is a feasible disassembly sequence. According to Eq. 10, the feasibility of this sequence would be 0.5.

$$F_{CH}(DS) = \frac{s_f}{s_p} \text{ for all population chromosomes} \tag{10}$$

Equation 10 sufficiently characterizes chromosome feasibility for problems with few disassembly nodes, but its effectiveness deteriorates for disassembly problems that have many nodes. To show this, let DS_1 be *1-2-5-9* and DS_2 be *1-2-5-40* and let the disassembly network have $K = 40$ nodes. Also, let all arcs of DS_1 be feasible except for *5-9* and let all arcs in DS_2 be feasible except for *5-40*. According to Eq. 10, DS_1 and DS_2 would have identical feasibility metric values even though it is more likely that DS_1 is closer to being feasible (*i.e.* if *5-9* was a feasible arc) than DS_2, which may require multiple arcs to get from node 5 to node 40.

For this reason, the denominator in Eq. 10 is altered to compensate for the worst-case scenario required to reach a feasible sequence, Eq. 11. This is represented by the variable s_{pen} in the denominator of the feasibility objective function. For sequence *1-2-5-9*, four nodes are required in the worst case (*5-6,6-7,7-8,8-9*). However, the worst-case scenario would require thirty-six nodes for sequence *1-2-5-40*. As a result of Eq. 11, the infeasible sequence *1-2-5-9* has a better feasibility metric value than *1-2-5-40*. This process is repeated for each infeasible gap in a sequence, and has the additional benefit of offsetting any tendencies the solution procedure may have to favoring longer sequences/latter end-nodes (due to the existence of more feasible sequences) since shorter sequences with early end-nodes are penalized less.

$$F_{CH}(DS) = \frac{s_f}{s_p + s_{pen}} \text{ for all population chromosomes} \tag{11}$$

3.2 Partial Disassembly Considering Uncertain Age Distributions

The multi-objective partial disassembly optimization considering random EoL product age is as follows: 1) maximize the expected profit of an EoL product, *E(f(DS))*; 2) minimize the profit variation of an EoL product, measured as profit standard deviation, *STD(f(DS))*; 3) maximize EoL product profit probability, *p(f(DS))*, which is the probability that the revenue from an EoL product is greater than the disassembly and reprocessing costs and 4) maximize the partial disassembly sequence feasibility, *F(DS)*, as shown below.

$$\max_{DS}\Big(E\big(f(DS)\big)\Big), \min_{DS}(STD(f(DS))), \max_{DS}(p(f(DS)) = P\{f(DS) > 0\}), \text{ and } \max_{DS}\big(F(DS)\big)$$

$$where\ DS \subseteq \{a_{1,1}, \cdots, a_{i,j}, \cdots, a_{K+1,K+1}\} \ \&\ f(DS) = \sum_{i=1}^{I_{DC}} V_i(x) - C_{DS} + S_{DS}$$

Where *DS* is a potential disassembly sequence dependent on the EoL product age distribution and is defined as a subset of the arcs in the directed flow network and *f(DS)* is the function representing the costs and revenues associated with *DS*. The function, *f(DS)* is dependent on the disassembly sequence and is composed of disassembly and remanufacturing costs (C_{DS}), salvage values (S_{DS}), and component value curves, $V_i(x)$. $V_i(x)$ is the value curve of the i^{th} component of an EoL product and is a function of the product age, *x*. It is assumed that the age distribution of acquired EoL products is known, that these distributions correlate to EoL product quality, and that $V_i(x)$ is an accurate estimate of the remaining value of the i^{th} EoL product component. Pareto optimal solutions are sought because tradeoffs exist between the expected profit, profit standard deviation, and profit probability.

Uncertainty is introduced via an acquired EoL product age distribution that is assumed to correlate to EoL product remaining life and quality. The uncertain age distribution partial disassembly sequence optimization approach is based on section 3.1, thus, sequence feasibility is included in the objective function in order to penalize infeasible disassembly sequences. The following sub-sections mathematically define the product value curve, EoL product age distribution, expected profit, profit standard deviation, profit probability.

3.2.1 Product Value Curve

Accurate product value curve estimation is critical to successfully predicting the remaining value of EoL products. Inaccurate estimations leads to poor decision making in terms of collection mechanisms, disassembly sequences, and EoL treatments, which leads to poor yield per EoL product. It is also important that each stakeholder, such as consumers (Kumar et al. 2007) or the recovery enterprise (Brown-West et al. 2010), is clearly defined as this can have a major impact on the associated value curve.

In this formulation, the total product value is the sum of individual component value curves. The life cycle value of each component are modeled as negative exponential functions (Eq. 12). The negative exponential function is monotonically decreasing and represents the recovery enterprise's estimation of value, not the consumer's. In Eq. 12, V_i is the remaining value of component i at time x, m_i is the scaling coefficient that controls the initial value of component i, and n_i is the depreciation coefficient of component i (I_{CT} is the total number of components in the EoL product). Component value curves only characterize the remaining functional value in a component for reuse and remanufacturing EoL treatments. Material value is assumed constant for the cases that a component is scrapped or recycled.

$$V_i(x) = m_i * e^{-n_i x} \; for \; i = 1 \cdots I_{CT} \tag{12}$$

3.2.2 *Acquired EoL Product Age Distribution*

For some systems, such as Xerox printer cartridges, age distributions are less of a factor due to controlled lease agreements and relatively consistent operating conditions. Kwak et al. (2011) illustrate the uncertainty that can accompany voluntary collection schemes. Returned printers ranged from 5 to 20 years, laptops 5 to 20 years, computer monitors 1 to 20 years, printers 1 to 20 years, and televisions 1 to 30 years old. Collected products were aggregated considering different models, which may account for some of the observed variability (Kwak et al. 2011). Brown-West et al. (2010) were able to best characterize EoL product age distributions with the gamma distribution. In addition, product age was found to be the most influential factor of revenue variation among volume of returns, depreciation rate, commodity prices, MSRP, product mix, and product age (Brown-West et al. 2010). Thus, acquired EoL product age distributions in this method are characterized as gamma distributions, Eq. 13. In Eq. 13, θ is the scale parameter, k is the shape parameter, and x is the random variable (EoL product age in this case).

$$f(x,k,\theta) = \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k}\ for\ x > 0, k > 0, \theta > 0 \tag{13}$$

The gamma distribution matches the characteristics of EoL products, *e.g.* the minimum age that acquired EoL products can have is 0 (immediately post-purchase) and the maximum age can theoretically be infinity. The gamma distribution accepts both of these characteristics and can be controlled by θ and k to create different age distributions that a recovery enterprise may encounter. Also, it is tractable with negative exponential value curves and is able to simplify the expected profit and profit variance to a closed form solution given the component value curve in Eq. 12.

3.2.3 *EoL Product Expected Profit Objective Function*

The expected profit objective function is constructed from the value curves of each component and the remanufacturing cost, disassembly cost, and salvage revenue that are assumed constant but dependent on *DS*. If a component is disassembled (*i.e.* reused or remanufactured) then the value curve is used, if it is not disassembled (*i.e.* scrapped or recycled), the value curve is replaced with a constant material value that is less than the value of the material (due to shredding or logistical costs). The expected revenue of the reused or remanufactured components of an EoL product is the expected value of the sum of these component revenues and costs, Eq. 14.

$$E\big(f(DS)\big) = E\left(\sum_{i=1}^{I_{DC}} V_i(x)\right) - C_{DS} + S_{DS} \tag{14}$$

Where i is the i^{th} disassembled component out of I_{DC} total disassembled components and $V_i(x)$ is the product value curve, Eq. 13. C_{DS} is the cost of disassembly and remanufacturing and S_{DS} is the revenue for salvaging components not disassembled. C_{DS} and S_{DS} are constant values that are not dependent on the product age like $V_i(x)$. In this form, the sum of the product value curves must be known or easily determined to calculate the expected profit. Alternatively, the expected profit can be divided into its individual component value curves as shown in Eq. 15. In this formulation, the component value curves are not aggregated to a single function, which is helpful in determining a closed form solution of $E(f(DS))$.

$$E\left(\sum_{i=1}^{I_{DC}} V_i(x)\right) = \sum_{i=1}^{I_{DC}} E\big(V_i(x)\big) \tag{15}$$

Calculating the expected profit of *DS* is, thus, simplified to calculating the expected revenue of each individual, disassembled component. The remanufactured or reprocessed expected revenue of a single component is determined by integrating the product of Eqs. 12 and 13 as is seen in Eq. 16.

$$E\big(V_i(x)\big) = \int_0^{inf} m_i * e^{-n_i x} * \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k} dx \tag{16}$$

By substituting Eq. 17 for x and dx (integration by substitution) in Eq. 16, a new integral, shown in Eq. 18, is formulated and is the gamma function of k, *i.e.* $\Gamma(k)$.

$$x = y\left(\frac{1}{n_i + \frac{1}{\theta}}\right) \;\&\; dx = dy\left(\frac{1}{n_i + \frac{1}{\theta}}\right) \tag{17}$$

$$E\big(V_i(x)\big) = \frac{m_i\left(n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k}}{\Gamma(k)} \int_0^{Inf} y^{k-1} e^{-y}\, dy \tag{18}$$

As a result, the expected revenue for each component that is disassembled by *DS* can be calculated using Eq. 19. The resulting expected profit of *DS* is the sum of the expected revenue of each disassembled component, Eq. 20, plus revenue from recycling or scrapping, S_{DS}, minus the cost of disassembly and remanufacturing, C_{DS}.

$$E\big(V_i(x)\big) = m_i\left(n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} \tag{19}$$

$$E(f(DS)) = \sum_{i=1}^{I} m_i\left(n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} - C_{DS} + S_{DS} \;\; for\; i = 1 \cdots I_{DC} \tag{20}$$

3.2.4 EoL Product Profit Standard Deviation Objective Function

The components that are disassembled and reused or remanufactured may have an associated variation in revenue, whereas non-disassembled components have an assumed constant material value revenue and cost (*i.e.* variance equal to zero). The closed form solution of the acquired EoL product profit standard deviation is formulated from the definition of the variance of a sum of random variables, Eq. 21.

$$Var(f(DS)) = Var\left(\sum_{i=1}^{I_{DC}} V_i(x)\right) = \sum_{i=1}^{I_{DC}} Var\big(V_i(x)\big) + \sum_{i \neq j} Cov\left(V_i(x), V_j(x)\right) \tag{21}$$

Equation 21 can be reformulated as expected values in Eq. 22. $E(V_i(x))^2$ is known from Eq. 19, and $E(V_i(x)^2)$ and $E(V_i(x)V_{i+j}(x))$ are determined using a similar substitution process that led to Eq. 19, resulting in the formulations shown in Eq. 23 and Eq. 24 respectively.

$$Var(f(DS)) = \sum_{i=1}^{I_{DC}} \left(E(V_i(x)^2) + E\left(V_i(x)\right)^2 \right) + \sum_{i \neq j} \left(E\left(V_i(x)V_j(x)\right) + E\left(V_i(x)\right)E\left(V_j(x)\right) \right) \tag{22}$$

$$E(V_i(x)^2) = m_i{}^2 \left(2n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} \tag{23}$$

$$E\left(V_i(x)V_{i+j}(x)\right) = m_i m_{i+j} \left(n_i + n_{i+j} + \frac{1}{\theta}\right)^{-k} \theta^{-k} \tag{24}$$

As such, a closed form solution for EoL product profit variance of a partial disassembly sequence is formulated in Eq. 25, from which the standard deviation, *STD(f(DS))*, can be determined, $Var(f(DS))^{1/2}$. The number of terms in Eq. 25 is dependent on the number of components disassembled, and increases as the number of disassembled components increases.

$$\begin{aligned} Var(f(DS)) = {} & \sum_{i=1}^{I_{DC}} m_i{}^2 \left(2n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} - \left(m_i \left(n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} \right)^2 \\ & + 2 \sum_{j=1}^{I_{DC}-1} \sum_{i=1}^{I_{DC}-j} m_i m_{i+j} \left(n_i + n_{i+j} + \frac{1}{\theta}\right)^{-k} \theta^{-k} \\ & - \left(m_i \left(n_i + \frac{1}{\theta}\right)^{-k} \theta^{-k} \right) \left(m_j \left(n_j + \frac{1}{\theta}\right)^{-k} \theta^{-k} \right) \; for\ i = 1 \cdots I_{DC} \;\&\; I_{DC} \\ & > 1 \end{aligned} \tag{25}$$

Equation 25 is only applicable if I_{DC} is greater than one. If I_{DC} is equal to one then only one product value curve is specified and the formulation for the variance of the sum of random variables is not necessary. Likewise, an I_{DC} value of zero indicates that the entire EoL product is salvaged. Salvage revenue is assumed constant with zero associated disassembly costs, thus, the variance of I_{DC} is zero. If salvage revenue, disassembly costs, and remanufacturing costs are not assumed constant, the EoL product profit standard deviation must be reformulated to include any salvage revenue, disassembly cost, or remanufacturing cost variance.

3.2.5 Profit Probability Objective Function

The EoL product profit probability is estimated by determining the product age at which the revenue from an EoL product is no longer greater than the cost of recovery (*i.e.* $f(DS)$ equal to zero). This point is determined numerical and is defined as $x_{f(DS)=0}$. It can be assumed that EoL products younger than $x_{f(DS)=0}$ have an $f(DS)$ greater than zero and, as such, are profitable. Products older than $x_{f(DS)=0}$ have an $f(DS)$ less than zero and are thus not profitable. As a result, the profit probability can be determined using the EoL product age distribution as shown in Eq. 26.

$$p(f(DS)) = P\{f(DS) > 0\} = P\{X < x_{f(DS)=0}\} \tag{26}$$

3.3 Integrating PrAM and Partial Disassembly Sequencing

PrAM's capability to influence and manage the quality, quantity, and timing of EoL product returns impacts subsequent recovery operations, including disassembly. This section details the process of integrating a consumer incentivized PrAM buy-back scheme into partial disassembly sequence optimization. Incentives alter the outcome of consumer decisions to return or keep EoL products, and can be set to regulate the parameters of acquired EoL products. Section 3.3 is divided into three subsections: 3.3.1 details a consumers return decision in order to illustrate, in detail, the decision process and provide a deeper meaning to the consumer incentive parameter in the PrAM integrated partial disassembly formulation, which is presented in 3.3.2. Section 3.3.3 extends 3.3.2 to consider EoL product return quantity.

3.3.1 Consumer EoL Product Return Decision

A decision tree, assuming a risk neutral consumer, characterizing consumer decisions to return, keep, or dispose EoL products is shown in Figure 9 (Rickli and Camelio, 2010). The decision tree is composed of two decision nodes (1 and 2) and two uncertainty nodes, where CI_v is the incentive gamble and CP_v is the consumer perceived value gamble. Oi $(i = 1,2,\ldots,5)$ corresponds to the potential outcomes, v is the product value, v_{IN} is the incentive value, v_P is the consumer perceived value, t_{IN} is the age associated with a specific incentive, t_v is the age of a consumer product, and t_K is the product age associated with the consumer perceived value. If the value of a product is known a priori to a consumer then no gambles are taken and the decision that maximizes utility is certain. The decision model formulation assumes the value of a product is not known, a consumer is risk neutral, and information regarding the age distribution of consumer owned products and the incentive is known.

The first decision node contains the consumer decision to either return or not return a product. If no return is selected, a consumer can choose to keep or dispose the EoL product at decision node two. An incentive would be offered if a consumer chooses to return the product. The result is a consumer gamble, CI_v, that has three outcomes: the consumer product value is less than the incentive offered (O1), equal to the incentive offered (O2), or greater than the incentive offered (O3). These

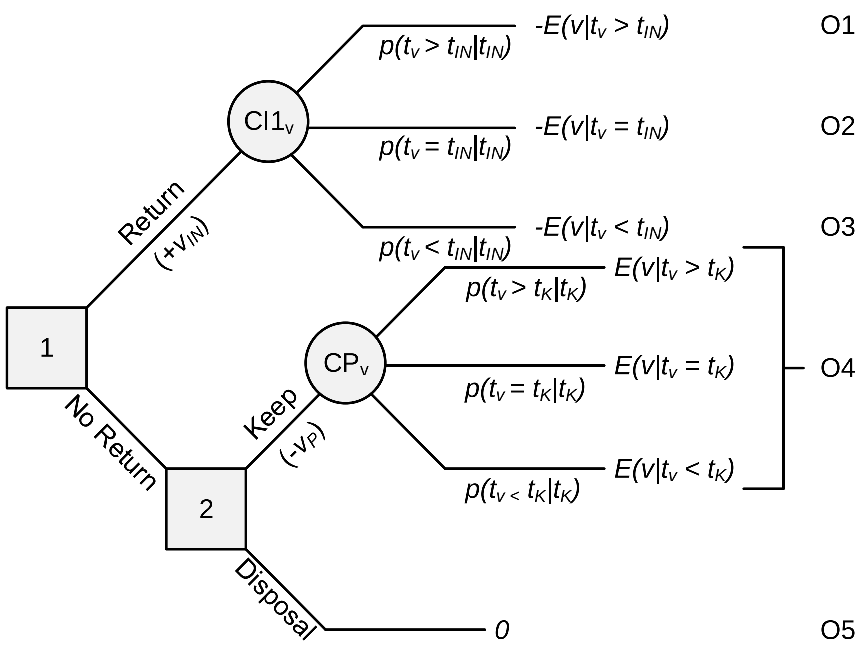

Figure 9 Consumer product return decision tree with incentives

outcome consequences are negative because if a consumer decides to return a product, the remaining product value is sacrificed for the incentive.

In the case that the consumer keeps the product, the value of the product is uncertain, gamble CP_v, and a total of three outcomes are possible. First, the value of the product is less than the consumer perceived value and a negative outcome is reached. The product value may be equal to the consumer perceived value, in which no gains or losses occur, and lastly, the value of the product may be greater than the perceived value and a positive outcome is reached. A consumer chooses to sacrifice the perceived value for the actual product value in a keep decision. To compensate for a lack of consumer preference data, the outcome of a “keep” decision is set equal to the product’s remaining value at the expected product age, O4.

