Improvement of Remanufacturing Profitability through Controlling the Return Rate: Consumer Behavior Aspect

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Abstract

The profitability of remanufacturing activities is affected by the uncertainty in returns rate. The return rate and time depend on consumer behavior. An Agent Based Simulation has been developed to analyze motivational policies which policy makers and manufacturers can adopt to influence consumer's behavior toward discarding their used items.

Keywords: Remanufacturing, Consumer Behavior, Agent Based Simulation

Introduction:

Environmental concerns along with the potential profitability of recovery operations have drawn tremendous attention to waste stream problem. Regulations such as Extended Producer Responsibility (EPR) motivate and even enforce Original Equipment Manufacturers (OEMs) to take the responsibility of their products for the whole life cycle even after the utilization period (Atasu and Subramanian 2012). For example, considering the electronic waste (e-waste) domain, 25 states in the United States (State Mandatory Electronics Recovery Programs 2015) and more than 25 members of the European Union have certain types of law to deal with the e-waste problem (European Association of Electric and Electronic Waste Take-Back Systems 2008). However, the profitability of recovery operations is still a challenge for remanufactures. They face many uncertainties in the time, quality and quantity of returns which result into limited control over the return rate. Return rate is highly affected by consumer behavior toward products usage, storage and return. It has been reported that consumers often store their electronic products after they stopped using them for a certain amount of time before returning them back to the waste stream (Sabbaghi et al. 2015). This delay can endanger the profitability of remanufacturing processes considering the technological breakthroughs and cannibalization effect.

Although the return rate is more influenced by the consumer behavior, OEMs and policy makers also have levers such as buyback price, trade-in programs, environmental regulations and advertisement to influence this rate. In addition to the end-of-pipe strategies mentioned above, the return rate of e-waste can be lined up at the early stage of the design using design concepts such as *Design for multiple life cycles* and *Design for ease of return*. Designer decision on the product design features will influence consumers' behavior at the end-of-use stage. In order to simulate the consumer behavior, Agent Based Modeling (ABM) seems a promising approach since it provides the ability to model each consumer as an individual decision making entity. An Agent Based simulation (ABS) framework is built in this study to investigate the impact of control factors such as design features and monetary incentives on the rate of returns. In addition, a simulation-based optimization has been developed to find the best strategy that OEMs should follow to achieve the maximum profit.

Literature Review:

The prior efforts on ameliorating the e-waste generation problem can be discussed under three broad spectrums of topics. The first group of studies is focused on *e-waste generation estimation*. The main purpose of these studies is to estimate and forecast the future trends of e-waste using previous sales data and extrapolating the future rate based on the products first life span distribution. For example, (Yang and Williams 2009) used the historical sales data for new computers and applied a logistic model to extrapolate the future trends of obsolete computers. In a similar study, (Yu et al. 2010) attempted to forecast the global trend of obsolete personal computers using logistic models and material flow analyses. They pointed out that the majority of e-waste is being produced in developed countries but exported to developing countries.

The second category of studies belongs to *Design for X (DFX)* techniques which generally can be referred to Design for Reuse, Design for Remanufacturing, Design for Recycling, Design for Life Cycle Management and Design for Sustainability (Arnette et al. 2014). These studies mostly focus on finding a solution to e-waste problem at the early stages of design instead of restoration strategies. Kwak et al. (2011) analyzed a dataset from an e-waste collection center and discussed the pivotal role of product design on upgrading and repurposing End of Life (EOL) products. Rai and Terpenny (2008) showed that a design which allows a renewed functionality by adding another component to the product can increase the life span of the product. In addition, choosing proper materials and design techniques will pave the way for future remanufacturing operations (Ijomah et al. 2007). Further, the design can directly affect the disassembly sequencing which is a key part of remanufacturing procedures and finally influences the profitability of recovery operations (Behdad and Thurston 2012).

