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Agent Based Simulation Optimization of Waste Electrical and Electronics Equipment Recovery

The profitability of electronic waste (e-waste) recovery operations is quite challenging due to various sources of uncertainties in the quantity, quality, and timing of returns originating from consumers' behavior. The cloud-based remanufacturing concept, data collection, and information tracking technologies seem promising solutions toward the proper collection and recovery of product life cycle data under uncertainty. A comprehensive model that takes every aspect of recovery systems into account will help policy makers perform better decisions over a planning horizon. The objective of this study is to develop an agent based simulation (ABS) framework to model the overall product take-back and recovery system based on the product identity data available through cloud-based remanufacturing infrastructure. Sociodemographic properties of the consumers, attributes of the take-back programs, specific characteristics of the recovery process, and product life cycle information have all been considered to capture the optimum buy-back price (bbp) proposed for a product with the aim of controlling the timing and quality of incoming used products to collection sites for recovery. A numerical example of an electronic product take-back system and a simulation-based optimization are provided to illustrate the application of the model. [DOI: 10.1115/1.4034159]

1 Introduction

Although the term e-waste or waste electrical and electronic equipment (WEEE) is often used to refer to obsolete or unwanted consumer electronics, these products are not waste at all and usually have significant value if recovered properly. Business aspects of remanufacturing have been already discussed in the literature [1–3]. Mining rare earth elements from e-waste is one example of business opportunities behind remanufacturing [4]. While the remanufacturing of end of use (EoU) electronics can be profitable [5], the improper recovery of such devices will lead to human health problems and economic loss. Therefore, proper e-waste recovery is an important issue. In contrast to the studies that reported remanufacturing a profitable part of a business, several barriers to efficient remanufacturing make the processes labor-intensive and costly. The cost barriers, as well as the time sensitivity of the value of electronics, impede the widespread adoption of WEEE recovery. Today, e-waste recovery is an extremely uncertain process, but very often this uncertainty is not adequately handled, and it is not appropriately considered in the end of life (EoL) decision-making process. Some of these uncertainties include consideration of quality, quantity, and timing of returns [6], as well as variability in processing times. Alleviating these sources of uncertainty often requires having access to product life cycle data. Cloud-based remanufacturing concept, as well as emerging data collection and information tracking technologies such as smart embedded systems and software applications, will provide a new environment in which the product life cycle actors are enabled to collect and analyze the lifecycle data.

Although the information available on the beginning of life (BoL), product life cycle data, and the original equipment manufacturer's (OEM) operations has the potential to improve the collection and recovery of used devices, this potential has not yet been used in the remanufacturing industry and challenges still remain. For example, considerable delay exists between the time that consumers stop using a device and the time that they return the product to waste stream for any recovery action (e.g., reuse, recycle, remanufacture, and disposal) [7]. The technological obsolescence resulting from consumers' product-storing behavior hampers the profitability of recovery practices. Therefore, the on-time and proper collection of used products influenced by consumers' behavior is an important factor in product recovery systems [8–10]. Even though previous studies have discussed the importance of collecting life cycle data and the necessity of having an information system for EoU recovery, the full implication of product life cycle data has not yet been investigated in the literature. The cloud-based remanufacturing infrastructure proposed in previous studies [11] requires consumers who willingly report the usage information of their product, as well as its EoU status. Nevertheless, the willingness of consumers to participate in recovery management programs seems dubious in the current web-based recovery systems. The effectiveness of cloud services to ameliorate this problem should be investigated further.

Of course, the real-time availability of more accurate data improves the performance of the recovery process. However, in the case of consumer electronics, it is not yet clear that even upon availability of usage and middle of life (MoL) information, in what ways they would influence the recovery operations, since various role players have different types of data and we are considering the types of data that are not currently available to remanufacturers. The contribution of cloud remanufacturing should be more than just providing access to the BoL information, which is currently accessible in a limited fashion. A profound study of the impact of MoL data on the performance of recovery operations is needed. Despite the feasibility of collecting middle-of-life data, current practices rely heavily on very simple rules for EoL recovery decisions and have not fully incorporated the potential available data to support decision making. To fill this gap, this research will improve understanding of how to collect and incorporate the information of previous product life cycles, particularly consumer decision about timing of return, into EoU product recovery decisions.

The current study provides insights on the linkage between the products' quality in the return stream, the remanufacturing efforts, and the costs associated with them. Also, we have investigated the

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direct and secondary effects of buy-back pricing on the characteristics of the return stream considering the recovery profit. The ABS framework developed in this study shows an application of cloud-based remanufacturing systems. We have analyzed the consumer's decisions about the time-of-return of products and participation in take-back programs, as well as the remanufacturer's decision about the EoL recovery fate of the products via product identity data available through cloud.

The rest of this paper is structured as follows: Section 2 summarizes the related literature about the main challenges in e-waste recovery systems and the applications of cloud-based systems. Section 3 provides the simulation framework and clarifies the exact research question. Section 4 showcases the study with a numerical example, and finally Sec. 5 concludes the paper.

2 Literature Review

Since the e-waste problem became a major issue, many efforts have been made in the academic community to shed light on the different aspects of this important subject. Therefore, the e-waste related literature has become quite extensive. A comprehensive survey of the literature in this domain is beyond the scope of this work. However, in order to highlight the contribution of the current paper, we strive to cover the main areas of study on e-waste and go over the literature most related to this work. The previous efforts are categorized under four main categories.

2.1 E-Waste Generation Forecasting. There are quite a few studies that aimed to estimate the e-waste generation rate or specifically the return stream. To name a few: Yu et al. [12] used material flow analysis to estimate and compare the return stream of obsolete computers in developed and developing countries. Wang and colleagues [13] studied the impact of input data on the estimation of return stream. Araújo et al. [14] claimed that the dominant factor that should be used to estimate the e-waste stream is the product life span. In a recent study, Petridis et al. [15] used several forecasting techniques to estimate the e-waste stream quantities in different regions. Their study reveals that a drastic increase will be observed in the e-waste generation rate in the U.S. and UK. Similar efforts have been made on case studies in Czech Republic [16], China [17], the United States [18,19], and India [20].

2.2 Identifications of Factors Influencing E-Waste Generation. A pivotal question in the e-waste domain is determining the factors that control the e-waste generation and its return flow. To answer this question, many survey-based studies have been conducted with the aim of examining the consumer behavior and inferring what factors influence the return stream. For example, Yin et al. [21] showed that education level, income, and region impact the consumers' willingness to pay for recycling. In another study, Afroz et al. [22] illustrated that more than half of the consumers in Kuala Lumpur are willing to pay to improve the e-waste recovery infrastructure. Annual income and gender are also shown to be important criteria in the recycling behavior of consumers. Lack of awareness regarding the recovery programs was found to be a possible barrier in efficient e-waste management [23]. In addition, brand, consumer type, and design characteristics have been reported to influence the consumer usage and product-storing behavior [7]. Moreover, Dwivedy and Mittal [24] concluded that income, recycling habits, and economic benefits are among the factors that influence consumer behavior toward e-waste recovery in India. Comparing the findings of these studies suggests that the consumer behavior and choice structure are very sparse and they depend on various factors, such as region, culture, financial standing, and economic environment. Such uncertainties make it even more difficult to estimate the return stream and further plan the infrastructure regarding using conventional methods.