A disposal scenario, O5, has the maximum expected utility if the incentive value is less than the expected product value and the consumer perceived value is greater than the expected product value. Approaches in literature for characterizing EoL product return decision assume that a consumer would purchase or take back a product only if the consumer surplus was positive (Guide Jr et al. 2003; Ray et al. 2005). Consumer surplus is defined as the difference between the consumer perceived value or reservation price and the actual cost. The decision tree formally breaks down the multiple ways that a consumer surplus could be achieved in order to facilitate a better understanding of integrating consumer incentives with partial disassembly optimization.

The outcome of the decision tree, using a beta distribution to represent the age distribution of consumer products, is shown in Figure 10. Incentive values and the beta distribution parameters were varied to determine the boundary between consumer decisions to return or not return a product. Figure 10 maps consumer decisions given the expected consumer perceived value of an EoL product and the corresponding incentive value offered for its return. The white space indicates consumer EoL product return decision while the dark space indicates that a keep decision would be made.

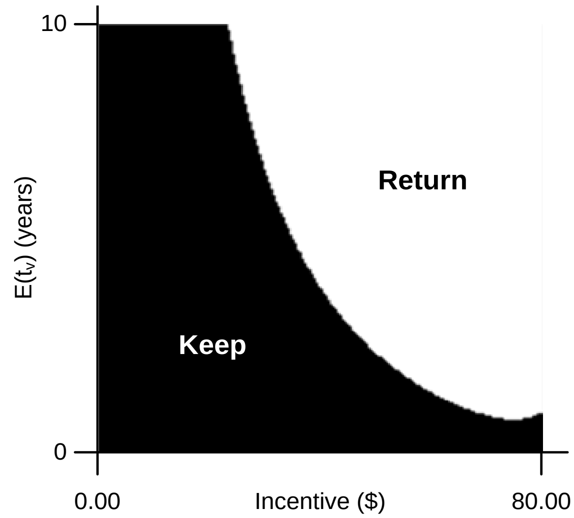

Figure 10 Return or no-return decision for beta age distribution case and variable incentive value

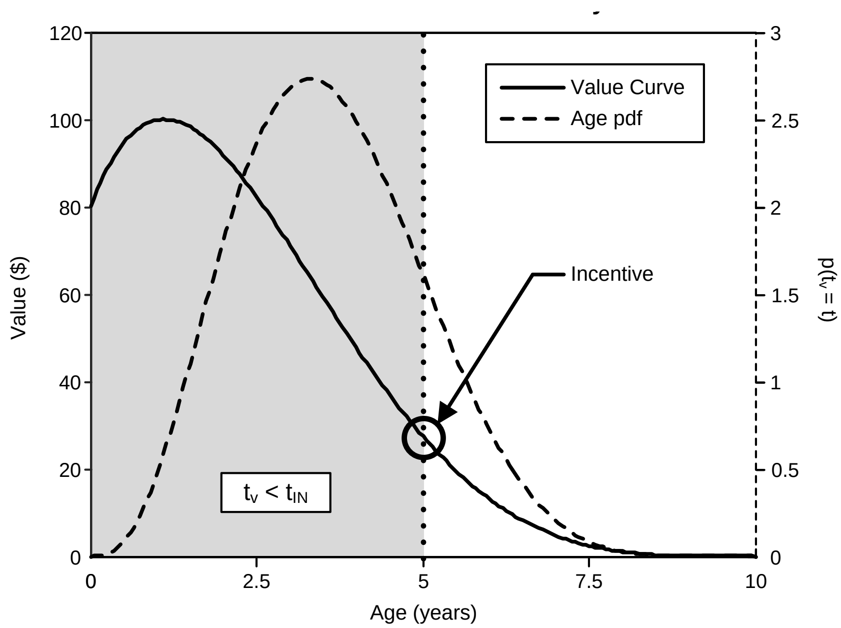

Figure 11 Consumer value curve, the consumer product age distribution, and the incentive value

Figure 11 illustrates a single iteration used to create Figure 10. A theoretical consumer value product curve was created that had a lifetime of 10 years, an initial value of $80, and a maximum value of $100. The consumer value curve increased the consumer product value within the first year to represent the time between first purchase and learning to maximize the potential product value. The y-axis on the left in Figure 11 is used to determine the value of a product from the consumer value curve.

The y-axis on the right in Figure 11 correlates to the probability density function of the age of the products currently owned by consumers.

A consumer's decision, *D*, was calculated based on the maximum expected utility, Eq. 27, where utility is a monetary measure. The resulting *D* value represents the consumers' actions at nodes 1 and 2, Figure 9, and populates the map in Figure 10. Each iteration of the decision tree utilized a constant consumer product value curve.

$$
\begin{aligned}
&P_{O1} = p(t_v > t_{IN}^k | t_{IN}^k) \\
&c_{O1} = v_{IN}^k - E[v | t_v > t_{IN}^k] \\
&P_{O2} = p(t_v = t_{IN}^k | t_{IN}^k) \\
&c_{O2} = v_{IN}^k - E[v | t_v = t_{IN}^k] = 0 \\
&P_{O3} = p(t_v < t_{IN}^k | t_{IN}^k) \\
&c_{O3} = v_{IN}^k - E[v | t_v < t_{IN}^k] \\
&P_{O4} = P_{O5} = 1
\end{aligned} \tag{27}
$$

Decision outcomes were determined using the results of Eq. 28, where c_{Oi} is the consequence and P_{Oi} is the probability of an outcome. A one-to-one relationship between the consequences and utilities is utilized in the model. The consequence of outcomes O2 of the decision tree, c_{O2}, and O5, c_{O5}, are zero because O2 corresponds to a product value equal to the incentive offered, and disposal is not rewarded, O5. A small upper and lower age bound centered at t_{INk} is used to estimate the probability of O2, P_{O2}, and the probability of O5 is trivial (P_{O5} = 1). In the case of O4, the value of a product is unknown but it is assumed that information on the distribution of product ages is known or can be

$$D = \arg max \left[\sum_{i=1}^{3} P_{Oi} c_{Oi} , P_{O4}\, c_{O4}, P_{O5}\, c_{O5} \right] \tag{28}$$

inferred. Thus, the consequence of O4, c_{O4}, is calculated as the consumer value at the product's expected age and its probability, P_{O4}, is equal to one. O1's consequence, c_{O1}, is the expected value of products older than the incentive age, t_{INk}. The probability of O1, P_{O1}, is defined as the probability that a product is older than t_{INk}. The variables c_{O3} and P_{O3} are calculated in a similar manner but for values of an age younger than t_{INk}.

The consumer return decision tree analysis provides insight into the reaction and thought process of a rational consumer weighing a decision to return an EoL product, and how the incentive effects the consumer decision process. However, the tree assumes no prior information regarding a product is known (*i.e.* individuals do not consider the known age of their product). As a result, return decisions apply to an entire population. Thus if an incentive value indicates consumer return, all products are returned by all applicable consumers and no information is known regarding the acquired EoL age distribution.

3.3.2 Consumer Incentivized Partial Disassembly Sequencing

Partial disassembly sequencing considering consumer incentivized take-back relies on acquired EoL age distribution information and, therefore, assumes that individuals have a perfect information regarding product age. Based on this assumption, any product with an age greater than the age correlating to the buy-back incentive is returned (*i.e.* all products older than five years in Figure 11). Thus, the acquired EoL product age distribution is transformed from Eq. 13 to Eq. 29, where x_{IN} is the age on the consumer value curve that correlates to the buy-back incentive, and the consumer value curve is defined as a monotonically decreasing negative exponential, similar to the product value curves represented by Eq. 12, Eq. 31. Considerations for product or consumer specific value curves can be made as well. Kumar et al. (2007) model customer satisfaction with parameters that can be set

$$f_X(x|x > x_{IN}) \tag{29}$$

$$cv = m_{CV}e^{-n_{cv}x} \tag{30}$$

for specific products and, potentially, consumers. Their method proposed that consumer value is the integral of consumer satisfaction, which could be used in place of the negative exponential curve.

Equation 29 requires adjustments to the expected profit and profit variance objective functions. The limits of the expected value integral of disassembled components is revised from zero to infinity to x_{IN} to infinity and the new expected value is a condition of the incentive value, Eq. 31. Summing individual disassembled component expected revenue, Eq. 31, results in the total expected revenue from remanufacturing disassembled components, Equation 32.

$$E(f(DS)|x > t_{IN}) = \sum_{i=1}^{I_{DC}} E(V_i(x)|x > x_{IN}) - C_{DS} + S_{DS} - IN \tag{31}$$

$$E(V_i(x)|x > x_{IN}) = \frac{\int_{x_{IN}}^{inf} m_i e^{-n_i x} * \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k} dx}{\int_{x_{IN}}^{inf} \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k} dx} \tag{32}$$

The EoL product variance, Eq. 33 and 34, is the variance of the sum of the revenue obtained from product disassembly and remanufacturing. Salvage revenue, disassembly costs, and

$$\begin{aligned} Var(f(DS)|x > x_{IN}) &= Var\left(\sum_{i=1}^{I_{DC}} V_i(x)\,|x > x_{IN}\right) \\ &= \sum_{i=1}^{I_{DC}} Var(V_i(x)|x > x_{IN}) + \sum_{i \neq j} Cov\big(V_i(x), V_j(x)|x > x_{IN}\big) \end{aligned} \tag{33}$$

$$\begin{aligned} &Var(f(DS)|x > x_{IN}) \\ &\quad = \sum_{i=1}^{I_{DC}} (E(V_i(x)^2|x > t_{IN}) + E(V_i(x)|x > x_{IN})^2) \\ &\quad + \sum_{i \neq j} \Big(E\big(V_i(x)V_j(x)|x > x_{IN}\big) + E(V_i(x)|x > x_{IN})E\big(V_j(x)|x > x_{IN}\big)\Big) \end{aligned} \tag{34}$$

remanufacturing costs are assumed constant and, thus, do not factor into the variance formulation. The sum of variances, for each component value curve, conditional on the consumer incentive is shown in Eq. 33. Expanding Eq. 33 results in a sum of conditional expected values, Eq. 34, which are determined using the conditional expected value formulation in Eq. 32, as shown for $E(V_i(x)^2)$ and $E(V_i(x)V_j(x))$ in Eqs. 35 and 36, respectively.

$$E(V_i(x)^2|x > x_{IN}) = \frac{\int_{x_{IN}}^{inf}(m_i e^{-n_i x})^2 * \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k}dx}{\int_{t_{IN}}^{inf}\frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k}dx} \tag{35}$$

$$E\left(V_i(x)V_{i+j}(x)|x > x_{IN}\right) = \frac{\int_{x_{IN}}^{inf}\left(m_i e^{-n_i x} * m_{i+j}e^{-n_{i+j}x}\right) * \frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k}dx}{\int_{x_{IN}}^{inf}\frac{x^{k-1}e^{-x/\theta}}{\Gamma(k)\theta^k}dx} \tag{36}$$

Including consumer incentives into the partial disassembly sequence formulation creates a piece-wise solution to EoL product profitability, Eq. 39. Two parameters define the piece-wise solution: $x_{f(DS)=0}$ which is the product age for a given product distribution where the costs of disassembly equal the recovery value and x_{IN} which is the product age that correlates to the consumer take-back incentive. An EoL product is profitable only if the value obtained from the product (via salvage or remanufacturing) is greater than the cost of acquisition, disassembly, and remanufacture. This can also be interpreted as any product that is younger than the product age correlating to the $x_{f(DS)=0}$. Since it is assumed that acquired EoL products have ages greater than or equal to the age correlating to the incentive value, x_{IN}, the profit probability is the probability that an EoL product has an age that is greater than x_{IN} but less than $x_{f(DS)=0}$ if $x_{f(DS)=0}$ is greater than x_{IN}. If $x_{f(DS)=0}$ is less than x_{IN} than the profit probability is equal to zero, Eq. 37.

$$P(f(DS) > 0) = \begin{cases} 0, & if\ x_{f(DS)=0} \leq x_{IN} \\ \frac{P\left(x < x_{f(DS)=0}\right) - P(x < x_{IN})}{1 - P(x < x_{IN})}, & if\, x_{f(DS)=0} > x_{IN} \end{cases} \tag{37}$$

Equations 29 – 37 require that x_{IN} be in units of product age, such as years. Realistically, consumers are offered monetary, or similar, incentives in units of dollars, euros, etc. As such, incentive values that are offered to consumers must be transformed to a unit of time in order to be tractable with the age distribution methodology. Here, a consumer value curve is utilized for this transformation. The consumer value curve is assumed to be an exponential curve that is monotonically decreasing from time equal zero, and represents the value an average consumer believes a product possesses throughout its lifetime. It should be noted that closed-form solutions of the incentive based objective functions were not able to be determined, requiring the use of numerical integration and estimation techniques within the programming language.

3.3.3 Consumer Incentivized Partial Disassembly Sequencing for EoL Product Quantity

Consumer incentives are capable of effecting the acquired EoL product quantity as well as EoL product quality. Since it has been assumed that products older than the incentive age, x_{IN}, are returned, it follows that younger incentive ages return a higher quantity of EoL products than older incentive ages. If the total available product age distribution and the total number of available products is known, then the quantity of returned products can be used to determine the total expected profit of recovery operations, Eq. 38, where *TP* is the total number of products available for value recovery.

$$E(f(DS)|x > t_{IN}) = P(x > x_{IN})(TP)\left(\sum_{i=1}^{I_{DC}} E(V_i(x)|x > x_{IN}) - C_{DS} + S_{DS} - IN\right) \tag{38}$$

This adds another dimension to the uncertain partial disassembly sequence optimization because it provides a measure of total (recovery system) expected profit, rather than on a per product basis. Equation 38 also introduces another type of tradeoff. Lower values of x_{IN} indicate a higher quantity of EoL product than for higher values of x_{IN}. From a per EoL product perspective and only considering expected profit, the x_{IN} and partial disassembly sequence correlating to the highest expected profit per EoL product would be chosen. This need not always be true when the quantity or acquired EoL product is considered. Assuming that lesser values of x_{IN} have a worse per EoL product expected value, the lesser/younger x_{IN} would be more optimal should the number of acquired EoL products be enough to counterbalance the high per product expected profit of the higher x_{IN} scenario.

4. PARTIAL DISASSEMBLY GENETIC ALGORITHM PROCEDURE

A specialized genetic algorithm (GA) is developed to determine the optimal or near-optimal partial disassembly sequence. Genetic algorithms for disassembly sequence optimization have been used in various forms by Tripathi et al. (2009), Seo et al. (2001), Giudice and Fargione (2007), Kongar and Gupta (2005), Dini et al. (1999), Caccia and Pozzetti (2001), and Galantucci et al. (2004). The multi-objective partial disassembly sequence GA structure is composed of a chromosome, initial population, objective functions, multi-objective fitness function, a crossover operation, and a mutation operation. These elements of the GA are critical to achieving convergence to optimal or near-optimal solutions, and can act as adjustable parameters to improve performance for unique disassembly situations.

4.1. Chromosome Representation

GA chromosomes are potential solutions that are analyzed during each GA generation. Construction of a chromosome is situation dependent and is heavily influenced by constraints and objectives. Typically, GA chromosome formulations are binary representations of problem variables in order to take advantage of sampling the hyper-plane partitions of a search space (Whitley 1994). Chromosome representation for disassembly optimization purposes has evolved to include information regarding various process parameters such as disassembly direction, sequence, and gripper changes (Galantucci et al. 2004); direction, disassembly method, demand, and material type (Kongar and Gupta 2005); disassembly sequence (Giudice and Fargione 2007), (Caccia and Pozzetti 2001), (Seo et al. 2001); and sequence, assembly direction, and gripper sequence (Dini et al. 1999).

Here, the GA employs a binary matrix chromosome that represents a set of disassembly operations, *DS*, to be performed during disassembly. This chromosome structure is chosen because it is easily expanded for networks with more arcs and it allows simple matrix operations to be used for objective function value computations. A disassembly sequence of the form *1-2-4-6-10-12* is represented in GA operations as a binary matrix with a value of one at the cells corresponding to the 1-2, 2-4, 4-6, 6-10, and 10-12 disassembly arcs, where the first number is the *from node* and the second is the *to node*. For matrix construction purposes, the *from node* is the chromosome cell row and the *to node* is the cell column. In this manner, the size of each chromosome is a function of the number of nodes in the disassembly network. More specifically, if a network has K nodes then chromosomes will be at least $K \times K$ in size.

The partial disassembly problem permits disassembly sequences to vary in operation order and vary in length, increasing problem difficulty. The GA addresses this difficulty by assigning a byte to all potential disassembly arcs in the chromosome. Sequence orders and sequence lengths both vary depending on the arcs that make up a disassembly sequence. However, a solution of no disassembly (which would be depicted by staying at node one in the directed disassembly network) is difficult with chromosomes designed for arcs because the no disassembly node can never be reached by an arc. To remedy this, a dummy node is added prior to node one, called node zero. Node zero only has one feasible disassembly operation; from node zero to node one with zero cost and zero environmental impact. An optimal disassembly sequence that requires no disassembly (*i.e.* ends at node one) is thus represented by a binary chromosome with a feasible 0-1 arc and with no other arcs activated. Due to this alteration, the actual *from node* is the cell row minus one and the *to node* is the cell column minus one.

The precedence matrix, Eq. 1, must be transformed to reflect the zero node addition as well, else arc 0-1 will be deemed infeasible. The matrix transformation requires that a column of zeros be inserted on the left side of the precedence matrix and a row of zeros be added at the top. Lastly a 1 is placed in row 1:column 2 to represent the feasible 0-1 arc. Equation 39 and 40 show the chromosome transformation require to account for the no-disassembly case.