The third category of studies focuses on building decision analysis tools to facilitate making informed decisions on the best EOL options for used products. Many studies attempted to determine the optimal EOL strategy with the aim of maximizing profit or minimizing environmental impact. To name a few Hula et al. (2003) focused on maximizing the environmental benefits of EOL products with different EOL situations using genetic algorithm. Kwak and Kim (2013) proposed an optimization method to search for the optimal design considering the initial manufacturing and future remanufacturing profit. Behdad et al. (2012) tackled the uncertainty in the quantity of return products. They considered the quantity of returns as an uncertain parameter and found the extent of disassembly and best EOL option using Mixed-Integer programming. In another work they determined the best upgrade level for refurbished products in the presence of variability in the quality of returns (Behdad and Thurston 2011). Another study investigated the effect of uncertainties in the quality and quantity of returns as well as market demand on the remanufacturing profitability (Raihanian Mashhadi and Behdad 2014).

There are notable numbers of studies which aimed at determining the factors that impact the return rate. These studies can be divided into two groups: *Survey based* studies aimed at capturing the consumer attitude and behavior toward product recovery in different geographical regions such as Kuala Lumpur (Afroz et al. 2013), Cardiff (Darby and Obara 2005), and China (Li et al. 2012). Consumers' education level, income, attitude toward recycling and region are among the factors influencing consumer behavior toward return. The second group of studies employed *Discrete Choice Analysis* (DCA) techniques to identify consumer choice decisions. For example, Milovantseva and Saphores (2013) applied multivariate nominal logit models to investigate the effect of different waste management policies on the consumers' decisions toward recovery operations.

The review of prior studies reveals that the consumer interactions and the effect of this factor on their choice decisions have not been sufficiently studied in the literature. To remove this gap, the objective of this paper is to build a simulation framework which facilitates consideration of different factors and their influence on consumers' behavior. Unlike the previous survey-based studies, the current work eliminates the situation and geographical dependency of the results where the proper calibration of simulation model enables decision makers to use the result of the model for any region and socio-demographic set of information.

Agent Based Simulation Framework:

Agent based simulation is an appropriate analysis tool in cases in which the interactions of elements play a big role on the final result. In ABS, systems are characterized such that the global properties cannot be deduced looking at just how each component behaves, since the interaction between components by itself is playing a pivotal role. ABS follows a bottom to up approach compared to other simulation approaches such as Discrete Event Simulation (DES) which follow top-down approach. Unlike DES, in ABS there exist agents that are capable of decision making on their own. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. This ABS methods' generative type of interactions with other agents and with the virtual environment through computer code enables us to focus on the microscopic individual behavior and at the larger scale macroscopic pattern of the consumer behavior. Moreover, agents can change their state and communicate based on simple rules (Kasaie and Kelton 2013). ABS has been widely used in the healthcare and epidemic modeling studies (Kasaie et al. 2010; Longini et al. 2007). ABS suits the consumer choice analysis well. Since simulation models require excessive computation, simpler approximations are constructed to find the best simulated system performance by running the simulation several times with different input parameter values (Barton and Meckesheimer 2006).

Our ABS frame work consists of four different types of agents: *consumers*, *OEM*, *collection center* and *product*. OEM releases the products to the market over time and consumers buy them and utilize them for a specific time period. We assume that each product is assigned to one consumer over a time period based on a distribution (i.e. uniform distribution over half a year). After usage cycle each product enters the 'storage' state until the consumer decides to return it to OEM, sell it in the second hand market or throw it away. Collection centers collect the returned products from the consumers and pass them on to the manufacturer. If a consumer decides to return his product, they have to do via collection centers. OEM agent defines the product design attributes and the return incentive offer to consumers. Anylogic 7 University software has been used to develop the simulation models. The product states have been illustrated in Figure 1.