As mentioned, the majority of studies in this domain utilize survey analysis techniques. However, there are limited studies that used simulation techniques to analyze the consumer behavior toward take-back programs. Mashhadi et al. [25] used ABS and considered sociodemographics, as well as design characteristics of the products, to study the consumer behavior in returning used electronics.

The above-mentioned studies mostly focus on analyzing the waste stream and do not usually incorporate the effect or the role of after-collection practices. However, the next category of studies focuses on the challenges in the recovery process.

2.3 Challenges in the Recovery Processes. Another group of studies are focused on addressing the challenges in the e-waste recovery process, including the uncertain nature of the process. In remanufacturing, more sources of uncertainty are present compared to manufacturing systems. Generally, the quality and quantity of inputs, processing time, and the final demand should be considered uncertain. The initial studies in this field have tried to handle the uncertainties in the closed-loop supply chain structure. The reverse logistic network design and the facility location were the major issues in those studies [26–28]. Later on, several studies considered various sources of uncertainty in order to find out the best EoU recovery decisions (e.g., reuse, recycle, remanufacture, and dispose) in order to maximize the recovery profit [29–31]. Nevertheless, more efforts are needed in this domain as the current recovery practices have not reached their full potential due to the uncertain, labor-intensive, and costly operations. Utilization of consumers' usage information and information sharing platforms may improve the performance of the recovery management schemes.

As mentioned above, the first two categories mainly focus on the consumer part of the e-waste problem while the third group looks at the issue from a recovery firm's perspective and through a recovery process lens. However, higher-performance recovery practices may require a more profound modeling mindset that connects both sides of the equation. Therefore, new business models (e.g., cloud-based remanufacturing) have been recently derived.

2.4 Cloud-Based Remanufacturing. Cloud manufacturing is a concept that has been recently derived from cloud computing technology [32]. Shared resource pooling, global network access, service-oriented platform, and worldwide distribution are among the major characteristics of cloud computing [33].

After the introduction of cloud manufacturing, many extensions of this concept have become available and various challenges in implementing it have been analyzed. For instance, Wu et al. [34] introduced the cloud-based manufacturing and design as a new paradigm in design innovation and manufacturing digitalization. Resources sharing, cost minimization, and rapid prototyping are highlighted as short term benefits of cloud manufacturing, while scalability is among the long term benefits [35]. Ren and colleagues [36] developed a specific user interface for cloud-based manufacturing applications which enables end users to use the cloud-based system based on their specific requirement. Cai et al. [37] also developed a customized encryption framework for collaborations in computer-aided design models in a cloud manufacturing environment since one of the major challenges in cloud-based design and manufacturing digitalization is the level of information sharing and intellectual property. Wu et al. [38] also analyzed the bottlenecks and challenges of resource sharing in the cloud-based manufacturing and presented a model to represent the complex material flows in such systems.

Supply chain design is another domain that has benefited from cloud-based implementation and the changes that it brings to the conventional systems. Radke and Tseng [39] addressed and analyzed the issues regarding the utilization of cloud computing in the structure of supply chains. Akbaripour et al. [40] proposed a conceptual model, using a cloud-based framework, to overcome and mitigate the current challenges in today's hypercompetitive global supply chain. Manufacturing equipment management [41], optimal utilization [42] and repair, maintenance and overhaul [43] are among other recent applications of cloud-based platforms.

E-waste recovery management is no exception. Xia et al. [44] proposed a cloud-based remanufacturing framework for sustainable e-waste recovery management. They suggested that current bottlenecks in information availability throughout the life cycle of the product are major barriers to efficient e-waste remanufacturing. They proposed that using quick response coding systems along with the sharing-data-enabled infrastructure of the cloud can fill the gaps in remanufacturing operations. Similarly, Ijomah et al. [11] put forward a cloud-based system for e-waste recovery and recycling. Their approach is the same as that of Xia's, such that the manufacturing and design stage information of the product (e.g., BoL information) should be provided by the manufacturers. The user is also required to provide the usage information and the service records of the product into the cloud. Using unique identification IDs and quick response codes at the end of the usage cycle, all these information will be available to the user, as well as the recyclers. As a result, an optimized decision can be made for the recovery option of the product. Esmaeilian et al. [45] also pointed out the concept of could-based remanufacturing and the application of product life cycle management in the product recovery domain. They discussed how future generation of intelligent products with extended data sensing features and decision-making capabilities will provide novel opportunities in remanufacturing infrastructure.

The objective of this paper is to optimize the EoL recovery decisions based on the product life cycle data available through cloud. However, the contribution of this work is not limited only to EoU recovery optimization made by manufacturers. The study combines the decision made by end users on the timing and quality of products returned to the waste stream with the manufacturers' decisions on the best EoU recovery decisions. The previous studies have mainly focused on only one side of the recovery system (i.e., remanufacturer's side or consumer's side), and no comprehensive model is available to combine these two decisions. The emergence of cloud-based manufacturing, and consequently, cloud-based remanufacturing, enabled decision makers to link these two sides upon ubiquitous access to the product life cycle data. The cloud remanufacturing framework that has been introduced [44] makes it possible for the remanufacturer to retrieve the life cycle data of the product for recovery purposes. Our model can be an application of the proposed cloud-based remanufacturing platform. We have integrated the ABS abilities and simulation-based optimization techniques with discrete choice analysis (DCA) and used the cloud remanufacturing framework as an input in order to propose a comprehensive model that takes the different aspects of the recovery management into account.

3 ABS Framework

ABS is a robust technique, helpful in simulating systems in which the interactions of different entities are quite important on the macroscopic behavior of the system [46]. Despite the fact that ABS is used for modeling systems in which the overall behavior cannot be reduced to individual components' behavior, complex systems can be modeled by defining simple decision-making agents via ABS [47]. In ABS, agents are capable of making decisions, learning from experiments and adopting new behaviors, communicating and interacting with each other [48]. Such characteristics have expanded the applications of ABS to various domains, such as economics [49,50], supply chain studies [51], social sciences [52], geography [53], and sustainability [25].