A chromosome filtering step is performed in order to extract only the chromosome cells that contribute to objective function values, *i.e.* only cells that have a value of one in the precedence matrix

$$CH = \begin{bmatrix} ch_{1,1} & \cdots & ch_{1,K+1} \\ \vdots & \ddots & \vdots \\ ch_{K+1,1} & \cdots & ch_{K+1,K+1} \end{bmatrix} \text{ where } ch_{i,j} = \{0,1\} \forall i,j \ \& \ i,j = 1,2,\ldots,K+1 \quad (39)$$

$$P_{RC} = \begin{bmatrix} 1 & 0 & \cdots & 0_K \end{bmatrix} \ \& \ P_{CC} = \begin{bmatrix} 0 & \cdots & 0_K \end{bmatrix}$$

$$P_{new} = \begin{bmatrix} 0 & P_{RC} \\ P'_{CC} & P \end{bmatrix} \quad (40)$$

and a one in the chromosome. An array matrix multiplication (designated as .*) filters the raw chromosome (*CH*), Eq. 41, where P_{new} is the precedence matrix from Eq. 40 and CH_F is the filtered chromosome. Equation 42 illustrates a filtered chromosome and an exact conversion of the filtered chromosome from a binary chromosome to a disassembly sequence in terms of arcs and nodes.

$$CH_F = P_{new} .* CH \quad (41)$$

$$CH_F = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (42)$$

where DS = 0 – 1, 1 – 3, 3 – 5, 5 – 6 for a final node sequence of 1-3-5-6

4.2. Initial GA Population

A GA initial population is a collection of potential solutions that initialize the evolutionary optimization heuristic. Typically, a randomly generated set of chromosomes is used as the initial population in order to introduce a sufficient degree of diversity. However, disassembly sequence problems are unique due to strict feasibility constraints on the order of disassembly operations. Lambert (2003) notes this dilemma and stresses the reduction of the search space prior to optimization routines, particularly as the problem size expands. Giudice and Fargione (2007), Kongar and Gupta (2005), Seo et al. (2001), Caccia et al. (2001), and Dini et al. (1999) all implement a type of feasibility constraint for initial population generation.

Contrary to previous research, the initial population in this GA is a randomly generated set of sequences that can either be feasible or infeasible. This is done in order to increase the resolution of the partial disassembly sequence problem search space. Each cell in each binary chromosome matrix has a 50% probability of being a one or a zero during the initial population creation. Due to the matrix representation, each chromosome has a higher probability of ending at a latter node than an earlier node. This may seem to be a disadvantage because initial population diversity is void of short sequences. However, the number of feasible disassembly sequence solutions with latter end-nodes is greater than the number of sequences with early end-nodes. Also, disadvantages resulting from less initial population diversity can be avoided so long as the GA can converge to shorter sequences with earlier end-nodes.

Accepting infeasible sequences allows for a near-optimal or optimal feasible chromosome to be reached from an infeasible chromosome that traditionally may be rejected from the initial or even subsequent GA generations. This advantage is illustrated by comparing raw chromosome one, CH_1, to raw chromosome two, CH_2 in Eq. 43 and Eq. 44 respectively. Assume that chromosome CH_1 is an infeasible *DS* and would therefore be excluded from the feasible search space even though differs from what is assumed to be the optimal feasible solution, CH_2, by only a single cell (shown as double underlined). A GA that recognizes and compensates for disassembly sequence infeasibility rather than rejecting infeasible chromosomes increases search space resolution and opens paths that lead to optimal or near-optimal solutions.

Considering consumer incentives in the partial disassembly sequencing method requires that a new chromosome be created in the GA for the incentive value. The incentive chromosome means that the incentive is a decision variable of the GA and will evolve in order to determine the optimal or near-

$$CH_1 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & \underline{\underline{1}} & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \text{infeasible} \tag{43}$$

$$CH_2 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & \underline{\underline{0}} & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \rightarrow \text{feasible \& } \textit{optimal} \tag{44}$$

optimal consumer incentive and partial disassembly sequence. The incentive value is a combination of two chromosomes, where each chromosome is 1x*L* in size. The first chromosome represents the incentive value to the left of the decimal place and the second chromosome represents the right hand side of the incentive value. In this chromosome, *L* represents the length of the binary incentive chromosome which controls the number of possible incentives. The results of the consumer incentive partial disassembly cases utilized an *L* value of 4 since the remaining product value in the case study is close to zero at product ages greater than 15 years (an *L* value of 4 allows for the incentive to range from 0 to 16).

4.3. Chromosome Fitness Evaluation

Fitness functions combine net profit, environmental impact, and feasibility objective functions into a single chromosome fitness value for multi-objective optimization. Parent selection for GA crossover operations is based on the fitness value, not individual objective function values. This type of fitness function is necessary because each objective function is based on independent units and scales.

4.3.1. Environmental Impact and Cost Fitness Function

Summing the net profit, environmental impact, and feasibility objective function values is not ideal for finding Pareto optimal solutions due to different units and scales. To counteract these challenges, the GA normalizes all chromosome objective function values in a GA generation to a unit-less, [0,1] scale. The worst value of each objective function in the current generation is mapped to zero and the best value mapped to one. In this manner, each objective function in the current generation has identical units and scales, and each can be maximized for optimal or near-optimal solutions. Equation 45 illustrates the normalization equation for net profit, C_{CH}, which is identical for environmental impacts, E_{CH}, and feasibility, F_{CH}.

$$C_{CH,N} = \frac{C_{CH} - min(C_{CH})}{max(C_{CH}) - min(C_{CH})} \tag{45}$$

A Euclidean distance function with weights, Eq. 46, is employed to calculate a single fitness value from the normalized objective function values. A weighting sum, not using Euclidean distance, for disassembly sequence optimization was shown to be effective in Giudice and Fargione (2007). The global optimal value, *(1, 1, 1)*, correlating to a chromosome with the current generation's maximum net profit, minimum environmental impact, and a feasibility equal to one, is the absolute optimal point that a chromosome can have in a GA generation. Example solution spaces with, (a), and without, (b), equal weights are shown in Figure 12.

In Eq. 46, FV_{CH} is the fitness value of chromosomes in a GA generation, w_C is the weight assigned to disassembly costs, w_E is the weight assigned to environmental impacts, and w_F is the weight assigned to sequence feasibility.

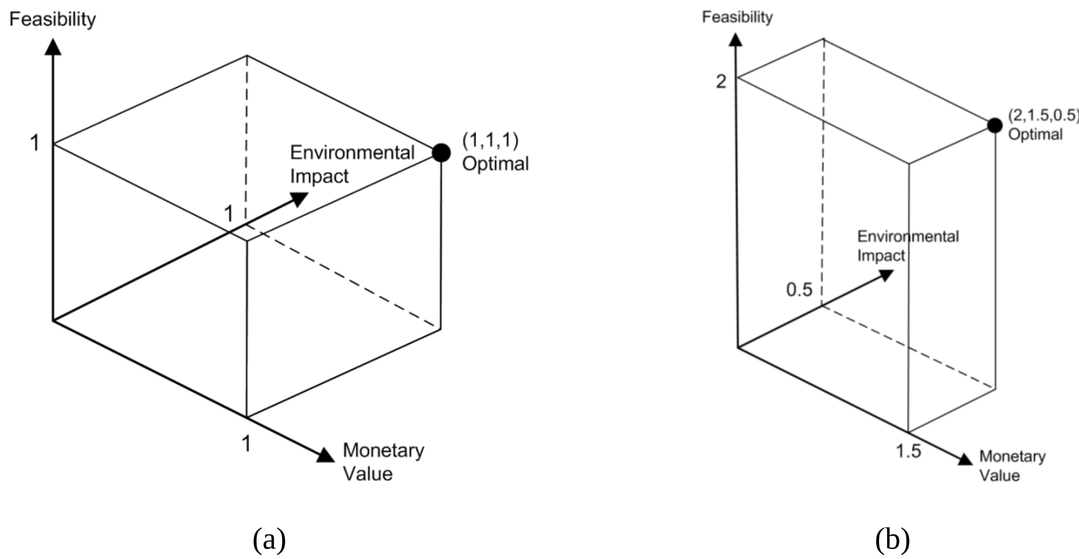

Figure 12 Euclidean distance solution space with equal (a) and with non-equal (b) weights

Pareto frontiers contain non-dominated solutions, requiring a decrease in one objective function to gain an increase in another objective function. This holds true for the disassembly sequence optimization except for feasibility. A chromosome cannot have a feasibility value greater than one and must have a feasibility value of one to be physically possible. Therefore, the Pareto frontier, when considering feasibility, profit, and environmental impact, is generally restricted to net profit and environmental impact.

$$FV_{CH} = \sqrt{\left(w_C * C_{CH,N}\right)^2 + \left(w_E * E_{CH,N}\right)^2 + \left(w_F * F_{CH,N}\right)^2} \tag{46}$$

4.3.2. Fitness Function for Uncertain Age Distributions

The fitness function for partial disassembly considering uncertain age distributions is identical to the fitness function for the partial disassembly problem that consider consumer incentives. Chromosome objective function values for expected profit, profit standard deviation, and profit probability are normalized in each GA generation in order to eliminate differences in scale and units. Expected profit and profit probability are normalized so that the maximum value of a generation is one and profit standard deviation is normalized so that the minimum value of a generation is one (Eq. 47).

$$E_N(f(DS)) = \frac{E(f(DS)) - \min\big(E(f(DS))\big)}{max\big(E(f(DS))\big) - \min\big(E(f(DS))\big)}$$

$$p_N(f(DS)) = \frac{p(f(DS)) - min(p(f(DS)))}{max\big(p(f(DS))\big) - \ min(p(f(DS)))} \tag{47}$$

$$STD_N(f(DS)) = \frac{max(STD(f(DS))) - \ STD(f(DS))}{max(STD(f(DS))) - \ min(STD(f(DS)))}$$

$$FV = \big(1 - w_{F(DS)}\big)\bigg(\Big(w_{E(DS)}E_N(f(DS))\Big)^{FVP} + \Big(w_{STD(DS^*)}STD_N(f(DS))\Big)^{FVP} + \Big(w_{p(DS^*)}p_N(f(DS))\Big)^{FVP}\bigg) + w_{F(DS)}\big(F(DS)\big)^{FVP} \tag{48}$$

As a result, the objective of the GA search is to maximize the multi-objective fitness function. Fitness function values, *FV*, are calculated as a sum of the weighted normalized values raise to a specific power, parameter *FVP*, Eq. 48, where $w_{E(DS)}$ is the weight of the normalized expected profit ($E(f(DS))_N$), $w_{STD(DS)}$ is the weight of the normalized profit variation ($STD(f(DS))_N$), w_p is the weight of the normalized profit probability($p(f(DS))$), and w_F is the weight of the feasibility objective, $F(DS)$. The feasibility weight, w_F, is held constant because it is critical to ensure convergence to viable solutions (*i.e.* infeasible sequences cannot physically be performed), and the power parameter, *FVP*, can be adjusted to improve convergence. The expected profit, standard deviation, and profit probability weights indicate the search direction of the multi-objective GA. These weights are randomly generated at the beginning of each generation. In this manner, all chromosomes in a generation use identical weights so that the chromosome fitness values, Eq. 48, can be ranked. Random weights allow the GA to search in multiple directions, which improves chromosome diversity (Murata and Ishibuchi 1995) and allow the GA to escape local minimums. Eq. 48 is applied to each chromosome in each GA generation in order to obtain a set of *FV* values that can be ranked for crossover operations, (Rickli and Camelio 2013).

The GA searches for Pareto frontiers containing non-dominated solutions for each objective function except for feasibility. No sequence can have a higher feasibility than one and any sequence with feasibility less than one is not viable. Thus, the Pareto frontier is dependent on EoL product expected profit, profit standard deviation, and profit probability. It is also true that profit probability cannot have a value greater than one; however, unlike sequence feasibility, a profit probability of one is not required to obtain a viable partial disassembly sequence solution.

The *FVP* power parameter (Eq. 48) is used as a measure of control over the search space of the GA. Multiple values of *FVP* and w_F were investigated in order to find parameters that exhibited an acceptable balance between feasibility, *F(DS)*, and the other objective functions (represented by expected profit, *E(f(DS))*, in Table 1and Table 2). The impact of *FVP* is shown in the Table 1. The mean expected profit and feasibility over ten GA runs are shown for *FVP* parameter values of 0.5, 1.0, and 1.5. As seen in Table 1, lower values of *FVP* favored expected profit over feasibility, while larger values of *FVP* favored feasibility over expected profit. Based on these results, a more detailed analysis of the impact of *FVP* was performed around a value of one. It was determined that a *FVP* parameter value of 0.90 sufficiently balanced feasibility and expected profit, profit variance, and profit probability. Results in Table 1 were obtained with a constant w_F value of 0.60.

Table 1 Convergence behavior of the multi-objective GA for varying *FVP* parameter values

FVP		**D_1**	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**D_9**	**D_{10-15}**
0.5	***E(DS)***	39.94	29.29	37.57	33.87	24.58	18.93	14.02	11.91	10.43	8.48
	F(DS)	0.94	0.91	0.94	0.91	0.97	0.96	1.00	1.00	1.00	1.00
1.0	***E(DS)***	32.06	22.46	28.80	27.22	17.51	16.42	13.33	11.83	9.81	8.48
	F(DS)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.5	***E(DS)***	26.42	15.94	31.31	17.01	16.34	15.42	13.00	11.70	10.12	8.48
	F(DS)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 2 shows the GA results by modifying the w_F parameter and holding *FVP* constant at 0.90. Lower values of w_F considered expected profit a higher priority than feasibility; however, a w_F value of 0.60 showed a sufficient balance between the objectives. The results of the disassembly cases in this dissertation were obtained with a w_F value of 0.60 and a *FVP* value of 0.90. Should parameter adjustments be necessary, it is encouraged that *FVP* be modified because Table 1and Table 2 suggest that it may be less sensitive to changes.

Table 2 Convergence behavior of the multi-objective GA for varying w_F parameter values

w_F		D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
0.20	***E(DS)***	147.06	101.44	132.62	112.16	119.77	94.96	81.97	53.41	35.98	31.05
	F(DS)	0.09	0.12	0.17	0.18	0.08	0.13	0.14	0.22	0.29	0.35
0.40	***E(DS)***	46.60	50.68	69.99	62.69	43.94	46.46	25.70	26.82	17.53	10.08
	F(DS)	0.74	0.65	0.59	0.52	0.65	0.52	0.79	0.71	0.80	0.95
0.60	***E(DS)***	30.48	19.61	30.12	26.30	21.21	16.70	12.29	12.14	9.81	8.48
	F(DS)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.80	***E(DS)***	31.73	24.49	32.31	22.76	19.45	16.60	12.67	11.80	10.43	8.48
	F(DS)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

4.4. Crossover Operation

Crossover parent selection is performed with the roulette wheel method, Eq. 49. The probability that a chromosome is selected as a parent is directly proportional to its fitness value from Eq. 46 and Eq. 48. Chromosomes with higher fitness values will have a higher probability, *P{*CH_k *is a parent}*, of being selected as a parent. The number of parents selected in the GA is equal to the number of chromosomes in a population, which means that the population of the next generation is composed entirely of offspring of the previous generation, save for elite chromosomes. Approximately 5.0% of the population, representing the fittest chromosomes of the current population, are randomly placed in the next generation's population.

$$P\{CH_k \rightarrow parent\} = \frac{FV_{CH_k}}{\sum_{i=1}^{K} FV_{CH_i}} \tag{49}$$

Parent crossover operations use a uniform crossover method. A uniform crossover creates a random mask (composed of zeros and ones) for each set of parents. Two offspring are created from the uniform crossover operation; if the bit value in the mask is a 0 then the bit in parent 1 is sent to the corresponding bit in offspring 1 and the bit in parent 2 is sent to the corresponding bit in offspring 2. If the mask bit value is 1 then the bit in parent 1 is sent to the corresponding bit in offspring 2 and the bit in parent 2 is sent to the corresponding bit in offspring 1 (Haupt et al. 2004). The uniform crossover can perform one-point and two-point crossover operations given that a certain mask is randomly generated.

4.5. Mutation Operation

Chromosome mutations enable the GA to escape local minimums and find new search areas. Each bit in each generation's chromosome has a probability of mutating from a 1 to a 0 or from a 0 to a 1. The mutation probability for each bit is an exponentially decreasing function designed so that the effective expected number of disassembly arcs per chromosome mutated is initially 1, eem_1, and decreases to 0.5, eem_G, Eqs. 50-52. Effective expected number of mutations is a term used to describe any mutation that actually impact chromosome objective function values, meaning the cells in the precedence matrix with a value of one.

Each chromosome will likely have more than one mutation but it is expected that only one mutation will actually alter the objective function values of the chromosome. In Eq. 50-52 $mut_{initial}$ is the desired per cell starting mutation probability, mut_{end} is the desired per cell ending mutation

$$mut_{initial} = \frac{eem_1}{\sum_{i=1}^{K+1}\sum_{j=1}^{K+1} p_{i,j}} \tag{50}$$

$$mut_{end} = \frac{eem_G}{\sum_{i=1}^{K+1}\sum_{j=1}^{K+1} p_{i,j}} \tag{51}$$

$$mut_g = mut_{initial} * e^{-\ln\left(\frac{mut_{end}}{mut_{initial}}\right)*g} \ \forall g \ \text{where} \ g = 1,2,\ldots,G \tag{52}$$

probability, g is the current generation, G is the number of generations the GA will complete, and mut_g is the per cell mutation probability for generation g. A decreasing mutation probability function expands the search space during initial generations and narrows the search space in later generations. Contrary to the crossover operation, elitism is not practiced for mutations. Therefore, "fit" chromosomes that were specified as elites during crossover operations may be subject to mutations. This allows the elite chromosomes to be mutated to a better chromosome or into a search area that may have a more optimal local-minimum.

5. RESULTS OF PARTIAL DISASSEMBLY FORMULATIONS

The results of this dissertation are organized into three sections. Section 5.1 presents the results of the profit, environmental impact, and feasibility multi-objective function partial disassembly GA. Results are included for an example product with zero sub-assemblies and for the classic coffee-maker example. Section 5.2 presents the results of extended the multi-objective GA to analyze the impact of acquired EoL age distributions on optimal and near-optimal partial disassembly sequences. Partial disassembly sequences are determined for a solenoid valve considering different acquired EoL product age distributions. Lastly, Section 5.3 presents the results of merging consumer decisions, PrAM, and the partial disassembly GA routine to link operational and strategic decisions in value recovery.

