Quantifying impacts of product return uncertainty on economic and environmental performances of product configuration design

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A closed-loop supply chain involves collecting used products from customers and performing product recovery strategies (i.e., reuse, remanufacturing, reconditioning, and recycling) as well as disposing unrecoverable components/items. However, impact of the uncertainty of product return rate on the economic and environmental performance of new product configuration designs has not been addressed in literature. In this study, a methodology is proposed to quantify the impact of product return rate uncertainty using Monte Carlo simulation. The proposed methodology is implemented on an industrial case study for quantifying the impact of product return rate uncertainty on the economic and environmental performance of toner cartridge configuration designs. The results of this study can provide useful information on the variation of total lifecycle cost, global warming potential, total water use, and total energy use of product configuration designs due to the uncertainty of product return rate.

1. Introduction

Growing global consumption and faster product retirement due to rapid technological advancement, have led to a majority of products being discarded after their use. These wasted products often lead to environmental pollution and the loss of the remaining value of the used products, particularly if they have not reached their end-of-life (EoL). Traditional manufacturing practices have not focused on recovering the value from EoL products (as well as end-of-use (EoU) products that have not reached their EoL) after the use stage of the product lifecycle [1]. Sustainable manufacturing practices by adopting a 6R (Reduce, Reuse, Recycling, Redesign, Recover and Remanufacture) methodology enables a total lifecycle-based closed-loop material flow [1,2]. Implementing product EoL recovery strategies, such as reuse, remanufacturing, and recycling, can help companies mitigate environmental impact and conform to strict regulations, while increasing global manufacturing competitiveness and promoting sustainable economic growth [3,4].

A closed-loop supply chain involves collecting used products from customers and performing product recovery strategies, such as reuse, remanufacturing, and recycling as well as disposing unrecoverable components/materials safely [5]. In closed-loop systems, products, components and materials can be utilized multiple times over multiple lifecycles before landfilled [6,7]. However, recycled materials are commonly used in different applications that leads to a challenge to close the loop in industrial practices [7].

EoL recovery strategies and lifecycle issues have been considered in the modeling of product design [8,9]. Product portfolio design optimization, incorporating reuse, remanufacturing and recycling, to balance tradeoffs between cost, reliability, and environmental impact of products were studied by Mangun and Thurston [10]. A multi-objective evolutionary algorithm was proposed by Jun et al. [11] to select EoL product recovery options (i.e., reuse, remanufacturing, reconditioning, or disposal and replacement). Mixed-integer programming for product family design profitability when selling used products [12] and a decision-support model to determine the optimal design of new and remanufactured products simultaneously and the number of returned products while investigating the trade-off between total profit and environmental impact [13] have been studied.

However, there are considerable uncertainties associated with EoL (and EoU) product returns (which collectively will be referred to as ‘product returns’ henceforth) that can have an effect on the economic (e.g., cost, profit) and environmental (e.g., emissions, energy use) impacts of recovering EoL products and using them in subsequent lifecycle products. Thus, the non-deterministic parameters related to product returns...
returns lead to the uncertainty relating to product recovery issues [14]. Some previous studies focused on the uncertainties associated with product returns in terms of quantity, timing and quality of returns [8,15,16,17]. Akcali and Getinkaya [15] reviewed previous studies on deterministic and stochastic product return models for inventory and production planning in closed-loop supply chains. Kim and Goyal [18] examined the effect of recovery rate of used products on the profitability of closed-loop supply chains under different recovery policies. Aydin et al. [8] studied the uncertainties in the quality and quantity of used products to determine the optimal product returns for remanufacturing. Ma and Kim [19] developed a predictive model to improve forecasting about future product return quantities and timing of returns. Uncertainties in the quantity and quality of product returns have been studied using a two-stage scenario-based optimization approach [16], and a stochastic optimization model [20], and with a fuzzy mixed integer algorithm to optimize the reverse logistics network [21]. A mathematical model was developed to explore the effects of uncertainties in data and parameters of LCA. Diaz and Marsillac [30] demonstrated the effect of uncertainties in environmental and eco-efficiency analysis on the evaluation of different electricity generation technologies.

Although quite a number of previous studies investigated the uncertainties in product return issues, they have not addressed the effect of product return rate uncertainty on the economic and environmental performances resulting from a product configuration design. In this study, the impact of product return rate uncertainty on the total lifecycle performance of product configuration designs is quantified by performing a Monte Carlo simulation-based methodology. Such an analysis will enable selecting the product configuration design(s) that are most robust in their ability to meet desired performance goals.

The remainder of this paper is organized as follows. Section 2 describes the proposed methodology for quantifying product return rate uncertainty on the economic and environmental performances of a product configuration design. Section 3 presents an industrial case study to demonstrate the proposed approach by quantifying the uncertainty of toner cartridge return rates on the total lifecycle performance of the toner cartridge configuration design. Results and discussion of the Monte Carlo simulation are shown in Section 4. Section 5 provides the conclusions and future research directions.

2. Proposed methodology

Sustainable product design requires being responsible for the products’ entire life from extracting materials to disposal of retired products. A closed-loop material flow system considers the total product lifecycle that includes the pre-manufacturing, manufacturing, use, and post-use stages [2]. Fig. 1 shows the total lifecycle-based closed-loop material flow system considered in this study. The straight-line and dashed-line arrows indicate the forward and reverse flow of materials/products in the supply chain, respectively. In this closed-loop system, EoL and EoU products can be collected and recovered through further post-use activities (i.e., reuse, remanufacturing and recycling) that enhance overall product sustainability. In this study, component reuse and remanufacturing are considered instead of product reuse and/or remanufacturing due to the focus on product configuration design. Components which are not reused or remanufactured can be recycled for material recovery or sold to third-party recyclers to gain revenue and reduce overall environmental impact. There could also be some components and materials that are disposed in the post-use stage.