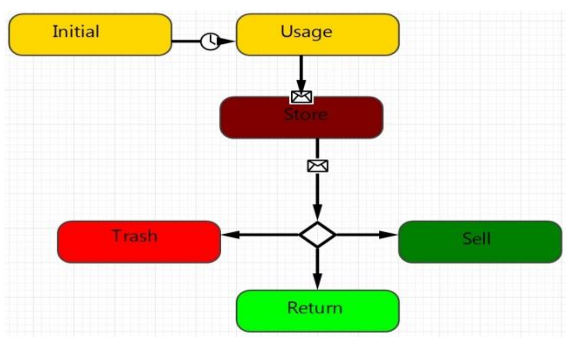

Figure 1- Different states of products

The logic behind the consumer decisions is based on Discrete Choice Analysis (DCA). DCA is a probabilistic choice modeling method which originally has been used to find the market demand for different design alternatives (Chen et al. 2013). We applied the concept of DCA to capture the choice probability of each decision. In order to take the heterogeneity of consumers into account and consider the socio-demographic information, a Mixed Logit model has been used. These models consider a utility function based on the linear combination of attributes and assume that in choice situations the alternative with the highest calculated utility will be chosen. Equation 1 shows the utility function and Equation 2 represents the deterministic utility of each outcome:

$$W_{in} = U_{in} + \varepsilon_{in} \tag{1}$$

$$U_{in} = \beta_{Ai} A_i + \beta_s S_n + \beta_{A.S}(S_n . A_i) \quad (2)$$

Where W_{in} and U_{in} are the utility and the deterministic utility of alternative i for consumer n respectively and ε_{in} is the error term. A_i defines the attribute of alternative i and S_n defines the socio-demographic attributes of the consumer n. β_{Ai} is a random coefficient for each consumer however β_s is fixed. It should be noted that some of these attributes are calculated in real time during the simulation. We also tried to improve the implication of DCA by considering the effect of each consumer's decision on other consumers' decisions as interactions between agents.

Decision Variables:

As mentioned above, the decision process is based on computing the utility of each outcome for every individual consumer. The attributes and factors for the logit model are defined as follows:

Education level (X_1): Four different levels for the education factor have been assigned, where individuals with higher education are more prone to return their product as an environmentally concerned manner. *Income* (X_2): A lognormal distribution has been assigned to simulate the income distribution over consumers. It is assumed that higher income level makes the consumer less interested in the monetary benefits of selling or returning the product. Product *data security* (X_3): Since cell phones usually contain personal information such as bank accounts, passwords, etc., people often are concerned about returning or selling their product to prevent any data leakage. A case of cellphone take-back system is modeled in this work. We consider a design in which the internal memory of the cell phone is detachable and consumers can remove it before handing it over to a third party. While this design is more desirable in terms of data security, on the other hand these products maintain a lower price or incentive since they lack a functional part. The percentage of products possessing this feature is the decision variable that the OEM controls to obtain the maximum profit. *Buyback price* (X_4): This is the OEM's incentive offer for the Trade-In programs. The higher buyback price motivates the consumers to return their product. A linear function is considered for the buyback price using an initial offer which decreases over time based on the product age and degree of obsolescence (Kwak et al. 2012). The initial offer is another factor controlled by OEM. *Second hand market price* (X_5): is the market value for the used product which is assumed to be slightly higher than the OEM's buyback price. The functionality of this attribute is the same as buyback price. *Accessibility* of return programs (X_6): As mentioned above consumers should return their product via collection centers. The accessibility of collection centers defines how convenient returning the products is. We calculate the accessibility for each consumer based on the average distance of collection centers to that individual. *Environmental friendliness* of individuals (X_7): Three types of consumers have been assumed, <u>*greener*</u> consumers, <u>*green*</u> consumers and <u>*brown*</u> consumers, where the greener consumers have the highest attitude toward returning products. Capabilities of ABS are used to model the effect of peer pressure in this attribute. Each individual has a network of neighbors in his vicinity and a network of friends over the simulation environment. The number of previous returns from each network affects the environmental friendliness state of the individual and consumers can immigrate between states based on their interactions with other consumers. Finally, the utility of each decision (store, sell, return, and trash) for every individual can be found as follows:

$$U_O = \sum_{i=1}^{i=7} \beta_{oij} X_{ij} \quad O \in \{Store,\ Sell,\ Return,\ Trash\} \quad \forall\, j = 1, 2, \ldots, total\ number\ of\ consumers \tag{3}$$

When a product enters the storage state it will remain there until the utility of another alternative becomes higher. In other words, consumers keep the product in storage until they find a better alternative.