5.1. Multi-Objective Partial Disassembly Optimization: Basic Case

The multi-objective partial disassembly problem considering profit, environmental impact, and feasibility is tested with an example case study and the classic coffee-maker example. In the example cast study, costs and revenues for each component and operation were arbitrarily estimated, and no subassemblies were considered. Subassemblies are considered blocks of three or more components that can be removed with one disassembly operation, and are critical because they increased the directed disassembly flow network complexity. The directed flow network of the example case study

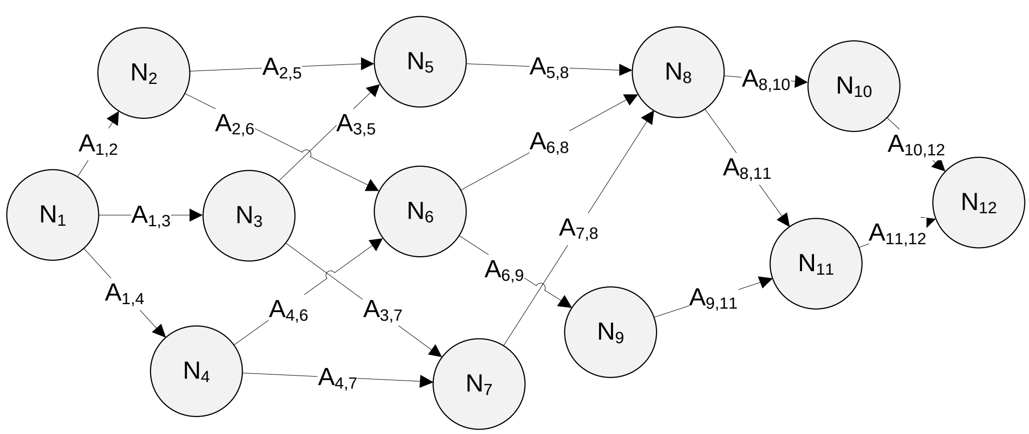

Figure 13 Directed flow disassembly network for the theoretical disassembly case study

is shown in Figure 13. N_1 is the fully assembled product, and N_{12} is complete disassembly. Disassembly operations are assigned to specific arcs, $A_{i,j}$, that bridge the nodes of the disassembly network. The cost, revenue, and environmental impact of terminating disassembly at node N_i are listed in Table 3. The cost and environmental impact of disassembly process $A_{i,j}$ are listed in Table 4.

Table 3 Cost, revenue, and environmental impact of each disassembly node

Disassembly Level	***Costs***	***Revenue***	***Env. Impacts (pts)***
N_1	$10.00	$20.00	0.143
N_2	$5.00	$20.00	0.0649
N_3	$15.00	$20.00	0.0782
N_4	$5.00	$20.00	0.0649
N_5	$1.00	$30.00	0.0148
N_6	$25.00	$10.00	0.03
N_7	$1.00	$30.00	0.0148
N_8	$25.00	$25.00	0.048
N_9	$70.00	$40.00	0.0568
N_{10}	$1.00	$40.00	0.0398
N_{11}	$70.00	$40.00	0.0398
N_{12}	$100.00	$50.00	0.0166

Single objective runs validated the GA's effectiveness prior to testing it on multi-objective scenarios. The net-profit results of the best chromosome found at the completion of the GA are shown

Table 4 Cost and environmental impact of disassembly operations/arcs

Disassembly Process	***Costs***	***Env. Impacts (pts)***	***Disassembly Process***	***Costs***	***Env. Impacts (pts)***
$A_{1,2}$	$1.00	5.76E-05	$A_{5,8}$	$2.88	0.0186
$A_{1,3}$	$5.00	0.0186	$A_{6,8}$	$7.20	0.0186
$A_{1,4}$	$2.00	5.76E-05	$A_{6,9}$	$15.00	0.0371
$A_{2,5}$	$6.00	0.0186	$A_{7,8}$	$1.44	5.76E-05
$A_{2,6}$	$2.40	5.76E-05	$A_{8,10}$	$18.00	0.0371
$A_{3,5}$	$3.40	5.76E-05	$A_{8,11}$	$18.00	0.0371
$A_{3,7}$	$1.20	5.76E-05	$A_{9,11}$	$8.64	0.0186
$A_{4,6}$	$1.20	5.76E-05	$A_{10,12}$	$25.00	0.0236
$A_{4,7}$	$6.00	0.0186	$A_{11,12}$	$25.00	0.0236

in Table 5. The global optimal value is a profit of $22.80 with a disassembly sequence corresponding to *1-3-7*. GA runs with more than 150 generations and population sizes greater than 80 consistently converged to the optimal solution. Population sizes of 40 and 60 generally found the optimal net-profit for all generation lengths, but a population size of 20 performed poorly for all generations. The proposed GA was consistently able to find the optimal solution by searching no more than 5.0% of the potential search space, and was able to converge to a feasible sequence in almost all of the runs regardless of the net-profit value, Table 6. For the case that only environmental impact feasibility is considered, the GA found the optimal environmental impact, -0.0301 and associated sequence, *1-2-6*, for the majority of the population sizes and generation lengths, Table 7.

The ability of the GA to converge to optimal or near-optimal short or long partial disassembly sequences is tested because optimal partial disassembly sequences may vary in length. In order to test

Table 5 Net-profit of the best chromosome (only cost objective function)

Net-profit ($)										
	Population Size									
Generations	**20**	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**200**
50	-9.44	10.60	22.80	22.00	22.00	22.00	21.00	22.00	21.00	22.80
100	14.00	22.00	22.80	22.00	21.00	22.80	22.80	22.80	22.80	22.80
150	20.60	22.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
200	-14.44	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
250	21.00	10.60	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
300	10.40	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
350	14.00	21.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
400	-6.00	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
450	22.00	22.80	22.00	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
500	21.00	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
550	9.72	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
600	4.20	22.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
650	21.00	22.00	21.00	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
700	10.60	22.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
750	21.00	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
800	11.12	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
850	-53.20	13.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
900	10.40	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
950	-14.44	22.80	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*
1000	11.12	22.00	22.80	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*	*22.80*

Table 6 Feasibility of the best chromosome (only cost objective function)

Feasibility										
	Population Size									
Generations	**20**	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**200**
50	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
100	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
150	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
200	0.67	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
250	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
300	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
350	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
400	0.31	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
450	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
500	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
550	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
600	0.71	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
650	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
700	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
750	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
800	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
850	0.67	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
900	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
950	0.67	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
1000	1.00	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*

Table 7 Env. impact of the best chromosome (only env. impact objective function)

Environmental Impact											
		Population Size									
		20	40	60	80	100	120	140	160	180	200
Generations	50	-0.067	-0.065	*-0.033*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	100	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	150	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	200	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	250	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	300	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	350	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	400	-0.015	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	450	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	500	-0.033	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	550	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	600	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	650	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	700	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	750	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	800	-0.015	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	850	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	900	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	950	-0.030	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*
	1000	-0.048	-0.030	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*	*-0.030*

this, the input parameters (Table 3 and Table 4) were modified to ensure a short and long optimal disassembly sequence. In the short sequence scenario, the optimal sequence was *0-1* with a net-profit of $25.00. It is shown that a population size greater than or equal to 80 resulted in the optimal sequence of *0-1*, Table 8. A population size of 60 found the optimal solution the majority of the time but population sizes of 20 and 40 performed poorly for all generations.

The optimal disassembly sequence for the long sequence scenario was *1-3-7-8-10-12* with a net-profit of $19.36. The GA performed poorly for population sizes of 20 and 40 for all generations tested, Table 9, and a generation size of 50 performed poorly for all population sizes. The GA had acceptable results (near-optimal or optimal) when the population size was 100 or greater and the number of generations was greater than or equal to 200. It can be seen that the GA converged to the global optimal solution for the majority of the runs; however, it also converged to near-optimal solutions with a net-profit of $18.16 and $17.12

Table 8 Net-profit results of single objective, short disassembly sequence scenario

	Net-profit ($)									
	Population Size									
Generations	20	40	60	80	100	120	140	160	180	200
50	9.40	25.00	10.60	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
100	25.00	13.36	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
150	8.28	16.16	11.56	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
200	13.92	25.00	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
250	12.36	9.72	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
300	-15.40	13.36	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
350	8.72	15.16	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
400	10.60	25.00	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
450	-2.00	10.60	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
500	3.80	25.00	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
550	10.16	13.36	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
600	5.40	9.72	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
650	7.76	10.40	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
700	25.00	10.60	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
750	9.68	11.12	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
800	14.92	10.60	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
850	13.36	25.00	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
900	11.12	25.00	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
950	10.40	10.60	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*
1000	17.36	11.12	25.00	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*	*25.00*

Table 9 Net-profit results of single objective, long disassembly sequence scenario

Net-profit ($)										
	Population Size									
Generations	**20**	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**200**
50	37.80	-10.60	14.96	16.60	14.00	19.36	17.56	19.36	16.60	17.56
100	37.36	16.60	19.36	17.12	19.36	17.96	19.36	19.36	19.36	17.12
150	17.12	17.12	17.12	15.72	19.36	17.56	18.16	19.36	19.36	17.56
200	13.96	19.36	19.36	15.72	*19.36*	*19.36*	*19.36*	*19.36*	*17.12*	*19.36*
250	36.28	18.16	17.96	19.36	*17.56*	*19.36*	*18.16*	*19.36*	*19.36*	*19.36*
300	14.96	19.36	17.12	19.36	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*
350	19.36	35.12	19.36	14.00	*19.36*	*18.16*	*19.36*	*19.36*	*19.36*	*19.36*
400	26.80	17.56	19.36	19.36	*17.12*	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*
450	41.80	8.92	17.12	19.36	*19.36*	*19.36*	*19.36*	*19.36*	*17.12*	*19.36*
500	30.16	19.36	19.36	19.36	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*
550	14.72	16.40	17.56	19.36	*19.36*	*19.36*	*19.36*	*19.36*	*18.16*	*19.36*
600	22.36	-13.28	17.12	19.36	*19.36*	*17.12*	*18.16*	*19.36*	*18.16*	*19.36*
650	4.16	19.36	19.36	19.36	*19.36*	*19.36*	*18.16*	*17.12*	*19.36*	*19.36*
700	23.36	19.36	17.56	19.36	*19.36*	*19.36*	*19.36*	*17.12*	*19.36*	*19.36*
750	22.16	16.40	19.36	17.56	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*
800	26.60	17.12	17.12	19.36	*19.36*	*18.16*	*19.36*	*19.36*	*19.36*	*18.16*
850	28.72	19.36	17.56	19.36	*19.36*	*18.16*	*19.36*	*18.16*	*19.36*	*19.36*
900	37.36	14.28	-9.88	18.16	*19.36*	*19.36*	*19.36*	*19.36*	*18.16*	*19.36*
950	22.36	18.16	19.36	17.12	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*	*19.36*
1000	15.72	19.36	19.36	19.36	*19.36*	*19.36*	*19.36*	*19.36*	*18.16*	*19.36*

The single objective analyses are inherently multi-objective because feasibility is always included; however, a tradeoff did not exist between feasibility and net-profit because the global optimal solution of feasibility is one. The multi-objective (net-profit and environmental impact) analysis reset the parameters of the example case study to their original values. The global optimal net-profit is $22.80 and the global optimal environmental impact is -0.0301. A net-profit of $22.80 has a corresponding environmental impact of -0.087, and an environmental impact of -0.0301 has a corresponding net-profit of $18.40. Another solution exists that has a near-optimal net-profit, $22.00, and near-optimal environmental impact, -0.0335.

Population sizes of 80 and above and generations of 100 and above yielded a net-profit of $22.00 (Table 10). Population sizes of 40 and 60 found the same solution the majority of the time and a population size of 20 performed poorly, converging to a variety of solutions. The GA found a near-

Table 10 Net-profit results of the multi-objective scenario

Net-profit ($)										
	Population Size									
Generations	**20**	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**200**
50	21.00	10.60	22.00	20.60	20.60	22.00	20.60	22.00	22.00	22.00
100	5.16	22.00	20.60	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
150	5.16	21.00	20.60	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
200	8.96	13.36	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
250	16.36	22.00	20.60	*20.60*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
300	20.80	22.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
350	11.12	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
400	20.60	22.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
450	12.00	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
500	20.60	21.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
550	22.00	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
600	20.60	22.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
650	-53.40	22.00	20.60	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
700	0.00	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
750	22.00	22.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
800	-9.40	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
850	22.00	22.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
900	10.40	20.60	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
950	9.72	21.00	22.00	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*
1000	20.60	22.00	20.60	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*	*22.00*

Table 11 Environmental impact results of the multi-objective scenario

Environmental Impact (pts)											
		Population Size									
		20	**40**	**60**	**80**	**100**	**120**	**140**	**160**	**180**	**200**
Generations	**50**	-0.106	-0.096	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	100	-0.114	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	150	-0.114	-0.106	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	200	-0.096	-0.096	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	250	-0.077	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	300	-0.106	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	350	-0.114	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	400	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	450	-0.065	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	500	-0.033	-0.106	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	550	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	600	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	650	-0.113	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	700	-0.097	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	750	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	800	-0.067	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	850	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	900	-0.096	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	950	-0.114	-0.106	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*
	1000	-0.033	-0.033	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*	*-0.033*

optimal environmental impact value, specifically -0.0335 (Table 11) for all cases with a population size of 60 or more. Compared to the global optimal net-profit and environmental impact, the GA sacrificed 0.0034 environmental points for a $3.60 increase in net-profit and it sacrificed $0.80 for a 0.0535 points decrease in environmental points.

These results show that the GA is able to converge to an optimal or near-optimal solution for the example case study. Results for the single objective (net-profit or environmental impact) show that the GA is able to find the global optimal solution for the single objective case in the majority of the GA runs. The coffee maker case study extends the partial disassembly problem because it considers a product that has multiple sub-assemblies and, thus, requires a hierarchical analysis that considers each subassembly sequentially.

5.2. Coffee-Maker Case Study

The coffee-maker case is analyzed due to its history in disassembly sequence planning research. Harjula et al. (1996), Lee et al. (2001), Hula et al (2011), Qian and Zhang (2009), and Azab et al. (2011) all use the coffee maker as a case study for disassembly sequence optimization. The coffee maker used here is a standard Chefmate® 12 Cup Coffee Maker. A Bill of Materials (BOM) is supplied

Table 12 (A) Bill of Materials for the Chefmate® 12 Cup Coffee Maker

Level	Part #	Assembly	Part Name	Quant/ Unit	# of Components
0	0001		Coffee Maker Assembly ($20)	1	66
1	1001		Carafe Assembly	1	6
1	1002		Brewer Assembly	1	60
2	2001	A	Glass Carafe	1	1
2	2002	A	Carafe Lid	1	1
2	2003	A	Carafe Handle	1	1
2	2004	A	Metal Carafe Band	1	1
2	2005	A	Metal Carafe Band Screw	1	1
2	2006	A	Metal Band to Handle Adapter	1	1
2	2007	B	Bottom Plate Grip Pads	2	2
2	2008	B	Reservoir/Heating Base Assembly Screw	5	5
2	2009	B	Bottom Plate Screw	2	2
2	2010	B	Bottom Plate	1	1
2	2011	BA	Reservoir Assembly	1	11
2	2012	B	Coffee Maker Base	1	1
2	2013	B	Heat Element Input Liquid Tube with Valve	1	1
2	2014	B	Heat Element Output Liquid Tube	1	1
2	2015	B	Tube Clamp	2	2
2	2016	B	Voltage Cord Clamp Screw	2	2
2	2017	B	Power Cord Clamp	1	1
2	2018	B	Heat Element Assembly Support Beam	1	1
2	2019	B	Heat Element Assembly Support Beam Screw	2	2
2	2020	B	Heat Element Support Beam Pads	2	2
2	2021	B	Heat Element On/Off Switch	1	1
2	2022	B	Carafe Heating Surface	1	1
2	2023	B	Heating Surface Support Ring	1	1
2	2024	B	Heating Surface Seal	1	1
2	2025	BB	Heating Element Assembly	1	22

Table 12 (B) Bill of Materials for the Chefmate® 12 Cup Coffee Maker

3	3001	BAA	Water Heater Spigot Assembly	1	3
3	3002	BC	Spigot Assembly Screw	1	1
3	3003	BAB	Filter Basin Assembly	1	4
3	3004	BC	Basin Spigot Support	1	1
3	3005	BC	Top Plate	1	1
3	3006	BC	Reservoir	1	1
3	3007	BB	Wire Clamp Nut (Power Cord - Heat Element)	2	2
3	3008	BB	Wire Zip Tie (Power Cord - Heat Element)	1	1
3	3009	BB	Power Cord	1	1
3	3010	BB	Red Wire to Switch from Power Cord	1	1
3	3011	BB	Red Wire with 2 fuses to Switch from HT	1	1
3	3012	BB	White Wire to Switch from Power Cord	1	1
3	3013	BB	White Wire from Power Cord to Black Cylinder	1	1
3	3014	BB	White Wire from Black Cylinder to HT	1	1
3	3015	BB	Nylon Fuse Coverings	2	2
3	3016	BB	Black Electronics Cylinder	1	1
3	3017	BB	Black Electronics Cylinder Ring	1	1
3	3018	BB	Black Electronics Cylinder Screw	2	2
3	3019	BB	Fuse Coverings Clamps	2	2
3	3020	BB	Power Cord Wire Zip Tie	1	1
3	3021	BB	Metal Heating Element Casing	1	1

in Table 12 (A) and (B) to identify components and subassemblies. Analyses were carried out hierarchically from the bottom-up, *i.e.* basic subassemblies (those with no subassemblies) are optimized first. Then the subassembly results were used to optimize the next, higher level of subassemblies. This continued until no subassemblies remained, and is necessary in order to make manageable directed disassembly networks.

Each coffeemaker subassembly has a unique, directed disassembly network, Figure 14-Figure 17. Figure 14 shows the network for level 1 from the BOM. Figure 15 illustrates the network of the carafe assembly, assembly A of level 2 in the BOM. Figure 16 shows the disassembly network for the brewer assembly, assembly B in level 2 of the BOM (an enlarged diagram is located in the Appendix, Figure A1). Figure 17 shows the reservoir subassembly disassembly network, Level 3. Networks for the heating element, spigot assembly, and basin assembly were not considered.