Different decision makers in the e-waste recovery system or in the cloud remanufacturing network are modeled and represented as agents. The capability of decision making based on specific decision criteria is programmed in each agent. Studying the local level decisions, as well as the higher level complex behaviors, is possible via analyzing the simulation results.

In this study, Anylogic software is employed to create the ABS platform. The first step in building the model is to identify the agents. Then, the corresponding attributes and properties have been determined. Different scenarios and interactions have been formulated based on the market behavior. The internal validity of the simulation has been tested after the implementation of the algorithms. Finally, the behaviors and properties of the system have been observed and analyzed.

To model the products' collection and recovery systems, the following four different types of agents have been included:

3.1 Manufacturers/Remanufacturers. Although third-party remanufacturers often run recovery facilities and not all manufacturers invest in remanufacturing, several cases exist in which OEMs conduct successful remanufacturing sectors as part of their business models [54]. In addition, many OEMs, particularly in the case of consumer electronics, currently have their own trade-in or return programs. Today, with the global infrastructure of the companies, corporates have migrated from a physical scheme to a more virtual layout, and therefore, information sharing and real time information availability can play a pivotal role even within companies. However, in a more general way, cloud-based structure contributes to the efficient information sharing across the companies. Here, for simplicity, a hybrid system is considered in this model, where one agent has been defined to present the manufacturer/remanufacturer duty. This agent plays two main roles in the market: (1) selling new products and (2) purchasing used products from consumers. The manufacturer releases the products in the market. At the EoU point, when the consumer requests a recovery service via cloud, the manufacturer agent assesses the product quality or obsolescence level based on the product identity data, which is made available via cloud. Based on the quality grade and the planning constraints, the manufacturer agent proposes a buy-back price to retrieve the product and collect it for EoU recovery.

3.2 Consumers. The consumer agent utilizes the product. When the usage cycle is over, the consumer requests a recovery service on the cloud. The consumer then makes a decision about the EoU fate of the product (e.g., store, return, sell, and trash) based on a utility maximizing behavior. In other words, the consumer agent chooses the option that maximizes his utility. In order to create the choice structure of the consumers, a DCA technique has been used. DCA was originally developed in the transportation engineering literature in order to model the choices that travelers and shippers make regarding different modes of transportation. DCA uses a probabilistic approach to predict the probability of choice alternatives [55]. The detail structure of the consumer choice model is presented in Sec. 3.5.

3.3 Collection Centers. The collection center agent is in charge of collecting the product for recovery. In other words, in the case that the consumer decides to return the product, this should be done via collection centers. The properties of the collection center agents also define the accessibility of the return program for the consumer.

3.4 Products. As the cloud-based recovery systems provide the capability of tracking every particular product via product identity information [44], each product is modeled as an individual agent. Although the product agent does not actively make any decisions, the overall behavior of the model is dependent on the interactions of other agents with product agents. Each product agent possesses its own specific usage and event data through the life cycle. In addition, product quality and obsolescence level will be available to the manufacturer through assessing the life cycle information.

3.5 Consumer Decision on EoU Fate of products. The consumers should decide about the EoU of their products. When the usage cycle is over, the consumer should choose between one of the four available EoU options. These options are to store the product, sell it to the second hand market, return it to the manufacturer, or throw it away. Based on the rational utility theory, we have considered that the consumers choose the option that maximizes their utility. A linear utility function has been assigned to each consumer based on the DCA [55]. The following equation represents the utility of each alternative for every individual consumer [25]:

$$U_O = \sum_{i=1}^{i=7} \beta_{oij} X_{ij} \; O \in \{\text{Store, Trash, Sell, Return}\} \quad \forall j = 1, 2, \ldots, \text{number of consumers} \tag{1}$$

where X_{ij} denotes the value of attribute i for consumer j and β_{oij} denotes the weight of attribute *i*, for consumer *j* for alternative o.

The EoU decision made by consumers is influenced by several factors or attributes, such as consumers' sociodemographic information, their awareness of the environmental issues, the buy-back prices offered by remanufactures through trade-in programs and so on. In order to capture the heterogeneity of consumers in DCA model, two points have been considered. First, we have taken sociodemographic properties of consumers into account. Second, we let the coefficients (β_{oij}) vary among consumers. In other words, the weight of each attribute for each alternative can be different for different consumers. Four types of attributes (sociodemographic properties of consumers, social network properties of consumers, product and alternative related attributes) have been considered. We have tried to choose the sociodemographic properties most often reported in the literature [21,23,56].

3.6 Factors Influencing Consumer's Decision

3.6.1 Education level (X_1). Four different education levels have been assigned to consumers. We have assumed that consumers with higher levels of education are more prone to green behavior (i.e., to return the product for recovery or sell it for reuse).

3.6.2 Income (X_2). The income of consumers has been assigned to them from a log-normal distribution. The log-normal distribution is one of the distributions commonly used to model income [57]. It is assumed that the weight of monetary incentives in the utility function (i.e., buy-back price and secondhand market price) is lower for individuals with the higher income level. In other words, individuals with higher income levels are more willing to throw away their products, since they can afford it.

3.6.3 Environmental Awareness (X_3). In order to differentiate the consumers' attitudes toward green behavior, the environmental awareness index has been developed. In addition, we assumed that social network and peer pressure influence the level of environmental awareness of the consumer. Every consumer agent is connected to other agents in two different networks: a distance-based network that mimics the effect of neighbors, colleagues, and family, and a random network that represents the network of friends. The effect of the peer pressure is modeled as follows. For any consumer agent, if more consumers in its networks choose to return their products for recovery, the chance of being aware of recovery programs is higher. An absolute approach is considered to model the environmental awareness. Consumers are categorized into three subgroups. If the number of returns in the consumer's neighborhood reaches a certain level, the consumer is moved from "not aware of return programs" subgroup to "aware of return programs" subgroup. Also, if the number of returns in the network of friends reaches a certain level, the consumer will be considered as "inclined to show green behavior." Accordingly, the highest value of environmental friendliness index is assigned to the third group. In other words, we captured the effect of other consumers' decision on the individual's decision structure. More discussion on the relative and absolute consideration of the impact of social influence on individual decisions can be found in Refs. [25,58].

3.6.4 Accessibility (X_4). In order to take the convenience of returning the product into account, the accessibility index has been considered. The collection centers and the consumers are randomly distributed in the simulation environment and this attribute is calculated based on the average distance of an individual to collection centers. The accessibility to the collection program is particularly important for return option and is a key element of a successful collection system [59]. Here, it is assumed that as the accessibility of the return increases, this option becomes more attractive compared to the other three.