Numerical Example:

A case of an OEM who aims to maximize profit by setting the buyback price and the ratio of product with a specific design feature (e.g. data security) has been considered here. The design ratio and buyback price control the return rate, however they affect the total cost of operations as well. The objective function is formulated as:

$$\sum S_i - buyback\ price_i - \mathrm{obsolescence}_{\ i} \qquad \forall i = 1,2,\ldots.,total\ number\ of\ returns \tag{4}$$

Where S_i is the selling price of remanufactured product i, buyback price is the incentive OEM pays to regain the product and the obsolescence is an index which shows the cost of remanufacturing. Obsolescence is a function of product age and a random coefficient which denotes how the consumer maintained the product. The Response Surface Methodology (RSM) has been used for the simulation based optimization, where different input values have been provided to the model and the results have been compared. Tables 1 and 2 summarize the list of parameters and values used in the model.

Table 1 – Simulation parameters and their corresponding values

Simulation Parameters	Value	Description
No. of Consumers	500	
No. of Cell Phones	500	
No. of Collection Centers	3	
Ratio of data secured products	R	
Product Availability Delay	Uniform (0,05)	
Usage Time by each consumer	Normal (0.5, 2) years	
Simulation Time	3650 days	
Education Level	Uniform discrete distribution (1,4)	

Simulation Parameters	Value	Description
Income	100000*(lognormal(μ=0,σ=1,min=0))	
Accessibility		Calculated during the experiment
Data Security	1 or 0	Calculated based on the probability that "Ratio of the secured products" defines.
Buy Back Price	P-(20.6*(obsolescence)-(Data Security)*20)	Changes over time
2^{nd}handMarket Price	Buy Back Price + 30	Changes over time
Environmental Friendliness		Calculated during the experiment
Obsolescence	Product age/functionality factor of product	Calculated during the experiment

Table 2 – Coefficients and corresponding values

Attributes / Coefficients	β_{Store} Normal(σ,μ)	β_{Return} Normal(σ,μ)	β_{Trash} Normal(σ,μ)	β_{Sell} Normal(σ,μ)
Education Level	(0.25,-0.5)	(0.25,0.5)	(0.25,0.5)	(0.25,0.5)
Income	(0.000002,0.000009)	(0.000002,-0.000005)	(0.000002,0.00002)	(0.000002,-0.000005)
Accessibility	(0.001,0.02)	(0.002,-0.004)	(0.001,0.002)	(0.001,0.002)
Data Security	(.5,-1)	(.5,2)	(.25,1)	(.5,1.5)
Buy Back Price	(0.01,-0.02)	(0.01,0.06)	(0.01,-0.04)	(0.02,0.02)
2^{nd}hand Market Price	(0.01,-0.02)	(0.02,0.02)	(0.01,-0.02)	(0.01,0.035)
Environmental Friendliness	(0.05,-1)	(0.05,1)	(0.05,-1)	(0.05,0.4)

Results and Discussion:

Figure 2 illustrates the simulation results for one set of inputs. As can be seen after products are released to the market and passing the utilization period, the majority of them remain in storage. However for many products this state is a temporary state, when a considerable portion of consumers find another option (i.e. selling the product) more desirable as time goes by. Another important point to be noted is the higher rate of sold products compared to the returned products. The reason is probably the higher monetary benefit of selling the product especially since these values decrease over time.