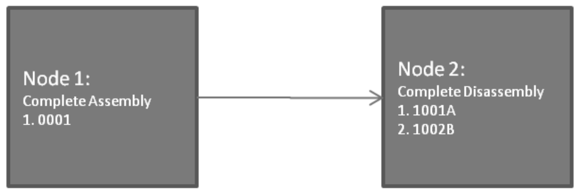

Figure 14 Directed disassembly network for the coffeemaker assembly level 1

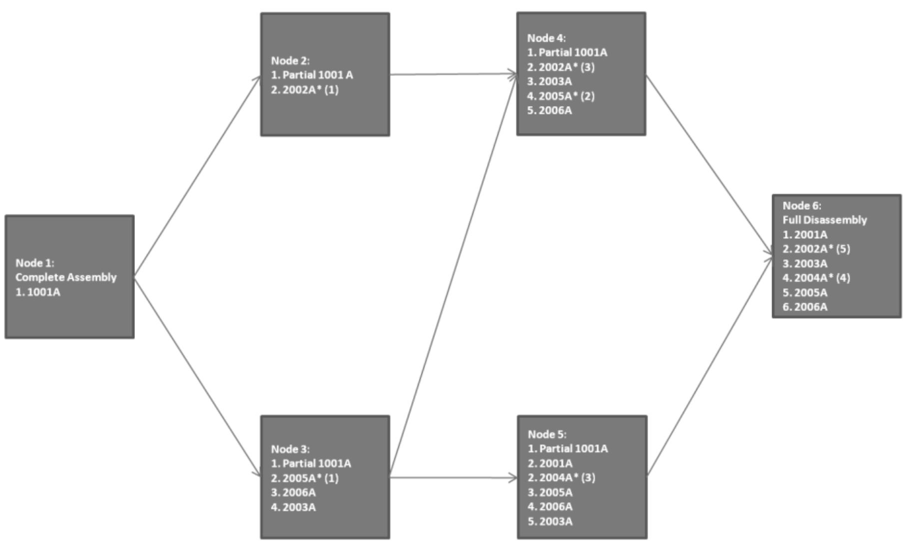

Figure 15 Directed disassembly network for level 2A – 6 total nodes

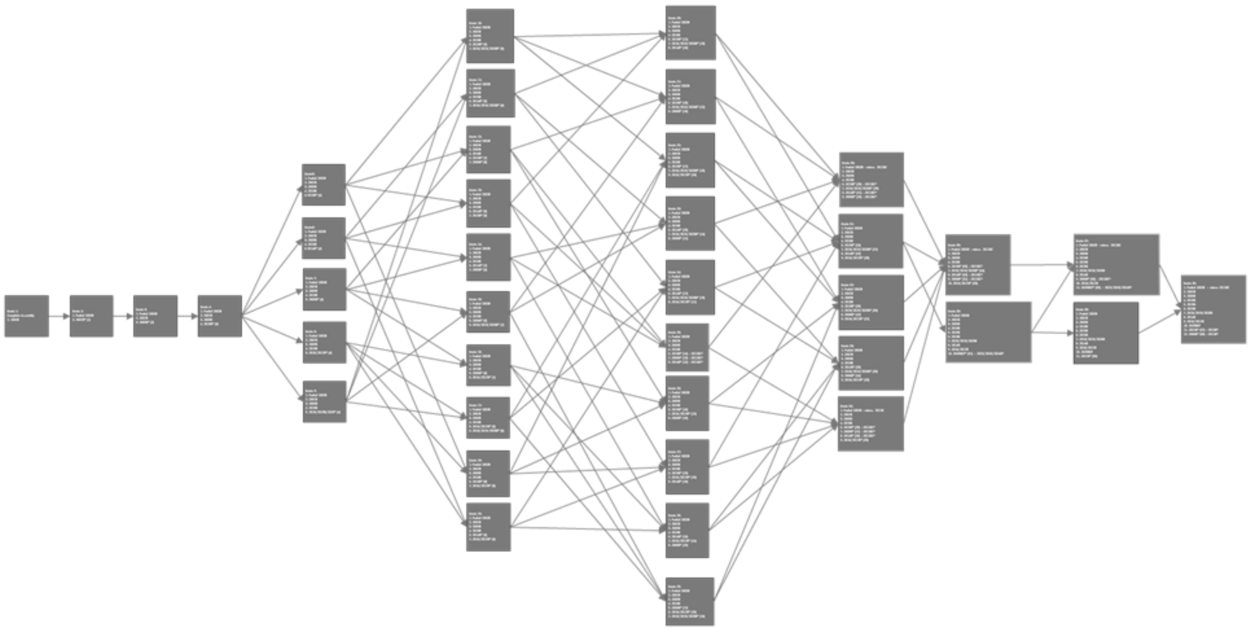

Figure 16 Directed disassembly network for level 2B – 39 disassembly nodes

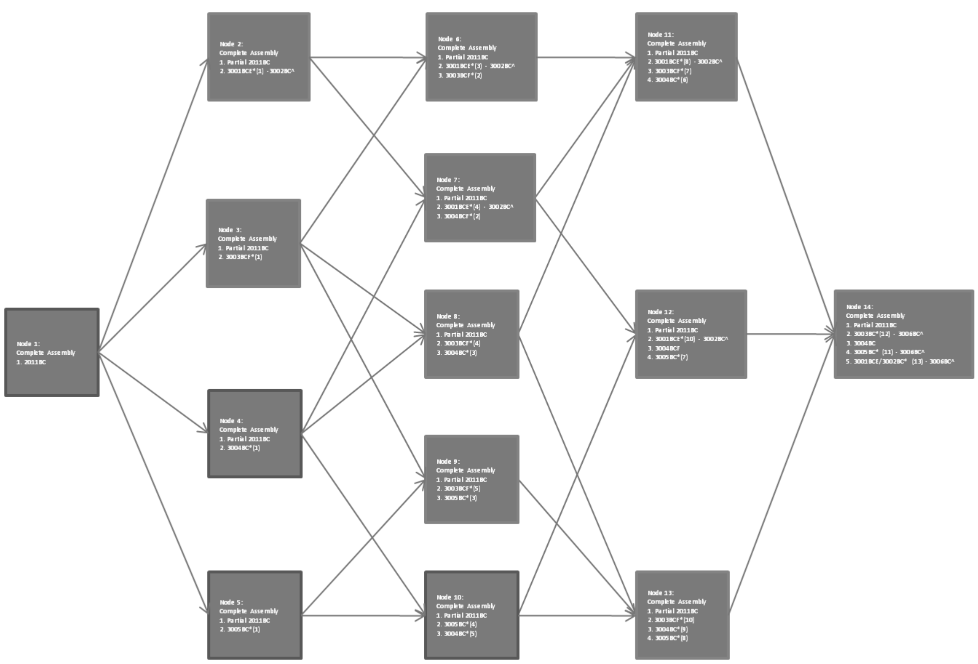

Figure 17 Directed disassembly network for level 3 – 14 total nodes

The base price of the listed coffee maker was used to estimate the value of remanufactured and reused components. In a practical application these values would ideally be known or predicted by recovery enterprise. Material value was estimated based on the mass of each component and its market value. Subassemblies composed of many material types scale down the originally estimated recycle/scrap cost by a higher percentage than those that are composed of few materials, Eq. 53, where $crsv_n$ is the adjusted recycle/scrap cost of component n, rsv_n is the recycling/scrap cost if the materials were identical, and nm_n represents one of five classes, each with a value less than one. Classes have decreasing values as the remaining assembly at the *DS* end-node has less material variety ($nm_n = 0$ for a single material type).

$$crsn_n = \frac{rsn_n}{1 - nm_n} \tag{53}$$

The reuse and remanufacture value of recovered components was estimated based on the contribution of each component to the coffee maker operation. Mass and functionality determine components total contribution to the value of the coffee maker. The mass contribution is the mass of a subassembly or component divided by the total mass of the coffee maker. Functionality is measured as the number of parts that make up a subassembly or component divided by the total number of components in the coffee maker. The total contribution is the average of component mass and functionality contributions, Eq. 54, where $crrv_n$ is the total remanufacture/reuse value of component n, frr_n is the functional percentage, and mrr_n is the mass percentage of component n.

$$crrv_n = vcm * \left(\frac{frr_n + mrr_n}{2} \right) \tag{54}$$

The results of the coffee maker partial disassembly analysis are presented from the lowest level disassembly network, Figure 17, to the highest level, Figure 14. At each level, results are presented for net-profit, environmental impact, and the ratio of search space searched. The vast majority of GA runs converged to a feasible solution, thus, feasibility results are not included. Level 3 is composed of parts

Table 13 Net-profit for the reservoir subassembly (level 3)

Net-profit ($)										
	Population Size									
Generations	20	40	60	80	100	120	140	160	180	200
100	0.09	0.13	0.13	0.09	0.13	0.13	0.13	0.13	0.13	0.13
200	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
300	0.04	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
400	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
500	0.09	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
600	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
700	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
800	0.02	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
900	0.09	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
1000	0.07	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13

Table 14 Environmental impact for the reservoir subassembly (level 3)

Environmental Impact (pts)										
	Population Size									
Generations	20	40	60	80	100	120	140	160	180	200
100	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
200	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
300	-0.135	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
400	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
500	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
600	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
700	-0.095	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
800	-0.114	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
900	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120
1000	-0.095	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120	-0.120

3001-3006 from the BOM and contains a total of 26 feasible arcs (including the 0-1 arc). The GA converged to a partial disassembly sequence of *0-1-3-9/0-1-5-9* with a net-profit of $0.13 per coffee maker, Table 13, with an environmental impact of -0.12 points, Table 14, for the majority of the population size/generation runs, Table 15. The negative environmental impact indicates a harmful impact to the environment.

Subassembly level 2B contains a majority of the main components of the coffee maker such as the reservoir, heating element, and heating pad. Results from Level 3 are used in Level 2B as the reservoir subassembly. Two sequences, *0-1* and *1-2-3-4-9*, dominated the GA runs. Sequence *0-1* opts

Table 15 Ratio of solutions searched compared to the total search space (level 3)

% of Solutions Searched by GA (in %)											
		Population Size									
		20	40	60	80	100	120	140	160	180	200
Generations	100	0.003	0.006	0.009	0.012	0.015	0.018	0.021	0.024	0.027	0.030
	200	0.006	0.012	0.018	0.024	0.030	0.036	0.042	0.048	0.054	0.060
	300	0.009	0.018	0.027	0.036	0.045	0.054	0.063	0.072	0.080	0.089
	400	0.012	0.024	0.036	0.048	0.060	0.072	0.083	0.095	0.107	0.119
	500	0.015	0.030	0.045	0.060	0.075	0.089	0.104	0.119	0.134	0.149
	600	0.018	0.036	0.054	0.072	0.089	0.107	0.125	0.143	0.161	0.179
	700	0.021	0.042	0.063	0.083	0.104	0.125	0.146	0.167	0.188	0.209
	800	0.024	0.048	0.072	0.095	0.119	0.143	0.167	0.191	0.215	0.238
	900	0.027	0.054	0.080	0.107	0.134	0.161	0.188	0.215	0.241	0.268
	1000	0.030	0.060	0.089	0.119	0.149	0.179	0.209	0.238	0.268	0.298

for no disassembly (complete recycling/outsourcing to recyclers), and has a net-profit of $0.0172, Table 16, per subassembly and an environmental impact value of -0.303 points, Table 17. Alternatively, sequence *1-2-3-4-9* calls for the disassembly of components 2007 (bottom plate grip pads), 2009 (bottom plate screws), 2010 (bottom plate), and 2018/2019/2020 (heating element support beam, support screws, and support pads). It has a net-profit of $0.045 per subassembly and an environmental impact of -0.391 points. In total, 36% of the test runs resulted in sequence *0-1-2-3-4-9*, 60% of the runs resulted in sequence *0-1*, and 4% in other sequences for the population size/generations runs, Table 18.

For disassembly Level 2B, the global optimal net-profit is $0.0713 and the global optimal environmental impact is -0.303. The global optimal environmental impact is part of the sequence *0-1* found by the GA, however, the global optimal net-profit was not found because it has an associated environmental impact of -0.4284. The solution with net-profit $0.0713 and environmental impact of -0.4284 appears to be a good solution that may belong in the same class as the two found in the aforementioned GA runs. However, the previous weight specifications (feasibility = 2.0, net-profit = 1.5, and environmental impact = 0.5) prevented convergence to this solution. Preliminary runs using a lower environmental weight and higher net-profit weight show convergence to $0.0713 and -0.4284 as well as the previous two sequences, Table 19. Overall, three candidate solutions that are optimal or

Table 16 Net-profit for the coffee maker brewer (level 2B)

Net-profit ($)						
		Population Size				
		100	150	200	250	300
Generations	3000	0.045	0.045	0.045	0.045	0.017
	3500	0.045	0.045	0.017	0.017	0.045
	4000	0.017	0.017	0.017	0.017	0.017
	4500	0.045	0.017	0.017	0.017	-0.669
	5000	0.017	0.045	0.017	0.017	0.017

Table 17 Environmental impact for the coffee maker brewer (level 2B)

Environmental Impact (pts)						
		Population Size				
		100	150	200	250	300
Generations	3000	-0.391	-0.391	-0.391	-0.391	-0.303
	3500	-0.391	-0.391	-0.303	-0.303	-0.391
	4000	-0.303	-0.303	-0.303	-0.303	-0.303
	4500	-0.391	-0.303	-0.303	-0.303	-0.435
	5000	-0.303	-0.391	-0.303	-0.303	-0.303

Table 18 Ratio of solutions searched compared to the total search space (level 2B)

% of Solutions Searched by GA (in %)						
		Population Size				
		100	150	200	250	300
Generations	3000	2.42E-20	3.64E-20	4.85E-20	6.06E-20	7.27E-20
	3500	2.83E-20	4.24E-20	5.65E-20	7.07E-20	8.48E-20
	4000	3.23E-20	4.85E-20	6.46E-20	8.08E-20	9.69E-20
	4500	3.64E-20	5.45E-20	7.27E-20	9.09E-20	1.09E-19
	5000	4.04E-20	6.06E-20	8.08E-20	1.01E-19	1.21E-19

Table 19 Net-profit results for level 2B with adjusted weights

Net-profit ($) - New Weights						
		Population Size				
		100	150	200	250	300
Generations	3000	0.071	0.017	0.017	0.045	0.071
	3500	0.017	0.045	0.045	0.017	0.071
	4000	0.071	0.071	0.017	0.045	0.045
	4500	0.045	0.017	0.017	0.017	0.045
	5000	0.045	0.045	0.017	0.045	0.045

Table 20 Net-profit for the carafe subassembly (level 2A)

Net-profit ($)						
	Population Size					
Generations	10	12	14	16	18	20
2	-0.128	-0.119	-0.114	-0.128	-0.095	-0.010
4	-0.134	0.004	-0.003	0.015	-0.003	0.021
6	-0.001	0.015	-0.017	-0.017	0.021	-0.003
8	-0.114	0.015	0.015	-0.095	0.015	0.021
10	0.021	-0.003	-0.114	-0.001	0.021	0.021
12	0.015	-0.010	-0.001	0.021	0.021	0.021
14	-0.120	-0.094	0.021	0.021	0.021	0.021
16	-0.094	0.021	-0.001	0.021	0.021	-0.001
18	0.021	0.021	0.021	0.021	0.021	0.021
20	0.004	-0.003	0.015	0.015	0.021	0.021

Table 21 Environmental impact for the carafe subassembly (level 2A)

Environmental Impact (pts)						
	Population Size					
Generations	10	12	14	16	18	20
2	-0.095	-0.100	-0.094	-0.095	-0.076	-0.121
4	-0.100	-0.121	-0.121	-0.106	-0.121	-0.108
6	-0.126	-0.106	-0.121	-0.121	-0.108	-0.121
8	-0.094	-0.106	-0.106	-0.076	-0.106	-0.108
10	-0.108	-0.121	-0.094	-0.126	-0.108	-0.108
12	-0.106	-0.121	-0.126	-0.108	-0.108	-0.108
14	-0.094	-0.076	-0.108	-0.108	-0.108	-0.108
16	-0.076	-0.108	-0.126	-0.108	-0.108	-0.126
18	-0.108	-0.108	-0.108	-0.108	-0.108	-0.108
20	-0.121	-0.121	-0.106	-0.106	-0.108	-0.108

Table 22 Ratio of solutions searched compared to the total search space (level 2A)

% of Solutions Searched by GA (in %)						
	Population Size					
Generations	10	12	14	16	18	20
2	7.81	9.38	10.94	12.50	14.06	15.63
4	15.63	18.75	21.88	25.00	28.13	31.25
6	23.44	28.13	32.81	37.50	42.19	46.88
8	31.25	37.50	43.75	50.00	56.25	62.50
10	39.06	46.88	54.69	62.50	70.31	78.13
12	46.88	56.25	65.63	75.00	84.38	93.75
14	54.69	65.63	76.56	87.50	98.44	109.38
16	62.50	75.00	87.50	100.00	112.50	125.00
18	70.31	84.38	98.44	112.50	126.56	140.63
20	78.13	93.75	109.38	125.00	140.63	156.25

near-optimal were identified. Selection of a single sequence would depend on the recovery enterprises disassembly strategy, policies, and risk.

Level 2A is the coffee maker carafe subassembly and contains no subassemblies. The GA converged to a sequence of *0-1* with a profit of $0.021, Table 20, and environmental impact of -0.108, Table 21, in 40% of the runs. GA performance for Level 2A, which only has eight feasible disassembly operations, was less consistent than in Level 3, Table 22, based on the ratio of search space searched. The final network, level 1, contains two nodes and a single arc (Figure 14), thus, only two disassembly sequence options exist: *0-1* or *0-1-2*. Sequence *0-1* has a net-profit value of $0.0185 and an environmental impact value of -0.519 points. Sequence *0-1-2* has a profit of $0.193 and an environmental impact value of -0.45 points. As such, the second sequence dominates the first, indicating that disassembly in the next hierarchical level, level 2, should be pursued.

In summary (Table 23), at level 2 the carafe disassembly sequence was determined to be no disassembly and the brewer disassembly was divided between disassembling the bottom plate, bottom grip pads, bottom plate screws, heating element pads, heating element beam, and the heating element screw or no disassembly. The reservoir subassembly (a subassembly of the brewer at level 3) analysis suggested partial disassembly to node 9. The complete coffeemaker disassembly plan suggested by the proposed GA is as follows: 1) remove the carafe, 2) scrap the carafe, and 3) disassembly the brewer assembly to node 9 or scrap. The brewer reservoir would never be disassembled to the indicated disassembly level because it would be recycled/scraped as a subassembly according to the analysis of Level 2B.