3.6.5 Product Obsolescence (X_5). Product obsolescence represents the product's quality grade. The cloud-based structure allows the manufacturer to track individual products and assess the product quality grade via the life cycle data. Note that producing a single obsolescence index is quite challenging, since obsolescence has multiple dimensions. Generally, it is assumed that higher obsolescence levels impose higher recovery costs [60]. However, obsolescence may refer to the technological obsolescence of the product, the fact that the product is too old that the recovery process is costly or there is no demand for remanufactured products, or technical obsolescence of the product, which takes into account the functionality and cosmetic issues and the costs associated with them. Therefore, in order to highlight the linkage between the quality level and the required remanufacturing effort and to consider both dimensions of obsolescence, we consider both the product age and the actual usage behavior of the consumer. We assume that the recovery revenue for each of the recovery options is a direct function of product obsolescence. The product obsolescence index is calculated based on the age of the product and a random coefficient that denotes how the consumer has maintained the product throughout its life cycle. It is assumed that if the degree of obsolescence is high, the consumer is less willing to keep the product.

3.6.6 Buy-back Price (X_6). Buy-back price is the monetary incentive offered by the manufacturer to motivate the consumers to return their products. Kwak et al. [61] showed that the market value of the EoU electronics can be formulated as a linear function of the product age. We have defined the product obsolescence index, which is a function of product age and quality and corresponding to which we have defined the buy-back price. An initial value is considered for the buy-back price, which decreases based on the obsolescence grade of the product.

3.6.7 Secondhand Market Price (X_7). The secondhand market price is the value of the product if the consumer wants to sell it in the secondhand market rather than selling to manufacturers. The same method has been applied to model this price, except the fact that the secondhand market price is considered to be higher than the buy-back price.

While the above-mentioned factors, except for the buy-back price, do not directly affect the recovery profit, they impact the consumers' decision about the fate of the EoL product and hence, will indirectly affect the final recovery profit.

3.7 Manufacturer Decision on the EoL Recovery. In addition to the consumer decision process, another decision process has been modeled that considers the manufacturer's behavior. The return stream of the products is a function of consumers' decisions whether to return the product or not. The manufacturer has to handle the uncertainties associated with the recovery process. The three major sources of uncertainty in the return stream are the quality of products, their quantity, and the time of return. The cloud structure provides more information regarding the quality of the product. However, the manufacturer still has to handle a large variation in the quality of the incoming products. We assume that the manufacturer has three EoL options to select from: refurbish, remanufacture, and recycle. Refurbish is used when the process is mainly focused on cleaning and software improvements. Thus, refurbishment is often used for products with high quality grades. If the product requires hardware improvement or part replacements in order to bring the product to an almost new condition, the recovery option is called remanufacturing. It is not economical to refurbish or remanufacture the low-quality grade products; therefore, the proper recovery option for these products is recycling. Based on the value added steps mentioned above, we assume that refurbishment can bring more revenue if it is done on a high quality grade product. Respectively, recycling can bring higher revenue in the case of low-quality grade products due to the high cost of remanufacturing or refurbishing. Remanufacturing falls between these two processes. Nevertheless, to capture the uncertainty of processing costs, we assumed random distributions for the revenue of each process. A truncated normal distribution based on the obsolescence index of each product is assumed for the cost of each recovery process.

The manufacturer agent chooses the recovery option that maximizes its expected profit. The total profit of the manufacturer is calculated from the following equation:

$$\sum \max\{R_{iF}, R_{iM}, R_{iC}\} - \text{ buyback price}_i \quad \forall i = 1, 2, \ldots, \text{total number of returns} \tag{2}$$

where $R_{iF}, R_{iM},$ and R_{iC} present the refurbishing, remanufacturing, and recycling revenue for product i, accordingly.

3.8 Optimization Problem. Whenever a consumer agent reaches the end of product's usage cycle, a buy-back price is offered to the costumer by the manufacturer agent based on the quality of the product. The proposed buy-back price impacts the manufacturer's profit in different ways:

(1) The buy-back price influences the consumers' decisions regarding returning the products. In other words, if the manufacturer increases the buy-back price, more consumers will decide to return the products. In addition, since the buy-back price is set based on the obsolescence of the product, a relative change in the buy-back price affects the distribution of the quality of the products that the manufacturer receives.
(2) If the distribution of the quality of products changes, the EoL strategy of the manufacturer changes as well. In other words, if the manufacturer receives more products with high quality, more products can be refurbished and more revenue will be made.
(3) As Eq. (2) illustrates, the buy-back price is the cost of persuading the consumers to return their products. Therefore, it directly affects the manufacturer's profit function.

Based on the discussion above, the following optimization problem has been formulated:

$$\text{Max profit} = \sum \max\{R_{iF}, R_{iM}, R_{iC}\} - \text{buyback price}_i \quad \forall i = 1, 2, \ldots, \text{total number of returns} \tag{3}$$

S.t.

$$R_{iF} = N\left(\min_F, \text{Max}_F, \mu_F(\text{obsolesence}_i), \sigma_F^2\right) \tag{4}$$

$$R_{iM} = N\left(\min_M, \text{Max}_M, \mu_M(\text{obsolesence}_i), \sigma_M^2\right) \tag{5}$$

$$R_{iC} = N\left(\min_C, \text{Max}_C, \mu_C(\text{obsolesence}_i), \sigma_C^2\right) \tag{6}$$

$$\text{buyback price}_i = \text{bbp} - f(\text{obsolesence}_i) \tag{7}$$

$$l \leq \text{bbp} \leq u \tag{8}$$

where R_{iF}, R_{iM}, and R_{iC} are drawn from a truncated normal distribution, the mean of which is a function of the product obsolescence. Also, the buy-back price for any product is an initial base value, bbp, which will be adjusted for each product using a linear function based on the product obsolescence. The manufacturer's decision variable is bbp, while the objective is to maximize the profit. l and u are the lower band and the upper band of the bbp, respectively. The uncertain nature of the consumer behavior coupled with the complexity of the structure of the manufacturer's profit make the simulation a good candidate for studying the problem. A simulation-based optimization has been done to investigate the optimization problem stated above.

4 Numerical Example

Currently, there are several web-based *trade-in* programs that offer quality dependent buy-back prices for electronics (e.g., gazelle, e-bay, and BestBuy). In the trade-in web sites, the user is asked to provide the quality level of his product and is then offered a quality dependent buy-back price. The presence of such services suggests a relatively big market for remanufactured products. A closer look at these programs reveals that the buy-back price for electronics is highly correlated with their obsolescence level (both technological and technical). Table 1 summarizes the available quality levels for cell phones and their corresponding descriptions in Gazelle [62]. Table 2 summarizes the product details for four different cell phone models and their original release dates. For comparison, the products are selected such that their specifications are similar. Figure 1 demonstrates the trend in buy-back price for all the models corresponding to each quality condition. As can be seen in the figure, both technological obsolescence and technical obsolescence impact the pricing policy. The older products are generally priced much less than the newer ones, which implies the impact of product age and their technological obsolescence. Within each model, as technical obsolescence increases, the buy-back price drastically decreases.