The optimization simulation has been done for 100 iterations in order to capture the optimum strategy to set the initial buyback price and design ratio. Figure 3 shows the results. It is assumed that the design ratio changes between 0 and 1 and the initial buyback price ranges from $80 to $150 per product. The selling price of remanufactured product is considered to be $150. The optimization simulation converges to the optimum after less than 20 iterations. The best answer is found to be 1 for the design ratio and $120 for S_i.

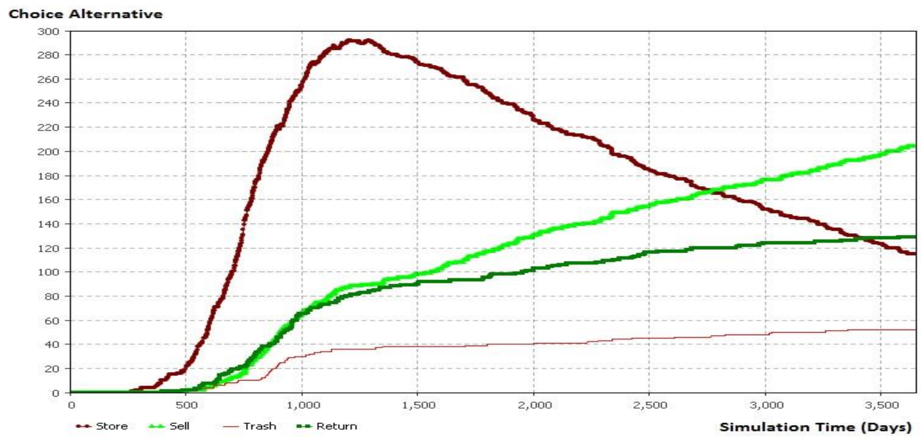

Figure 2 – Simulation results for different alternatives

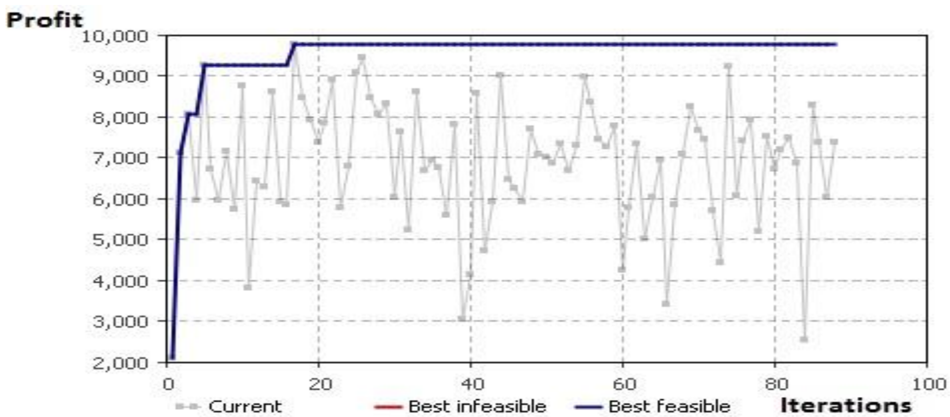

Figure 3 – Optimization results

Conclusions and Future Work:

The return rate of products and the amount that OMEs should invest to increase the return rate have pivotal influence on the profitability of remanufacturing operations. In addition to the buyback price and monetary incentives, there are some other factors that can affect the consumer behavior toward usage, return or storage of products. An Agent Based Simulation model is built to simultaneously consider the consumer decisions, the effect of OEMs policies and the interactions between consumers on the return rate and the OEM's profit. A numerical example has been provided to show the application of the model. The optimum scenario for the numerical example is found to be for OEM to include the data security feature in the design of all products and set the initial buyback price to $120. The results of the model would be more precise if the simulation was calibrated using real survey data. Currently, the coefficients of the utility function are randomly generated assuming the normal distributions. However, they can be defined precisely for each individual using survey-based analysis methods. In addition, it is assumed that all OEMs are able to remanufacture all products and sell them without consideration of the market demand effect. Adding the demand elasticity to the model will enrich the results of simulation.

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