Table 23 Overview of partial disassembly sequences for each BOM level

BOM Level	Part Description	Partial Disassembly
Level 1	Carafe & Brewer Assembly	0-1-2
Level 2	Carafe	0-1
	Brewer Assembly	0-1-2-3-4-9 or 0-1
Level 3	Brewer Reservoir	0-1-3-9/0-1-5-9

5.3. End-of-Life Product Age Distribution Disassembly Sequence Planning

The partial disassembly sequencing given uncertain EoL product age distribution is tested on a solenoid valve. A solenoid valve, Figure 18, was selected for the case study because it is an assembly with a variety of components that have different value curves. The solenoid valve considered is composed of: 1) top brass housing, 2) bottom brass housing, 3) magnetic coil assembly, 4) o-ring, 5) steel plunger housing, 6) plunger assembly (primarily steel with a plastic flap for sealing purposes and a spring), and 7) four bolts that attach the top and bottom brass housings (Table 24).

The associated directed disassembly network has 15 disassembly nodes and 23 feasible disassembly arcs (the 23 arcs correlate to five different disassembly operations), Figure 19. The network in Figure 19 is the basis of the disassembly sequencing GA and disassembly precedence matrix, representing all feasible disassembly operations. Any components disassembled are assumed to be sent to reprocessing (cleaning, inspection, remanufacturing, etc.), whereas parts not disassembled are assumed to be scrapped and recycled for a constant material revenue per component.

Disassembly operation costs are assumed constant, and are estimated for each feasible arc in Figure 19. Each disassembly operation has an associated base cost that represents the cost of performing the disassembly operation at its easiest state. Additional costs are added to the base

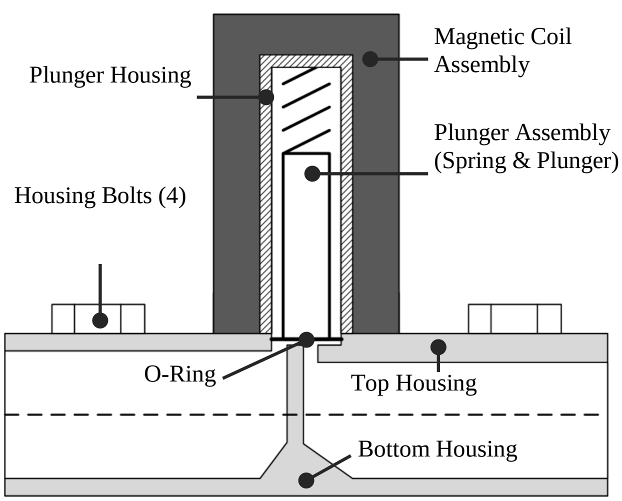

Figure 18 Solenoid valve used for the disassembly case study

Table 24 The solenoid part number codes used in the results tables

Part Description	# Code
Top Casing	1
Bottom Casing	2
Coil Assembly	3
Bolts x4	4
Plunger Casing	5
Plunger Assembly	6
O-Ring	7

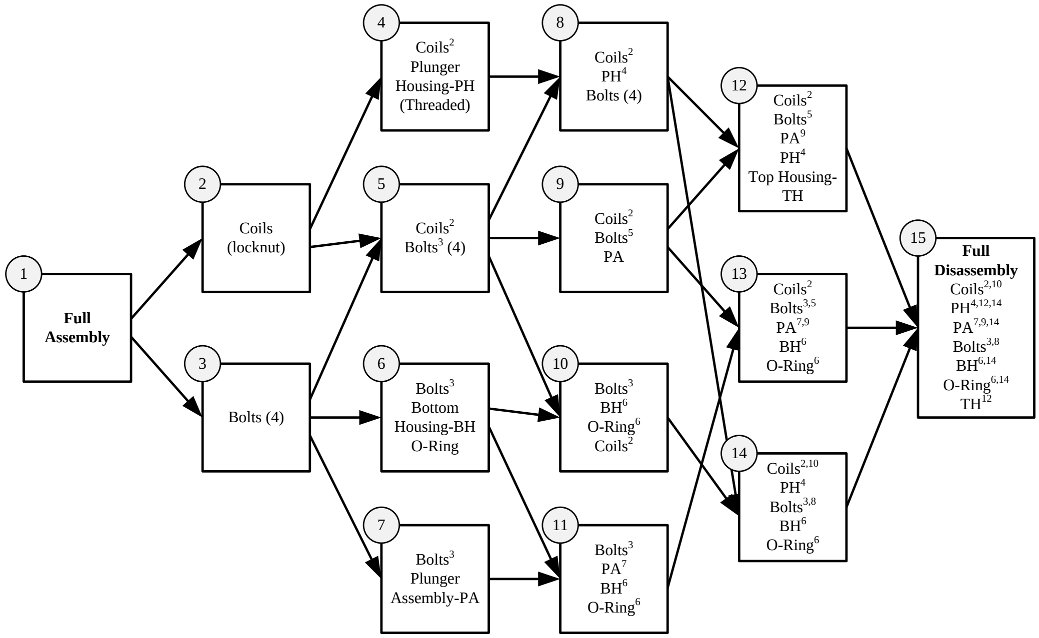

Figure 19 Directed disassembly network of the solenoid valve

disassembly cost if, when the operation takes place, the state of the remaining assembly makes the operation more difficult. Each component is also assigned a constant reprocessing cost and a non-reprocessing (*i.e.* scrap material) revenue. The revenue from reprocessing components is represented by component value curves. Scrap material revenues are estimated from current material value prices, and it is assumed that a facility would incur 20% logistical costs necessary to attain the material value. Reprocessing costs are estimated to be 50% of the original, age equal to zero years, value of each component based on research in (Savaskan et al. 2004) that reported that Xerox saved 40-65% of original manufacturing costs

The solenoid valve is restricted to a twelve year lifespan. The o-ring and plunger assembly have the highest depreciation rate due to their constant movement. The top housing, bottom housing, bolts, and plunger housing have the lowest depreciation rate because they have no movement. The magnetic coil is assumed to have a medium value depreciation rate because it does not contain moving parts and because it is not as robust as the machined housing or bolts. A plot illustrating each of the seven component value curves over a twelve year period is shown in Figure 20. Fifteen acquired EoL

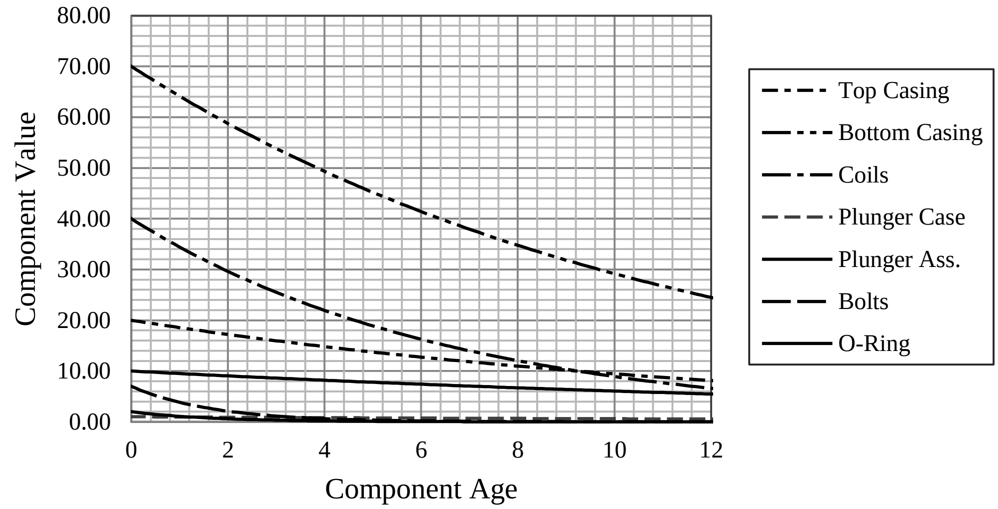

Figure 20 Expected component value curves for the solenoid case study.

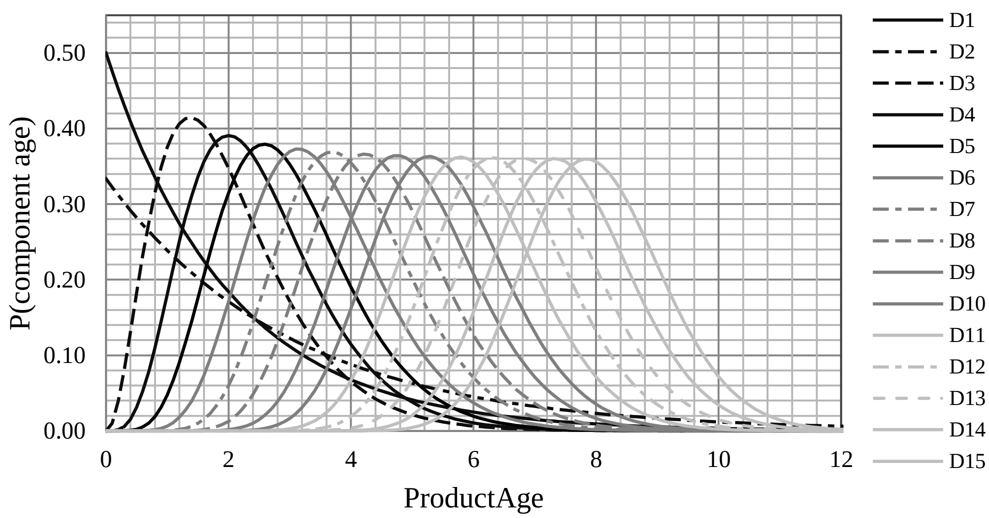

Figure 21 Age distributions for the solenoid case study correlate to different life-cycle stages

product age distributions, generated with the gamma distribution, are studied, Figure 21 and Table 25. Distributions reduce to practically zero by twelve years, and monotonically decreasing distributions (D_1 and D_2) indicate that a batch of acquired EoL products contain many young products. Age distributions (except for the monotonically decreasing functions) are adjusted to satisfy a series of increasing mean product ages.

Table 25 Gamma distribution parameters for distributions one through fifteen

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
k	1.0	1.0	3.2	5.0	7.2	9.8	12.8	16.2	20.0	24.2	28.8	33.8	39.2	45.0	51.2
θ	2.0	3.0	0.63	0.50	0.42	0.36	0.31	0.28	0.25	0.23	0.21	0.19	0.18	0.17	0.16

Table 26 presents the expected profit results for each acquired EoL product age distribution when only expected profit and feasibility were considered in fitness value calculations. The maximum expected profit was not found in all runs of the GA for a specific age distribution, for example, 38.2 was the most common value found for the expected profit D_1 but 38.5 and 37.7 were also found. Similar behavior was observed for D_2-D_{10}, but the GA consistently optimized to an expected profit of 8.5 in D_{11}-D_{15} in nearly all cases. Sequence feasibility was equal to one (*i.e.* feasible sequence) for almost all of the instances of the GA in Table 1 and the subsequent tables.

The associated partial disassembly sequences for the set of age distributions are described as follows; D_1-D_6 disassemble all solenoid valve components, D_7-D_9 generally disassemble the bolts, bottom housing, and o-ring, and D_{10}-D_{15} generally had no disassembly. This shows that, even only considering expected profit and feasibility, the partial disassembly sequence was dependent on the age of acquired EoL products, as expected. Distributions with younger mean ages specified more disassembly but had greater expected profits while distributions with higher mean ages had less

Table 26 Maximum expected profit considering expected profit and feasibility)

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
1	38.2	28.6	36.2	29.8	23.9	18.2	14.7	9.5	4.9	8.5	8.5	8.5	8.5	8.5	8.5
2	38.5	28.8	36.0	29.6	23.7	18.2	14.7	9.2	10.4	8.5	8.5	8.5	8.5	8.5	8.5
3	38.2	28.8	36.2	29.6	23.9	18.2	13.4	9.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
4	38.2	28.8	36.0	29.6	23.2	18.5	13.5	12.5	4.9	8.5	8.5	8.5	8.5	8.5	8.5
5	38.5	28.1	36.2	29.6	23.2	18.2	13.5	12.5	10.4	2.1	8.5	8.5	8.5	8.5	8.5
6	38.2	28.1	36.2	29.6	23.2	18.2	13.5	8.6	10.4	8.5	8.5	8.5	8.5	8.5	8.5
7	38.2	28.8	47.5	29.6	23.9	18.2	28.9	8.7	10.4	8.5	8.5	8.5	8.5	8.5	8.5
8	38.2	28.6	36.0	29.8	23.7	17.7	13.5	9.5	4.9	2.1	8.5	8.5	8.5	8.5	8.5
9	49.1	28.8	36.2	29.6	23.9	18.2	14.7	8.7	4.2	8.5	8.5	8.5	8.5	8.5	8.5
10	38.5	28.6	36.0	29.6	23.2	18.5	13.1	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
Mode	38.2	28.8	36.2	29.6	23.9	18.2	13.5	9.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5

disassembly but a lower expected profit.

The GA converged to no disassembly (*i.e.* all components recycled) in each run for the case that standard deviation and feasibility were the only objective functions considered. This sequence has an expected profit of 8.5 and a profit standard deviation of 0. The GA was also able to converge to the maximum profit probability value of one in each run when only profit probability and feasibility are considered. However, a profit probability of one is not unique to a single disassembly sequence. A profit probability of one also has associated expected profits that range from 2.37-8.48, standard deviations that range from 0.00-4.60, and various partial disassembly sequences.

Including two objective functions, in addition to feasibility, into the chromosome fitness value calculations resulted in tradeoffs between expected profit and standard deviation, and expected profit and profit probability. An extra row, *EP*, has been added to Table 27 - Table 30 to represent the mode of the expected profit, standard deviation, and profit probability from the expected profit plus feasibility case in Table 26. In the case that expected profit and standard deviation are considered, the expected profit was generally lower than the mode from Table 3 until D_{10} (Table 27). At and after D_{10} no disassembly was the optimal sequence with an expected profit of 8.5, standard deviation of 0 and profit probability of 1.

As is seen in Table 28, the standard deviation values tended to be lower than the single objective expected profit scenario. Compared to the single objective expected profit scenario, higher expected profits were sacrificed for lower standard deviations. Partial disassembly sequences for D_1-D_6 in Table 28 were a mix of full disassembly, disassembling five components, or disassembling two components, contrary to Table 26. D_7-D_8 generally suggested disassembling three components and D_9-D_{15} suggested no disassembly, similar to Table 3.

A similar situation occurred for the case that expected profit and profit probability were considered as the primary objectives, Table 29 and Table 30. However, in this case higher expected profits, Table 6, were sacrificed for a higher profit probability, Table 30. Column D_6 in Table 30 is a

Table 27 Maximum expected profit considering feasibility, expected profit, and standard deviation

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
1	33.7	28.6	36.0	24.2	22.2	17.0	13.5	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
2	25.5	28.8	31.9	22.0	19.5	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
3	33.7	11.8	28.8	29.8	23.9	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
4	38.2	21.1	24.8	22.0	19.6	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
5	37.7	25.5	14.6	24.2	22.2	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
6	38.5	28.1	36.2	22.0	22.2	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
7	38.2	28.6	31.9	22.0	21.5	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
8	23.7	25.0	26.4	12.4	23.9	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
9	32.9	28.1	11.7	22.0	19.5	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
10	12.5	21.1	36.2	12.2	22.0	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
Mode	33.7	28.6	31.9	22.0	22.2	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
EP	38.2	28.8	36.2	29.6	23.9	18.2	13.5	9.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5

Table 28 Minimum standard deviation considering feasibility, expected profit, and standard deviation

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
1	56.1	70.3	70.3	42.4	47.9	9.3	43.1	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
2	14.2	70.3	53.5	10.6	9.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
3	56.1	18.5	45.0	66.4	62.7	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
4	73.9	15.6	11.5	10.6	39.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
5	73.9	53.9	18.3	42.4	47.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
6	73.9	70.3	70.3	10.6	47.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
7	73.9	70.3	53.5	10.6	47.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
8	20.9	53.9	47.8	17.4	62.7	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
9	56.1	70.3	7.0	10.6	9.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
10	9.1	15.6	70.3	17.4	47.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
Mode	73.9	70.3	70.3	10.6	47.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
EP	73.9	70.3	70.3	66.4	62.7	59.4	43.1	40.9	7.8	0.0	0.0	0.0	0.0	0.0	0.0

Table 29 Maximum expected profit considering feasibility, expected profit, and profit probability

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
1	38.5	28.6	32.2	27.0	22.2	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
2	38.5	28.8	31.4	27.0	21.5	18.5	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
3	38.5	25.7	32.2	22.0	22.0	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
4	7.5	21.1	36.0	29.6	9.4	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
5	38.5	28.8	36.0	26.3	19.5	17.0	13.2	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
6	38.5	28.1	36.2	29.8	23.7	17.0	14.7	12.5	5.7	8.5	8.5	8.5	8.5	8.5	8.5
7	32.9	28.8	31.9	12.4	19.5	17.0	14.7	9.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
8	8.5	21.1	32.2	11.7	19.5	17.7	13.5	12.5	7.3	8.5	8.5	8.5	8.5	8.5	8.5
9	7.5	25.7	24.8	29.8	19.5	18.2	13.5	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
10	25.5	21.1	24.8	22.0	22.0	18.5	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
Mode	38.5	28.8	32.2	27.0	19.5	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
EP	38.2	28.8	36.2	29.6	23.9	18.2	13.5	9.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5

Table 30 Maximum profit probability considering feasibility, expected profit, and profit probability

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}	D_{11}	D_{12}	D_{13}	D_{14}	D_{15}
1	0.94	0.86	1.00	0.99	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.94	0.86	1.00	0.99	0.99	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	0.94	0.87	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	1.00	0.94	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	0.94	0.86	0.99	0.99	1.00	0.98	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	0.94	0.86	0.99	0.99	0.98	1.00	1.00	1.00	0.86	1.00	1.00	1.00	1.00	1.00	1.00
7	0.95	0.86	1.00	1.00	1.00	1.00	1.00	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8	1.00	0.94	1.00	1.00	1.00	0.98	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	1.00	0.87	1.00	0.99	1.00	0.97	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10	0.99	0.94	1.00	1.00	0.99	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mode	0.94	0.86	1.00	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
EP	0.94	0.86	0.99	0.99	0.98	0.97	0.96	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00

particular example of this tradeoff. In the single, expected profit objective analysis, the mode of the profit probability of 10 GA runs was 0.97 with an expected profit mode of 18.2, whereas, Table 29 and Table 30 show that these values were 1.0 and 17.0, respectively, when both objectives were considered. Compared to the single objective function, profit probability case, the profit probabilities were generally lower. This was due to profit probability being sacrificed for higher expected profits.