Our model can provide insights for remanufacturers and trade-in programs on the collection process by obtaining the optimal

Table 1 Quality levels and their descriptions (extracted from www.gazelle.com [62])

Condition	Quality	Description
1	Flawless	• Works perfectly • No noticeable flaws, still in its package, or looks like new • Has zero scratches or scuffs
2	Good	• No cracks on screen or body • Powers on and makes calls • No major scratches or scuffs
3	Broken—phone turns on	• Cracked screen or body • Broken or cracked hardware • Missing buttons or parts
4	Broken—Phone does not turn on	

Table 2 Sample of cellphone models checked in the trade-in program

Model No.	Brand	Capacity (GB)	Carrier	Release date
1	A	64	Unlocked	Oct. 11
2	A	64	Unlocked	Sept. 13
3	A	64	Unlocked	Sept. 14
4	A	64	Unlocked	Sept. 15

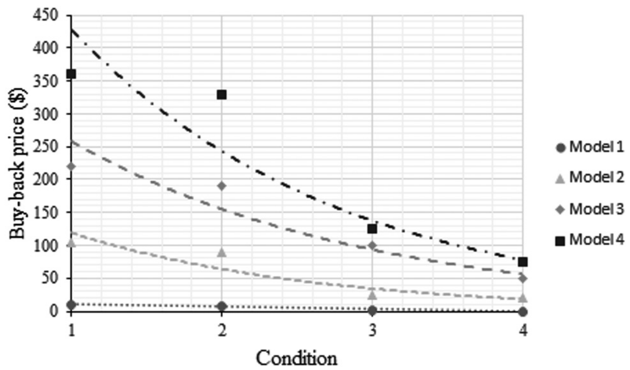

Fig. 1 The buy-back price offered by the trade-in program for four different models of cellphones with different quality condition

price, while considering the linkage between the obsolescence level and the subsequent recovery efforts required. In addition, it alleviates two other issues:

(1) In the current implementation of the trade-in programs, the consumer is supposed to assess the product quality level for the pricing quote. After acquiring the product, it will be evaluated in order to assess its actual obsolescence level. Recent literature [63] suggests that a great inconsistency is present between the quality levels claimed by the consumers and the actual quality levels of the products. Using product MoL data (e.g., repair and maintenance events) via cloud may be a solution to this problem.

(2) Since the consumers are not experts, a detailed evaluation process cannot take place during the pricing procedure and trade-in programs are usually confined to categorizing the quality of the products into limited nominal levels. However, the proposed infrastructure can provide more accurate ranking systems.

A numerical example has been provided to show the application of the model. Tables 3 and 4 illustrate the attribute values and the coefficients used in utility functions of DCA to model the consumers' decision structure. Table 5 represents the global parameters of the simulation. The authors have modeled the consumers' EoL decision process under various scenarios previously in [25] in order to estimate the return stream focused solely on the *collection* process. However, the current work provides insight about different direct and secondary effects that the buy-back price can have on the EoL *recovery* process. Here, the objective is to determine the optimal price to manipulate the quality distribution over the return stream in order to maximize the profit of the recovery process. We incorporate the lessons learned from Ref. [25] into the EoL recovery decision process, while focusing on the linkage between the quality of the return stream and the remanufacturing efforts required. It should be noted that while consumers consider four options when discarding a used device (store, sell, trash, and return), we only consider the information of the number of returns to the manufacturer and not the values of trash, sell and store.

4.1 Internal Validity of the Model.

The simulation has been tested for extreme values, different number of agents and the presence or lack of different agent types, in order to evaluate the internal validity of the model. In addition, in order to check the statistical integrity of the simulation, the sensitivity of the simulation to random seeds has been examined. One hundred simulations have been performed with the same input and different random seeds. If the results of the simulation are very sensitive to the seed of random, the robustness of the model is questionable. Figure 2 represents the distribution of the results (in this case,

Table 3 Value of attributes and local parameters (extended from Ref. [25])

Parameter	Value	Description
Education level	Uniform discrete distribution (1,4)	—
Income	$(100{,}000 \times (\text{lognormal}(\mu = 0, \sigma = 1, \min = 0)))$	—
Environmental awareness	—	Calculated during the experiment
Accessibility	—	Calculated during the experiment
Product obsolescence	Product age × usage index	Calculated during the experiment and changes over time
Buy-back price	bbp − 110 × obsolescence	Changes over time
Secondhand market price	Buy-back price + 30	Changes over time
Usage index	Uniform (0,1)	—
R_{iF}	$N(0, 400, 150 \times \sqrt{1 - \text{obsolesence}}, 20)$	Calculated during the experiment
R_{iM}	$N(0, 400, 130, 20)$	Calculated during the experiment
R_{iC}	$N(0, 400, 220 \times \sqrt{\text{obsolesence}}, 20)$	Calculated during the experiment

Table 4 Value of coefficients used in utility functions of consumers (modified from Ref. [25])

Parameter / Coefficient	β_{Store} Normal(μ, σ^2)	β_{Return} Normal(μ, σ^2)	β_{Trash} Normal(μ, σ^2)	β_{Sell} Normal(μ, σ^2)
Education level	(−0.5,0.25)	(0.5,0.25)	(0.5,0.25)	(0.5,0.25)
Income	(0.000007,0.000002)	(−0.000005,0.000002)	(0.00002,0.000002)	(−0.000005,0.000002)
Environmental awareness	(−1.5,0.05)	(0.5,0.05)	(−1,0.05)	(0.2,0.05)
Accessibility	(0.02,0.001)	(−0.004,0.002)	(0.002,0.001)	(0.002,0.001)
Product obsolescence	(−5,0.5)	(5,0.5)	(5,0.5)	(5,0.5)
Buy-back price	(−0.02,0.01)	(0.06,0.01)	(−0.04,0.01)	(0.02,0.02)
Secondhand market price	(−0.02,0.01)	(0.05,0.01)	(−0.04,0.01)	(0.01,0.02)

Table 5 Global simulation parameters (same parameters as Ref. [25])

Simulation parameter	Value
No. of consumers	500
No. of products	500
No. of collection centers	3
Ratio of data secured products	0.5
Product availability delay	Uniform (0,05)
Usage time by each consumer	Normal (0.5, 2) years
Simulation time	1800 days

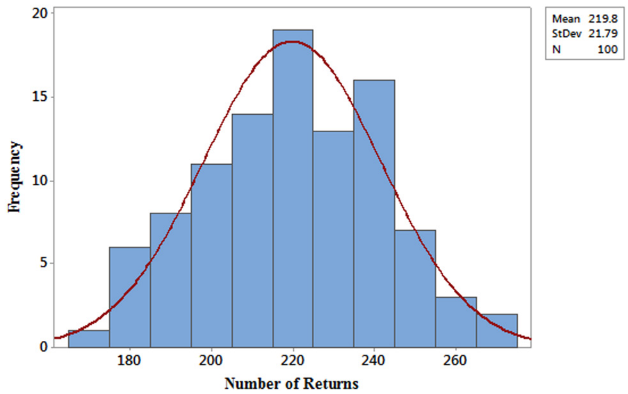

Fig. 2 Histogram of the number of returns after 1800 simulation days. This figure is based on 100 simulation runs with different random seeds.

number of returns). As can be seen, the desired Gaussian behavior is observed.