The case where standard deviation and profit probability were used for fitness value calculations had a global optimal solution of no disassembly. This resulted in a standard deviation of 0 and a profit probability of 1 due to the design of the solenoid case study. The GA converged to the global minimum standard deviation and the global maximum profit probability for all runs and age distributions. However, this sequence has an associated expected profit of 8.48, which is considerably less than expected profits for distributions D_1-D_7 in previous analyses.

Figure 22 - Figure 24 display the results of the partial disassembly optimization GA using the parameters indicated by Table 1 and 2 and including feasibility, expected profit, standard deviation, and profit probability objective functions in fitness value calculations. Figure 22 plots expected profit versus profit probability, Figure 23 plots expected profit versus standard deviation, and Figure 24 plots

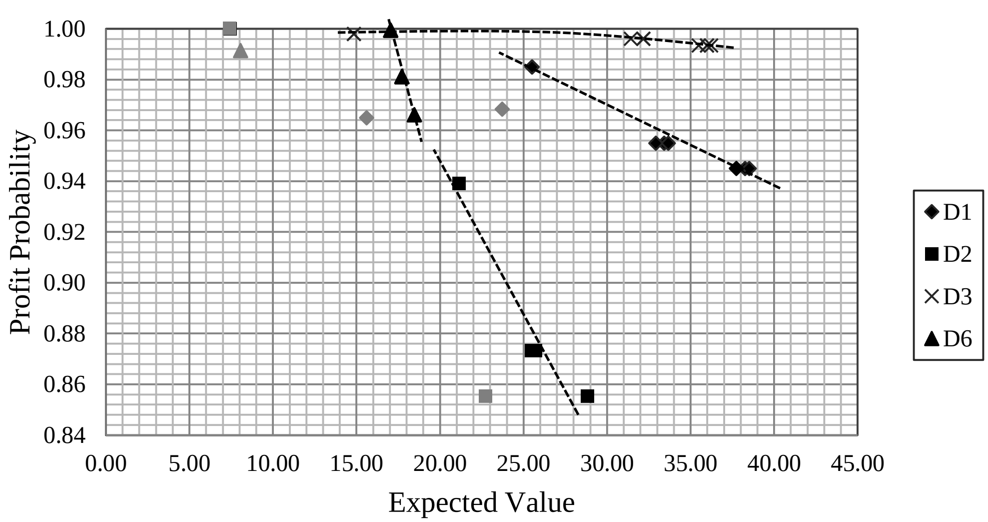

Figure 22 GA solutions plotted as expected profit vs. profit probability for selected age distributions

standard deviation versus profit probability. Selected results (age distributions D_1, D_2, D_3, and D_6) are displayed in the following figures. The exact objective function values for all age distributions have been included in Table 31 - Table 33 and the sequences found in each GA run are listed in Table 34.

Figure 22 - Figure 24 show the optimal or near-optimal sequence objective function values on a two-axis plot in order to show the interpreted Pareto boundary. Results from D_{10}-D_{15} are not included because they had a common, global optimal solution of an expected profit of approximately 8.5, standard deviation of 0, profit probability of 1, and required no disassembly. This was consistent with

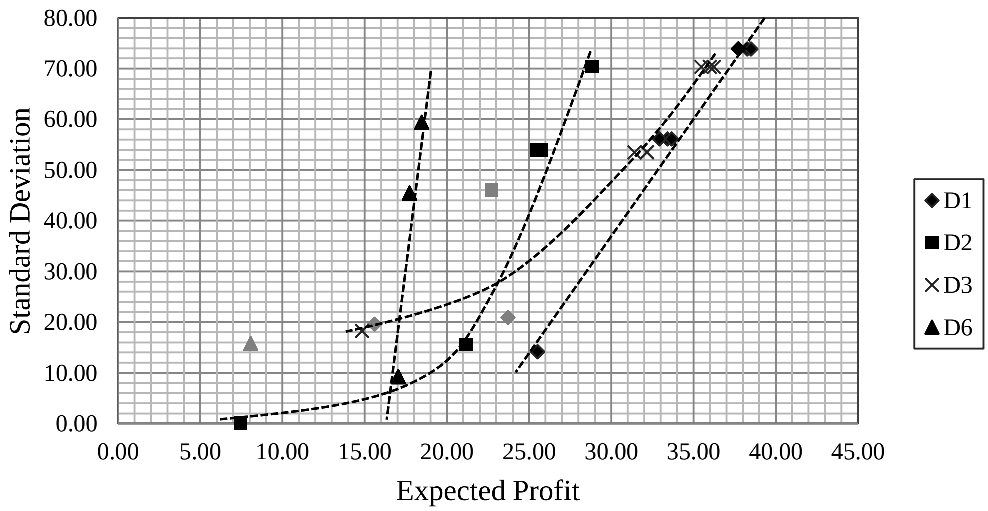

Figure 23 Expected profit vs. standard deviation for selected age distributions

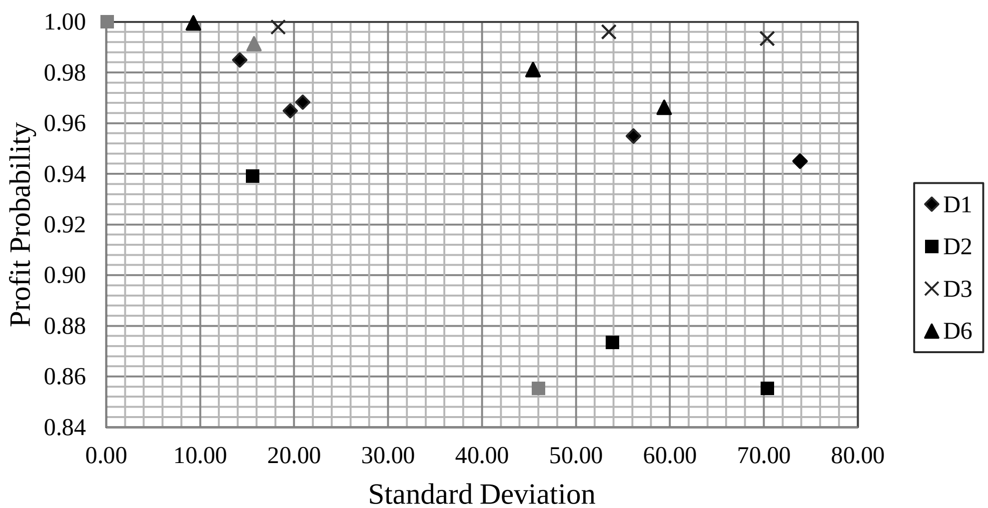

Figure 24 Standard deviation vs. profit probability for selected age distributions

the results previously discussed and the design of the case study. Optimal and near-optimal disassembly sequences identified in Figure 22 - Figure 24 differed within the runs of certain age distributions as well as between age distributions. D_1, D_2, D_5 converged to three component, five component, and full disassembly, but D_9 generally converged to a three component disassembly sequence with some a run specifying five component disassembly. Each run for age distributions D_{10}-D_{15} converged to a solution of no disassembly.

The GA also converged to non-Pareto optimal solutions. For example, in run eight of D_1, the GA converged to 15.61, 19.58, and 0.96 for expected profit, standard deviation, and profit probability respectively. This solution was not grouped near the interpreted Pareto boundary in Figure 22 and Figure 23 and could be considered dominated by points found in runs three and five which converged to an expected profit of 25.51, standard deviation of 14.18, and profit probability of 0.99. Figure 24 does not indicate a Pareto boundary because limited trade-offs exist between standard deviation and profit probability in the case study. Lower profit probability and higher standard deviation values are dominated by higher profit probability and lower standard deviation values for all cases, which can be expected. However, the rate at which the profit probability and the standard deviation decrease and increase, respective, seems to change with the acquired EoL product age distribution.

The results in Figure 22 - Figure 24 confirm what is intuitive, that less quality parts warrant less disassembly because their remaining value is less than higher quality parts. However, the results also indicate that there may not be a global optimal partial disassembly sequence for an acquired EoL product age distribution. Rather, different sequences exhibit trade-offs in expected profit, profit standard deviation, and profit probability. Due to the uncertain nature of EoL products, it is beneficial that each of these parameters, not only expected profit, be considered in disassembly decisions, which this GA and EoL partial disassembly formulation make possible. The selection of a final partial disassembly sequence from results such as those presented in Figure 22-Figure 24 would be dependent on a recovery enterprise's preferences towards expected profit, profit variation, and profit probability (*i.e.* a type of risk) as well as secondary market forecasts and facility capabilities.

Overall, the results indicate that it is beneficial to consider variance and profit probability in disassembly sequence decisions as these factors can impact disassembly sequence decisions. This extends previous disassembly sequence decision processes that traditionally focus on expected profit, thus improving recovery enterprise and product design disassembly decision making processes. As remanufacturing and recovery become more globally widespread, it will be essential to understand the impact of uncertainty throughout the entirety of the recovery process. Accounting for uncertainty in disassembly decisions is one step towards this goal, however, disassembly decisions can be integrated with other aspects of recovery (supply chain design, product acquisition management, etc.) via EoL product age distributions used in this formulation and the distribution of all consumer owned products (*i.e.* available EoL product recovery supply).

Considering uncertain EoL product age distributions was essential to the overall objectives of this dissertation research because it models the critical link between EoL product return and disassembly sequencing. This methodology makes it possible to determine the overall impact a buy-back incentive value (which controls the EoL product age distribution) may have on operational level disassembly sequencing decisions, as discussed in the following section. The method also provides a guideline for mathematically formulating acquired EoL product age distributions in disassembly sequencing problems. If the EoL product age distributions can be characterized as a gamma distribution then it can simply be inserted into the proposed methodology to determine the optimal or near-optimal partial disassembly sequence.

Table 31 Maximum expected profit considering all objective functions

	D_1	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**D_9**	**D_{10}**	**D_{11}**	**D_{12}**	**D_{13}**	**D_{14}**	**D_{15}**
1	33.4	21.1	36.2	29.6	23.9	17.0	13.5	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
2	15.6	22.7	32.2	29.6	10.2	17.0	6.1	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
3	25.5	25.7	32.2	22.0	23.7	18.5	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
4	32.9	7.4	36.0	12.2	22.2	8.1	13.5	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
5	25.5	7.4	31.4	29.1	23.9	17.7	5.4	12.5	7.3	8.5	8.5	8.5	8.5	8.5	8.5
6	38.2	28.8	35.5	29.8	22.2	18.5	13.5	8.7	7.3	8.5	8.5	8.5	8.5	8.5	8.5
7	23.7	28.8	32.2	27.0	22.2	17.7	13.5	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
8	37.7	21.1	14.8	29.8	22.0	17.7	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
9	33.7	7.4	36.0	26.8	22.2	17.7	13.4	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5
10	38.5	25.5	14.8	27.0	19.5	17.0	14.7	12.5	10.4	8.5	8.5	8.5	8.5	8.5	8.5

Table 32 Minimum standard deviation considering all objective functions

	D_1	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**D_9**	**D_{10}**	**D_{11}**	**D_{12}**	**D_{13}**	**D_{14}**	**D_{15}**
1	56.1	15.6	70.3	66.4	62.7	9.3	43.1	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
2	19.6	46.0	53.5	66.4	16.6	9.3	15.0	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
3	14.2	53.9	53.5	10.6	62.7	59.4	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
4	56.1	0.1	70.3	17.4	47.9	15.7	43.1	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
5	14.2	0.1	53.5	66.4	62.7	45.4	15.0	8.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	73.9	70.3	70.3	66.4	47.9	59.4	43.1	40.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	20.9	70.3	53.5	50.6	47.9	45.4	43.1	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
8	73.9	15.6	18.3	66.4	47.9	45.4	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
9	56.1	0.1	70.3	50.6	47.9	45.4	56.3	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0
10	73.9	53.9	18.3	50.6	9.9	9.3	8.7	8.2	7.8	0.0	0.0	0.0	0.0	0.0	0.0

Table 33 Maximum profit probability considering all objective functions

	D_1	**D_2**	**D_3**	**D_4**	**D_5**	**D_6**	**D_7**	**D_8**	**D_9**	**D_{10}**	**D_{11}**	**D_{12}**	**D_{13}**	**D_{14}**	**D_{15}**
1	0.95	0.94	0.99	0.99	0.98	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	0.96	0.86	1.00	0.99	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
3	0.99	0.87	1.00	1.00	0.98	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	0.95	1.00	0.99	1.00	0.99	0.99	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	0.99	1.00	1.00	0.99	0.98	0.98	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	0.94	0.86	0.99	0.99	0.99	0.97	0.96	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	0.97	0.86	1.00	0.99	0.99	0.98	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8	0.94	0.94	1.00	0.99	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
9	0.95	1.00	0.99	0.99	0.99	0.98	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10	0.94	0.87	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 34 Disassembly sequences for the all objective solenoid valve analysis

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10-15}
1	[0;4;3;5;2;7]	[0;4;2;7]	[0;3;4;5;1;2;7;6]	[0;4;3;2;5;1;7;6]	[0;3;4;5;2;1;7;6]	[0;4;2;7]	[0;3;4;2;5;7]	[0;4;2;7]	[0;4;2;7]	0
2	[0;3;4;5]	[0;4;2;3;7]	[0;3;4;2;5;7]	[0;4;3;5;1;2;7;6]	[0;3;4;5]	[0;4;2;7]	[0;3;4;5]	[0;4;2;7]	[0;4;2;7]	0
3	[0;4;2;7]	[0;3;4;5;2;7]	[0;3;4;5;2;7]	[0;4;2;7]	[0;4;3;5;2;1;7;6]	[0;3;4;5;2;1;7;6]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]	0
4	[0;3;5;4;2;7]	[0;4]	[0;4;3;6;1;2;7;5]	[0;4;3;5]	[0;3;4;5;2;7]	[0;3;4;5]	[0;3;4;2;5;7]	[0;4;2;7]	[0;4;2;7]	0
5	[0;4;2;7]	[0;4]	[0;3;5;4;2;7]	[0;3;5;4;2;1;7;6]	[0;3;4;6;1;2;7;5]	[0;3;4;5;2;7]	[0;3;5;4]	[0;4;2;7]	[0;4]	0
6	[0;4;3;2;5;1;7;6]	[0;3;4;5;2;1;7;6]	[0;3;5;4;2;1;7;6]	[0;3;4;6;1;2;7;5]	[0;3;4;2;5;7]	[0;3;4;5;2;1;7;6]	[0;3;4;5;2;7]	[0;3;5;4;2;7]	[0;4]	0
7	[0;4;6;2;7]	[0;3;4;5;2;1;7;6]	[0;3;4;2;5;7]	[0;3;4;2;5;7]	[0;3;4;5;2;7]	[0;3;4;2;5;7]	[0;3;4;2;5;7]	[0;4;2;7]	[0;4;2;7]	0
8	[0;3;5;4;2;1;7;6]	[0;4;2;7]	[0;3;4;5]	[0;3;4;6;2;1;7;5]	[0;4;3;2;5;7]	[0;3;4;5;2;7]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]	0
9	[0;3;4;2;5;7]	[0;4]	[0;4;2;3;5;1;7;6]	[0;4;2;3;5;7]	[0;3;4;5;2;7]	[0;3;4;5;2;7]	[0;3;4;6;2;1;7;5]	[0;4;2;7]	[0;4;2;7]	0
10	[0;3;4;2;5;1;7;6]	[0;4;3;2;5;7]	[0;3;4;5]	[0;3;4;5;2;7]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]	0

5.4. Incentivized Consumer Take-Back and Partial Disassembly Optimization

The solenoid valve, Figure 18 and Figure 19, from the previous section was used to investigate the impact of introducing incentives into the uncertain EoL product age distribution partial disassembly sequencing problem. Section 5.3 assumes that the acquired EoL product distribution is known and that product collection has already occurred (*i.e.* collection costs are out of the scope). Section 5.4 drops those assumptions and studies the problem by determining the optimal or near-optimal partial disassembly sequence for varying system parameter values. Three aspects were considered: 1) the impact of component remanufacturing cost on the partial disassembly sequence, 2) the impact of the consumer value curve on partial disassembly sequences, and 3) the effect of uncertain EoL production quantity, as well as uncertain quality, on partial disassembly sequences. The third aspect assumes that the number of available products for remanufacturing and recovery is known. For each aspect, the consumer incentive is treated as an additional decision variable, and the GA evaluated approximately one hundred thousand chromosomes.

5.4.1. Varying component remanufacturing cost

The remanufacturing cost of each component was scaled, based on a percentage of the base cost in Section 5.3, to investigate the relationship between remanufacturing cost and partial disassembly sequences, incentivized EoL product return and uncertain product quality. It was assumed that the negative exponential consumer value curve has m_{CV} equal to 150 (the sum of the component values at time zero) and a decay parameter, n_{CV}, equal to 0.66. The results are presented in Table 35-Table 39, where the remanufacturing cost is scaled by 0.33, 0.66, and 1.00 for runs $s = 1, 2,$ and 3 of the GA for each age distribution, respectively. The feasibility of each of the disassembly sequences correlating to the results in Table 35 - Table 39 are not shown because each disassembly sequence had a feasibility of one. The GA runs were performed for the remanufacturing cost case, which is shown in Table 35 - Table 39, i.e. each s value has three associated rows.

Table 35 Expected profit for incentivized remanufacturing cost sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	33.86	47.60	5.74	40.75	25.31
	19.70	47.60	44.20	8.45	14.75
	33.71	48.14	45.60	41.25	30.17
2	8.47	12.35	14.06	12.85	9.74
	8.47	21.46	19.70	9.07	8.47
	8.47	20.15	14.16	8.47	8.47
3	8.47	8.47	8.47	8.47	8.47
	8.47	8.47	8.47	8.47	8.47
	8.47	8.47	8.47	8.47	8.47

Table 36 Profit standard deviation for incentivized remanufacturing cost sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	16.84	6.20	1.01	5.36	2.83
	7.36	6.20	4.59	0.58	1.47
	16.56	6.49	5.03	6.16	4.13
2	0.00	4.20	2.09	2.47	2.64
	0.00	6.49	6.21	3.22	0.00
	0.00	6.01	2.13	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00

Table 37 Profit probability for incentivized remanufacturing cost sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	0.97	1.00	1.00	1.00	1.00
	0.99	1.00	1.00	1.00	1.00
	0.97	1.00	1.00	1.00	1.00
2	1.00	0.99	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00

Table 35 lists the expected value of the partial disassembly sequence found by the GA, Table 36, lists the profit variance, Table 37 shows the profit probability, Table 38, lists the incentive value, and Table 39 indicates the specific disassembly sequences. The results of the GA for the incentivized problem confirm what was expected, as the remanufacturing cost of the EoL product increases the amount of disassembly decreases until, eventually, the solenoid valve is completely salvaged and not disassembled.

At the original remanufacturing values ($s = 3$) the GA indicates that an EoL product would not be disassembled, but would be salvaged for the material value. This outcome is due to the extra incentive cost that was introduced into the expected profit calculations. However, if the remanufacturing cost is decreased by a third ($s = 2$) the GA indicated disassembly in D_3 and D_7 for all

Table 38 Incentive value for incentivized remanufacturing cost sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	4.13	4.30	14.30	5.70	9.12
	6.15	4.30	5.40	13.80	11.14
	4.30	4.00	5.00	5.20	7.80
2	15.90	6.00	5.80	6.00	7.00
	15.90	4.00	4.15	7.00	15.90
	15.90	4.50	5.70	15.90	15.90
3	15.90	15.90	15.90	15.90	15.90
	15.90	15.90	15.90	15.90	15.90
	15.90	15.90	15.90	15.90	15.90

Table 39 Partial disassembly sequences for incentivized remanufacturing cost sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	[0;4;2;3;5;1;7;6]	[0;4;3;5;1;2;7;6]	[0;4;2;3;5;7]	[0;3;4;6;1;2;7;5]	[0;4;2;3;5;1;7;6]
	[0;4;2;7]	[0;4;3;6;1;2;7;5]	[0;4;3;6;1;2;7;5]	[0;4;6;2;7]	[0;3;5;4;2;7]
	[0;4;2;3;5;1;7;6]	[0;4;2;3;5;1;7;6]	[0;4;3;5;1;2;7;6]	[0;4;3;5;2;1;7;6]	[0;4;2;6;3;1;7;5]
2	0.00	[0;3;5;4;2;7]	[0;4;2;7]	[0;4;2;7]	[0;4;2;7]
	0.00	[0;3;4;5;2;1;7;6]	[0;3;5;4;2;1;7;6]	[0;3;4;2;5;7]	0.00
	0.00	[0;4;3;2;5;1;7;6]	[0;4;2;7]	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00

three runs, D_{11} in two of the runs, and D_{15} in one run. The disassembly trend when incentives are considered is to disassemble as the age of available products increases, whereas, when the age distribution represented the distribution of EoL products at the facility (Section 5.3), the trend was to disassembly less as the age of the acquired EoL product increased, Table 34. Consider D_2 in Table 34 and Table 39, in Table 39 disassembly is not indicated by the GA for the case $s=3$ because the incentive required to acquire a population of EoL products akin to D_2 in Table 34 is too costly. Instead, no incentive is offered and, according to the available product age distribution, the remanufacturer would acquire a population of products to salvage. However, in D_3, D_7, D_{11}, and D_{15} for $s=2$ in Table 39, the remaining value of the components is high enough, the remanufacturing cost is low enough, and the incentive cost is affordable enough to warrant disassembly. In the case that $s = 1$, the remanufacturing cost is low enough (0.33 times the original values) that complete disassembly and high incentive values are indicated as optimal or near-optimal.

5.4.2. Varying the component value curve depreciation rate

The depreciation rate of the consumer value curve, n_{CV}, was varied in order to determine its effect on the optimal or near-optimal disassembly sequence and product take-back incentive values. Based on the results from 5.4.1, the remanufacturing cost is set 0.66 to ensure that the $s=2$ is consistent between the two analysis, and because this value provided a problem space that exhibited objective function trade-offs. Like 5.4.1, the depreciation rate of the consumer value curve is equal to 0.33, 0.66, and 1.0 for $s = 1, 2,$ and 3 respectively. A higher depreciation rate indicates that the product loses value to the consumer quicker than lower depreciation rates (e.g. cell phones have a higher depreciation rate than automobiles). The results of the consumer value curve analysis are show in Table 40 - Table 44. Table 40 lists the expected profit of the optimal or near-optimal sequence indicated by the GA. Table 41 lists the profit standard deviation, Table 42, lists the consumer return incentive value, and Table 43 lists the disassembled parts of the disassembly sequences. Each sequence in the tables had a feasibility equal to 1, as such, the feasibility table is not shown.

Table 40 Expected profit for incentivized depreciation rate sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	7.73	-2.76	7.73	-3.98	7.73
	7.73	7.73	7.73	7.73	7.73
	7.73	7.73	7.73	-4.61	7.73
2	8.47	16.89	20.71	13.97	8.47
	8.47	21.68	14.19	13.12	8.47
	8.47	21.36	21.25	11.76	8.47
3	8.48	21.35	16.16	14.46	8.48
	8.48	34.09	8.87	20.11	8.48
	18.39	7.91	28.27	5.00	8.48

Table 41 Profit standard deviation for incentivized depreciation rate sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	0.00	4.76	0.00	3.85	0.00
	0.00	0.00	0.00	0.00	0.00
	18.39	7.91	28.27	5.00	8.48
2	0.00	4.73	5.54	5.07	0.00
	0.00	6.29	3.80	2.38	0.00
	0.00	6.38	6.21	1.84	0.00
3	0.00	3.29	1.96	4.06	0.00
	0.00	7.83	1.83	6.81	0.00
	18.53	1.95	6.29	1.38	0.00

Table 42 Profit probability for incentivized depreciation rate sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	1.00	0.65	1.00	0.59	1.00
	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	0.47	1.00
2	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00
	1.00	1.00	1.00	1.00	1.00
	0.86	1.00	1.00	1.00	1.00

Table 40 shows that the expected profit per EoL product generally increased for each age distribution as the depreciation rate of the consumer value curve increased, as may be expected. There appeared to be an error in D_3 and D_{11}, $s = 1$, as these initial values converged to negative expected profit though a positive profit (no disassembly) is known. Intuitively, a higher depreciation rate means that the product loses value to the consumer faster, thus, the incentive value can be lowered because higher quality parts are collected for less. Table 40 and Table 43 suggest such a trend, as the depreciation rate increased the correlating incentive age and expected profit, generally decreased and increased, respectively. This was evident in D_3 and D_{11} and to some extent in D_7 but less so in D_2 and D15 which may be a due to the shape of the age distribution. Interestingly, an increase in expected profit and decrease in the incentive age would seem to also indicate an increase in disassembly in order

Table 43 Incentive value for incentivized depreciation rate sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	15.90	6.20	15.90	6.90	15.90
	15.90	15.90	15.90	15.90	15.90
	15.90	15.90	15.90	7.90	15.90
2	15.90	5.11	4.60	5.90	15.90
	15.90	4.20	6.30	6.14	14.70
	15.90	4.11	4.15	7.13	15.90
3	15.90	3.60	6.14	6.15	15.90
	15.90	2.90	5.10	4.80	15.90
	3.20	5.40	4.10	6.90	15.90

Table 44 Partial disassembly sequences for incentivized depreciation rate sensitivity

s	D_2	D_3	D_7	D_{11}	D_{15}
1	0.00	[0;3;4;6;1;2;7;5]	0.00	[0;3;5;4;1;2;7;6]	0.00
	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	[0;3;5;4;2;7]	0.00
2	0.00	[0;3;4;5;2;7]	[0;3;4;6;1;2;7;5]	[0;3;4;2;5;1;7;6]	0.00
	0.00	[0;4;2;3;5;1;7;6]	[0;3;4;6;2;1;7;5]	[0;4;2;7]	0.00
	0.00	[0;3;5;4;2;1;7;6]	[0;3;4;2;5;1;7;6]	[0;4;2;7]	0.00
3	0.00	[0;4;2;7]	[0;4;2;7]	[0;3;4;5;2;7]	0.00
	0.00	[0;3;4;6;2;1;7;5]	[0;3;4;5]	[0;3;4;6;1;2;7;5]	0.00
	[0;3;4;6;2;1;7;5]	[0;4;3;5]	[0;4;2;3;5;1;7;6]	[0;3;4;5]	0.00

to remanufacturing more components. However, this is not clearly evident in Table 44, which shows an increase in disassembly from $s = 1$ to $s = 2$ but then a decrease in disassembly from $s = 2$ to $s = 3$ even though the consumer values the product less.

5.4.3. Extending the incentive formulation to EoL product quantity

Incorporating incentive values into the uncertain EoL product partial disassembly sequence optimization allowed for initial investigations into the impact of EoL product quality and quantity. The consumer incentive value is the condition that is used to determine the acquired EoL product age distribution, which provides an estimate to the portion of EoL products returned. By assuming a known value of all available consumer products, the number of products that are returned can be calculated as the portion of products returned times the total number of available products. The formulation in section 5.3 was not capable of this because the age distribution of all available products is not considered.

Total profit, a function of EoL product quantity, influences the optimal or near-optimal disassembly sequence. For example, consider option one where a disassembly sequence indicates an expected profit of $10.00 per EoL product but the incentive value indicates that only 1,000 products are returned, resulting in a total profit of $10,000. Alternatively, in option two, instituting a higher incentive value results in a new disassembly sequence with a lower associated expected profit of $8.00 per EoL product, but it also results in more returned EoL products (1,500 products) for a higher total profit of $12,000. Even though the per product expected profit of option one is higher, the total profit of option two is greater and would be selected over option one. Table 45 - Table 47 show the results of the EoL product quantity analysis. The total amount of consumer products in use was varied from 10^3, 10^4, and 10^5 for $s = 1, 2,$ and 3 respectively, the consumer value curve had a depreciation rate of 0.66, and the remanufacturing cost was set to 0.66 of its original value. The depreciation rate and remanufacturing cost parameter were selected based on the results in 5.4.1 and 5.4.2

Table 45 Expected profit for incentivized return quantity analysis

s	D_2	D_3	D_7	D_{11}	D_{15}
1	7.60E+05	5.21E+04	5.51E+06	1.04E+07	5.89E+06
	7.60E+05	5.21E+04	5.51E+06	1.04E+07	5.89E+06
	7.60E+05	5.16E+04	6.45E+06	2.91E+06	4.89E+06
2	7.60E+07	5.21E+06	2.04E+07	1.15E+09	5.85E+08
	7.60E+07	5.21E+06	2.04E+07	1.15E+09	5.85E+08
	7.60E+07	6.69E+07	1.08E+09	2.26E+08	9.03E+08
3	7.60E+09	1.79E+09	3.66E+09	1.32E+09	4.86E+10
	7.60E+09	1.79E+09	3.66E+09	1.32E+09	4.86E+10
	7.60E+09	6.25E+09	6.28E+10	2.28E+10	5.90E+10

Table 46 Incentive value for incentivized return quantity analysis

s	D_2	D_3	D_7	D_{11}	D_{15}
1	6.00	5.00	4.12	4.80	6.50
	6.00	5.00	4.12	4.80	6.50
	6.00	5.10	3.60	5.70	6.70
2	6.00	5.00	6.10	4.80	6.40
	6.00	5.00	6.10	4.80	6.40
	6.00	4.13	3.30	5.80	6.60
3	6.00	5.10	5.20	7.90	6.50
	6.00	5.10	5.20	7.90	6.50
	6.00	4.20	3.80	5.70	6.60

Table 47 Partial disassembly sequences for incentivized return quantity analysis

s	D_2	D_3	D_7	D_{11}	D_{15}
1	0.00	0.00	[0;4;2;7]	[0;4;2;7]	0.00
	0.00	0.00	[0;4;2;7]	[0;4;2;7]	0.00
	0.00	0.00	[0;4;2;7]	0.00	[0;4]
2	0.00	0.00	[0;4]	[0;3;4;5;2;7]	0.00
	0.00	0.00	[0;4]	[0;3;4;5;2;7]	0.00
	0.00	[0;4;2;7]	[0;3;4;5;2;7]	[0;4]	[0;4;2;7]
3	0.00	[0;4;6;2;7]	[0;4]	[0;3;4;5]	[0;4]
	0.00	[0;4;6;2;7]	[0;4]	[0;3;4;5]	[0;4]
	0.00	[0;4;2;7]	[0;4;2;7]	[0;4]	0.00

D_3, D_{11}, and D_{15} show slight variations in the incentive age and an increase in disassembly. It was expected that the incentive age would decrease in order to collect more EoL products and take advantage of smaller margins per EoL product, but this was not the case. However, the system was adjusting the incentive age and disassembly sequence in order to optimize the objectives. If these adjustment were not necessary the expected profit would represent the $s = 1$ scenario multiplied by factors of 10. The previous statements do not apply to age distribution D_2. The results for D_2 indicate that a no disassembly solution is optimal for each scenario, *s*. In general, the amount of disassembly increased as the number of available products increased as indicated by Table 47, however, these results were obtain considering all objective functions (expected profit, profit standard deviation, and profit probability). Profit standard deviation and profit probability continue to be on a per EoL product scale which may contribute to the behavior of the results in Table 45 - Table 47.

The results of this section show that incentives can play a significant role in determining the supply to recovery enterprises and the partial disassembly sequences. The effects of incentives, whether they be monetary, legislative, or deposit refund, must be understood in order to properly select a PrAM scheme, predict the flow of products throughout the life cycle of a product, and optimally design recovery operations. As shown in this section, disassembly operations can be sensitive to product age distribution and the incentive amount, which may change due to creep (slowly aging product population) or can change due to sudden events (new model introduction or competitors). However, disassembly sequence decisions can also be dependent on the total available supply of EoL products. Total profit, a function of the number of returned EoL products, can cause a disassembly sequence with less expected profit per EoL product to be considered more optimal than a higher expected profit per EoL product because more EoL products are returned.

6. CONCLUSIONS

The research presented in this dissertation advances EoL product recovery by addressing gaps in the interaction between End-of-Life (EoL) Product Acquisition Management (PrAM) and disassembly sequencing. The research focused on two remanufacturing research problems; 1) modeling uncertain EoL product quality, quantity, and timing in regards to EoL product acquisition and disassembly sequencing and 2) designing EoL product acquisition schemes considering EoL product uncertainty. These problems were addressed by researching a methodology to determine optimal or near-optimal partial disassembly sequences while considering EoL product quality uncertainty. Incentivized consumer return was then integrated into the methodology to study the effect of EoL product take-back incentives on partial disassembly sequences, but it also allowed for the study of EoL product quantity uncertainty. The EoL product age distribution was the key parameter that linked the partial disassembly sequence method (operational decision) with EoL PrAM (strategic decision). It acts as both an indicator of quality and as a basis for determining return quantity when considering incentivized take-back.

A partial disassembly sequence, multi-objective genetic algorithm (GA) solution procedure, novel to this research, was developed to determine the optimal or near-optimal partial disassembly sequence. The procedure was verified on a discrete, economic and environmental impact case study, and was then adapted for continuous EoL product age distributions. Considering the age distribution of acquired EoL products allowed for partial disassembly sequence convergence to be based not only on expected profit, but also on profit variance and profit probability per EoL product. This was not observed in previous literature, but is critical due to presence of EoL product uncertainty. Specifically, the research provides three contributions to disassembly and EoL product acquisition research: 1) integrating EoL product age distributions into partial disassembly sequencing objective functions, 2) accounting for partial disassembly sequence expected profit, profit variation, and profit probability as compared to disassembly sequencing methods that have, historically, only considered expected profit, and 3) studying the impact of EoL product age distributions and consumer take-back incentives on optimal or near-optimal partial disassembly sequences.

Results presented in this dissertation show how the partial disassembly sequence changes in response to environmental impacts, EoL product age distributions, and incentivized EoL product take-back. Partial disassembly encourages intelligent decision-making at the product EoL. It may be more optimal to directly dispose of subassemblies that retain minimal remaining value rather than incurring disassembly, inspection, and reprocessing costs. Section 5.1 and 5.2 show these trade-offs between environmental impacts and costs for an example case study and the classic coffee-maker example. Section 5.3 shows these trade-offs for the case the EoL product age is uncertain. The results indicate that optimal or near-optimal partial disassembly sequences change as the EoL product age distribution changes. As such, the results encourage a more adaptive approach to disassembly and remanufacturing planning that reacts to the current population of products available for recovery. Section 5.4 extends the uncertain EoL product age case even further to account for incentivized take-back. The results show that incentives and partial disassembly sequences, together, change based on the acquired EoL product age distribution and can be optimized to improve disassembly decisions. In addition, the results indicate that optimal or near-optimal partial disassembly sequences and incentives were dependent on total available product population. Certain instances of incentive values and partial disassembly sequences resulted in a higher cumulative profit by collecting more EoL products with less per EoL product expected profit than incentive value and partial disassembly sequence instances that collect less EoL products with higher per EoL product expected profit.

From a broader perspective, the research and results showcase the need to account for and characterize uncertainty in EoL product recovery systems. Recovery systems are disadvantaged by the lack of control, in most systems, of returned EoL products. As a result, managing, reducing, and understanding this uncertainty is essential to enhancing recovery and remanufacturing operations. The partial disassembly optimization formulations presented in this dissertation address only the disassembly and PrAM aspects of EoL product recovery area, but the framework and formulation of EoL product uncertainty may be used to enhance other areas of recovery and remanufacturing systems. It is envisioned that the model, formulations, and results will also support the efforts of future policy-makers as they create EoL product policies that encourage sustainable manufacturing without prohibitive drawbacks. Thus, the long-term impact of the research may have the potential to influence each pillar of sustainable development.

The methods, formulations, and results presented here assume that age distributions are at steady state, however, it may be valuable in future work to consider the response of consumer and disassembly decisions to transient age distributions resulting from such events as new product model introduction, disruptive technologies, etc. Additional future directions for this research include the following; 1) application and experimentation with a physical EoL product from a recovery enterprise, 2) adapting the formulation to address other types of PrAM schemes such as deposit/refund or governmental legislation, 3) further investigating the consumer decision process to more accurately characterize consumer EoL product return decisions and consumer value curves, and 4) reducing the partial disassembly sequence optimization time in order to create a tool that may be used in real-time to aid product designers and EoL product recovery enterprises.

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