Figure 3 represents the histogram of simulated revenues for each EoL recovery process (refurbish, remanufacture, and recycle). The values have been drawn randomly during the experiment, based on the formulation presented in Table 3. The parameters of the recovery revenues are estimates based on the logic that usually, refurbishing provides more profit compared to remanufacturing and recycling if applied to a high quality product. On the other hand, recycling is more profitable for low-quality products, as the cost to remanufacture them or refurbish them is relatively higher. As can be seen from the figure, moving from recycling to refurbishing, the mean of the distribution shifts slightly to the right. This indicates that, as expected, the revenue for refurbishing is slightly higher than remanufacturing and then recycling.

Figure 4 illustrates the results of the simulation for four different values of bbp and the extent to which higher buy-back price increases the rate of return. Increasing bbp, and consequently the buy-back price, increases the total number of returns. In other words, when higher prices are offered for the EoU products, more consumers would choose to return their products. In addition, increasing bbp means that the manufacturer would propose a better offer for lower quality products as well. In other words, if we increase the bbp to a sufficient extent, even the consumers that previously did not care about the monetary incentives or the consumers that have very low-quality products may consider returning or selling their products. Thus, two different behaviors can be observed. First, increasing the buy-back price motivates the consumers who own high quality grade products to return them. Higher buy-back price would decrease the tendency to store the product for these consumers. Second, because bbp is a constant value in the buy-back price calculation formula, increasing it would increase the buy-back price offered for low-quality grades as well. As a result, both the number of high quality grade products and low-quality grade products will be increased in total

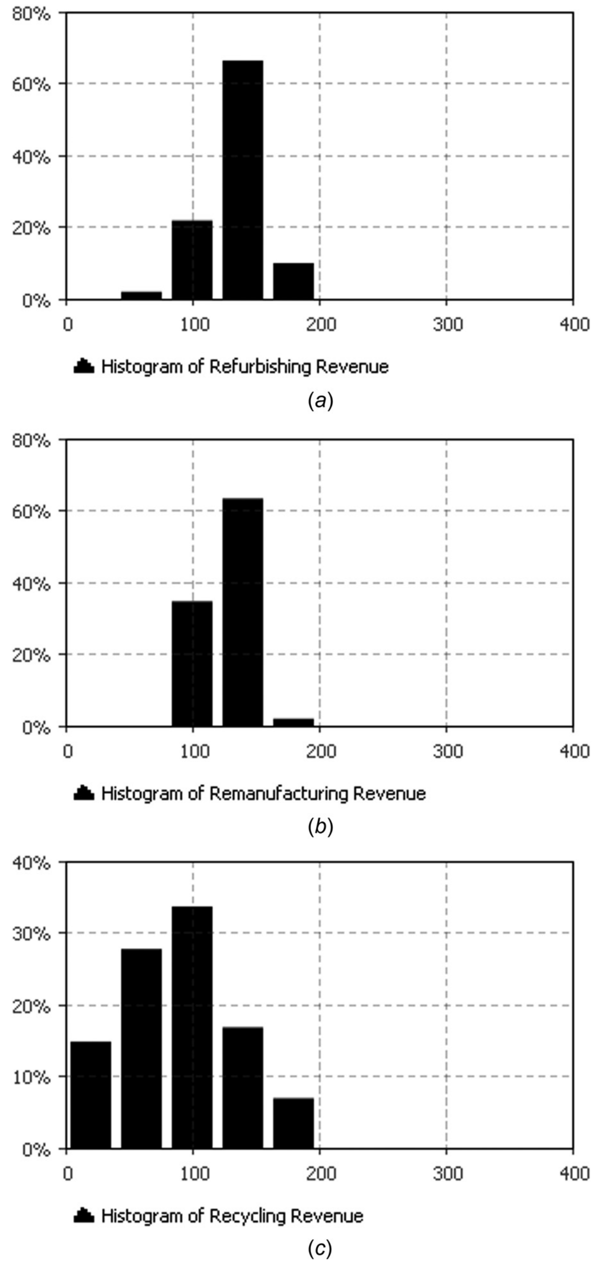

Fig. 3 Histogram of simulated revenue for each EoL process. a) Refurbishing, b) remanufacturing, and c) recycling.

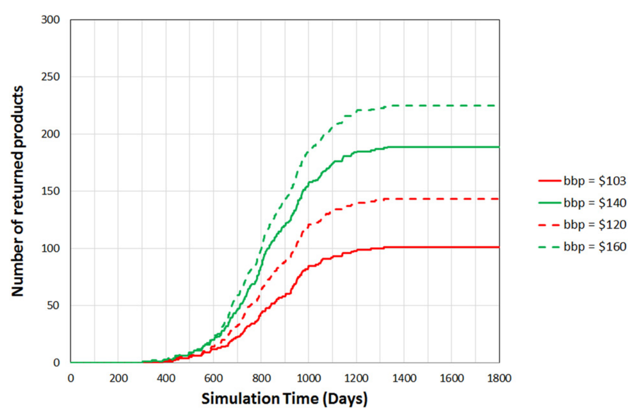

Fig. 4 Total number of returned products to the manufacturer per different initial buy-back prices

number of returns. Combining these two effects prevents a great change in the quality of returns. Figures 5–8 illustrate the distribution of quality grade of the products received by the manufacturer for each bbp. As can be seen, increasing the buy-back price only slightly increases the quality grades.

Although increasing the buy-back price increases the total number of returns and revenue, it does not necessarily improve the profit. There are two reasons behind this. First, increasing the buy-back price increases the cost and based on Eq. (1) decreases the profit. Second, increasing the buy-back price allows more low-quality products (high obsolescence value products) in the return stream, which creates less profit. Table 6 summarizes the profit for the four values of bbp in Fig. 4 and the corresponding EoL options. Table 6 indicates that, since the total number of returns increases, generally more products will be refurbished, remanufactured, and recycled. However, the profit increases in the case of bbp = $120, but decreases afterwards.

This fact can also be verified in Figs. 9–12. Figures 9–12 and Table 6 indicate that as the total number of returns increases, a bigger portion of products are remanufactured and recycled. Therefore, the average profit made per product decreases as bbp increases. The increase in the revenue compensates this loss for bbp = $120. However, the total profit decreases afterwards.

This is due to the fact that from the manufacturer's perspective, lower quality grade products may not be profitable to be recovered. Thus, an optimum buy-back price should be defined in order to achieve a desirable return stream with a good quality

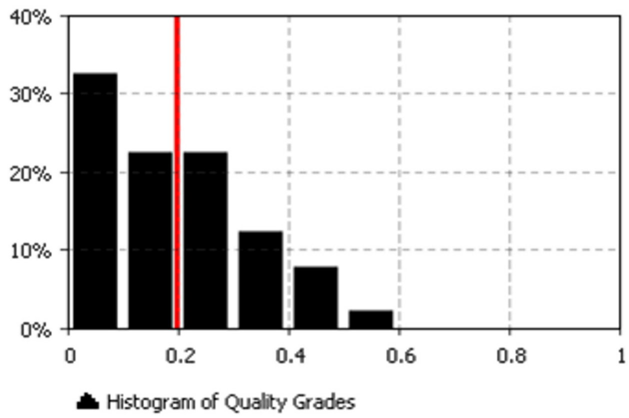

Fig. 5 Distribution of quality grade of products received by the manufacturer for bbp = $103. The red line indicates the mean.

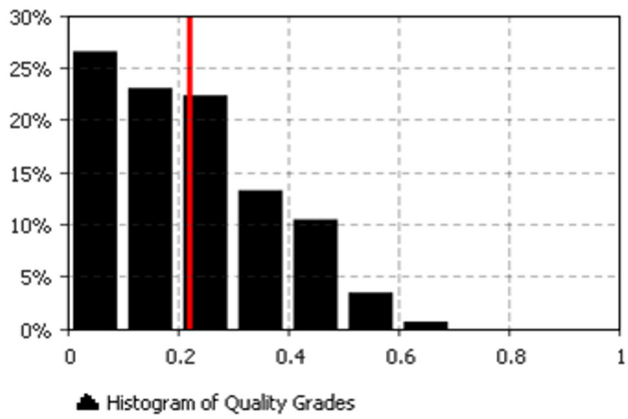

Fig. 6 Distribution of quality grade of products received by the manufacturer for bbp = $120. The red line indicates the mean.

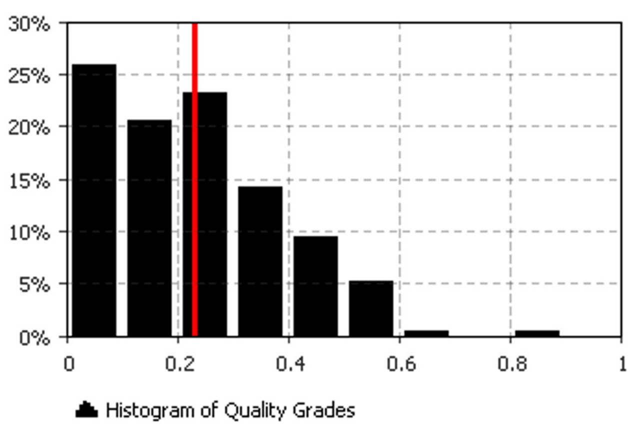

Fig. 7 Distribution of quality grade of products received by the manufacturer for bbp = $140. The red line indicates the mean.

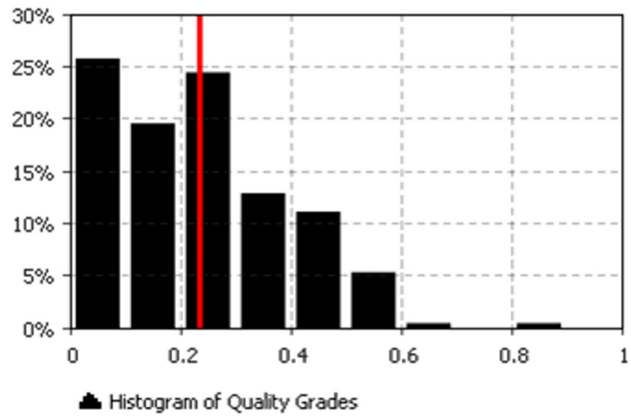

Fig. 8 Distribution of quality grade of products received by the manufacturer for bbp = $160. The red line indicates the mean.

Table 6 Detail results of the experiments (profit, No. of return, number and percentage of refurbished, remanufactured, and recycled products) for four different buy-back prices

bbp($)	103	120	140	160
Profit($)	6675.5	7357.2	6191.5	3047.4
No. of returns	101	143	189	225
Refurbish (%)	57(56%)	62(43%)	79(42%)	108(48%)
Remanufacture (%)	29(29%)	58(41%)	73(39%)	71(32%)
Recycle (%)	15(15%)	23(16%)	37(19%)	46(20%)

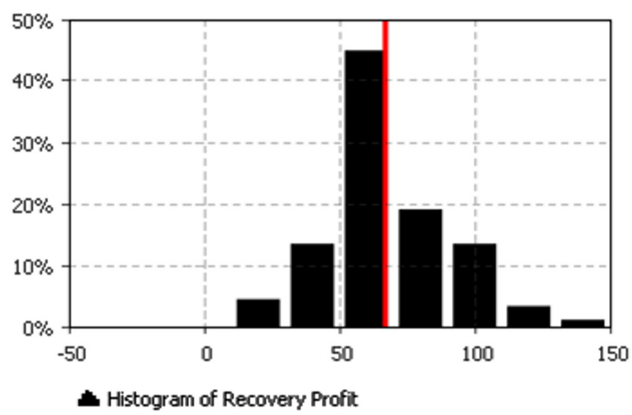

Fig. 9 Distribution of the recovery profit of the manufacturer for bbp = $103. The red line indicates the mean.

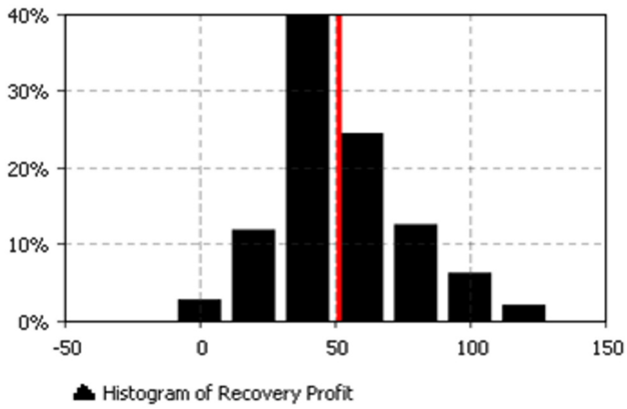

Fig. 10 Distribution of the recovery profit of the manufacturer for bbp = $120. The red line indicates the mean.

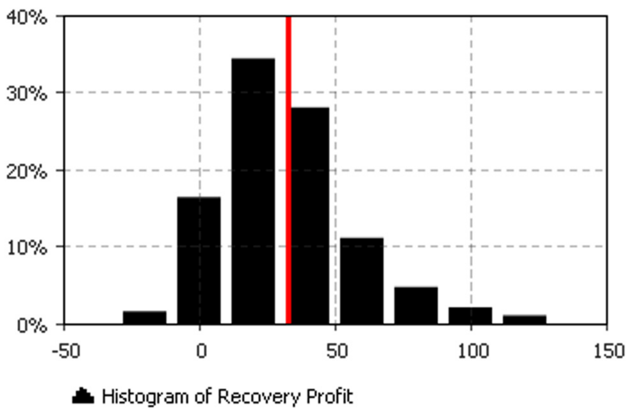

Fig. 11 Distribution of the recovery profit of the manufacturer for bbp = $140. The red line indicates the mean.

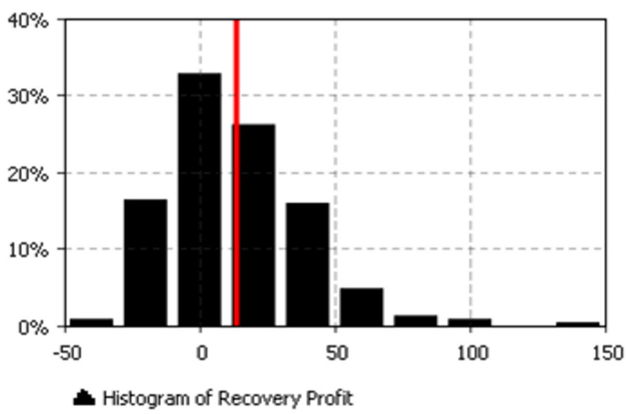

Fig. 12 Distribution of the recovery profit of the manufacturer for bbp = $160. The red line indicates the mean.

distribution. Therefore, we developed a simulation-based optimization model to find the best bbp value that maximizes the profit.

Based on the results of the experiments presented in Table 6, the lower band and upper band for bbp are defined. The profit value shows an increase-then-decrease behavior as the bbp value changes from $103 to $160. Hence, the bbp variable is defined in a continuous format restricted between $100 and $150. The simulation-based optimization has been conducted for 500 iterations. The OptQuest engine has been used as the simulation-based optimization solver. As can be seen in Fig. 13, the objective converges to the maximum value. The optimum is found and

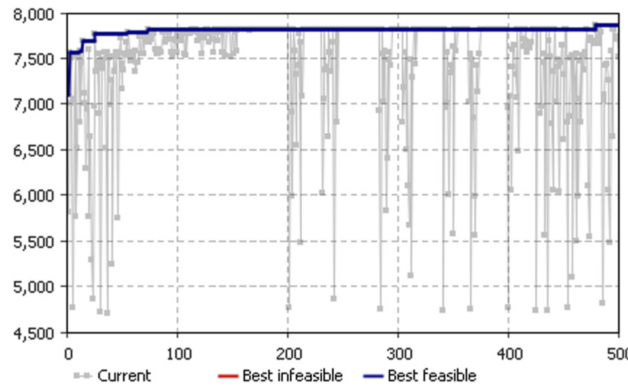

Fig. 13 Result of the optimization

bbp* = $119.92. The corresponding objective (maximum) is $7858.72. Therefore, if the manufacturer sets the initial buy-back price to $119.92, its profit would be the maximum profit earned. Note that, the OptQuest solver uses Tabu Search, Neural Networks and Scatter Search in order to search the solution space for the global optima [64]. However, due to nonlinearity of the problem the global optima cannot be guaranteed. The closeness of the solution to the global optima can be tested via availability of external validation data and establishing a ground truth. However, further analysis of the solution quality is beyond the scope of this work.

5 Conclusion and Future Work

An application of the product life cycle information available through cloud has been discussed in this paper. Selecting the best strategy to recover the EoL electronics, as well as understanding the consumer's choice structure about EoU electronics are necessary in order to improve the performance of recovery operations. This paper used the ABS abilities to model manufactures decisions on the buy-back prices that motivate consumers toward on-time return of their devices. Sociodemographic properties of the consumers, as well as specific properties of the take-back programs have been considered to model consumers' utility. In addition, the remanufacturer's decision-making process about the best EoL strategy for products upon availability of the product identity data via cloud has been modeled. A numerical example of an electronic product take-back system is provided to illustrate the application of the model.

This work has presented an application of the cloud-based remanufacturing infrastructure. However, while the emergence of cloud-based remanufacturing and ubiquitous information access may pave the way to appropriately handling the uncertainties associated with the recovery process, the level of implementation of such technologies is still debatable. The manufacturers should be clear about why and to what extent they should share design and manufacturing information. It has been shown that in other domains, such as supply chain management, information sharing can actually be beneficial for different entities [65]. However, different aspects of adapting this concept, particularly intellectual property issues should be investigated further in the manufacturing context.

This work can be improved in different ways. The provided results are used for a comparison between different scenarios and the specific values of attributes may not be translated to reality. However, using real world data, the model can be calibrated, so that the results of the experiments can be used to predict real values of the attributes. Moreover, the rationale behind assigning values to the coefficients in the consumers' decision model is such that the final values of the model factors become comparable. This assumption is made without the loss of generality in order to compare different scenarios, but may be violated in real situations. However, the paucity and scarcity of real world data make any further investigation for parameter estimation beyond the scope of this work.

The product identity data considered in this work is in the form of product quality level. Other attributes, such as design features and event data can be also considered in the model, which were neglected in this work to avoid over complexity. Also, in addition to the pricing strategies, collection type and shipping method (e.g., drop of, pick up, and prepaid shipping), as well as payment type (e.g., cash, check, and purchase credit) are other strategies that the remanufacturer can adopt to motivate the consumers to return their electronics.

Although environmental legislations can play a pivotal role in WEEE management, the current inconsistency among different rules and regulations on what they mandate and what they ban in different geographical locations makes it quite challenging to address them comprehensively in the model. However, future work aims to address the impact of various environmental policies on the economics of remanufacturing.

The discrepancy in the various types of collection options makes it challenging to come up with a standard index and introduce an accessibility index for other EoL options (e.g., sell to the secondhand market) that can be comparable to return accessibility index. In this study, only the accessibility of the collection programs is considered in the model. However, in reality, selling the product to the secondhand market may or may not be more accessible, depending on the geographical location or the availability of waste recovery regulations at each location. Further investigation of such factors should be a priority in the future work.

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