Designing products considering total lifecycle-based closed-loop material flow is much more complex than the traditional, open-loop material flow based approach which does not require collecting back
and recovering products at the end of the use stage for use in subsequent lifecycles. The complexities arise because the quantity and quality of product returns are unknown and random.

One approach to analyze the impacts of product return rate uncertainty on the economic and environmental performances of product configuration design is to first identify Pareto optimal solutions for the design of the product under consideration and then evaluate the robustness of those designs. To follow this approach presented here, we use the optimal solutions obtained in our previous study [32] which focused on identifying the optimal product configuration design (i.e., specific variants to be used for each component) considering multi-lifecycle material flow (with component reuse and remanufacturing, and material recycling) and several objectives. The multi-objective optimization problem was solved using a non-dominated sorting genetic algorithm (NSGA-II). In that study [32], issues related to all lifecycle stages, from extracting raw materials to product EoL recovery (i.e., pre-manufacturing, manufacturing, use, and post-use) were considered; the entire demand cycle and the changes in the quantity of product sold over that period is also considered. The three conflicting objectives of the first study [32] are minimizing total lifecycle cost, global warming potential, and total water use. And, the objectives of the second study [32] are maximizing total lifecycle profit, and minimizing total energy use, and total water use. We evaluated the results of the product configuration obtained in the first study [32] and incorporated total energy use functions into the proposed methodology in this study. Cost is one of the most important objectives when designing products. In addition, GWP, water use and energy use are also considered as objectives to assess environmental impacts. Industry has widely used LCA tools (i.e., Simapro, Ecoinvent or any other software) in order to measure GWP, water use and energy use and support decision making in developing sustainable products [33].

In this study, a methodology is proposed to assess the impact of the potential variations and uncertainties in the product return rate. Fig. 2 shows the proposed methodology for quantifying the effect of product return rate uncertainty on the economic and environmental performances of product configuration design using Monte Carlo simulation. The approach uses the following as inputs for the analysis: product configuration design; demand estimates; cost, global warming potential, water use, and energy use throughout the entire lifecycle; and product return rate (as a distribution function). Monte Carlo simulation is then conducted to quantify the impact of the product return rate variation on total lifecycle cost, global warming potential, total water use, and total energy use.

Further details of the proposed methodology are described in the following sub-sections.

2.1. Estimation of product return and post-use processing quantities

Product returns are highly dependent on the number of previously sold products [8,34]. The number of products returned after EoU and EoL at the end of each period can be estimated considering product demand and the return rate parameter as follows:

\[ R_{i+u}(i) = D_i \beta(t), \text{ for } t = 1, 2, 3, ..., \text{T}. \]  

\[ R(i) = 0, \text{ for } t = 1, ..., u. \]  

where \( D_i \) is the product demand in time \( t \), \( \beta(t) \) denotes the random distribution function for return rate of previously sold products in the \( i \)-th simulation run, and \( R_{i+u}(i) \) is the number of products returned in time \( t + u \) in the \( i \)-th simulation run in which \( u \) is the use life of the product (in use stage). \( T \) is the length of the demand cycle. Eq. (2) ensures that there will be no product returns until products complete their use stage.

After used products are collected, they are disassembled to recover some components for reuse, remanufacturing or recycling. Components which are not reused or remanufactured are recycled for material recovery or sold to third-party recyclers to gain revenue and reduce overall environmental impact. Unrecoverable components are disposed without a cost. The number of components reused, remanufactured, recycled, sold, and disposed at the end of each time period can be estimated using the relative percentage of components processed following each of post-use strategies, respectively, at the component variant level as shown below:

\[ n_{ki}^{pu}(i) = \delta_{ki}^{pu} R_{ki}(i) \]  

\[ \sum_{pu=1}^{5} \delta_{ki}^{pu} = 1 \]

where \( n_{ki}^{pu}(i) \) represent the number of the \( l \)-th variant of the \( k \)-th component processed following different post-use strategies (i.e., reused, remanufactured, recycled, sold, and disposed) at time \( t \) for the \( i \)-th simulation run; \( \delta_{ki}^{pu} \) denotes the percentage of the \( l \)-th variant of the \( k \)-th
component processed following different post-use strategies (i.e., reused, remanufactured, recycled, sold, and disposed) at time \( t \). These post-use percentages may not necessarily change from on time period to the other. However, they may change as a product goes through the introduction, growth, maturity and decline phases of its demand cycle. Eq. (4) ensures that the sum of the post-use percentages is equal to 1.

Products can be (re)manufactured using new, reused, and remanufactured components, as well as those made from recycled materials. The product return rate directly impacts the number of returned products and also the quantities of components available for reuse, remanufacturing, recycling, and selling. These quantities can be represented as shown below.

\[
D_{kl} = \delta_{kl} \lambda_t, \quad \text{for } t = 1, 2, 3, \ldots, T
\]

\[
n_{nit}^{new} (i) = D_{nit} - n_{nit}^{rcy} (i) - n_{nit}^{mf} (i) - n_{nit}^{sy} (i)
\]

where \( D_{nit} \) is the demand for the \( k \)-th variant of the \( k \)-th component at time \( t \), \( \lambda_t \) is the number of units of component \( k \) needed for each product (as per the bill of materials); \( n_{nit}^{new} (i) \), \( n_{nit}^{rcy} (i) \), \( n_{nit}^{mf} (i) \), and \( n_{nit}^{sy} (i) \) represent the quantity of the \( t \)-th variant of the \( k \)-th component that is new, reused, remanufactured, and recycled, respectively, at time \( t \) for the \( i \)-th simulation run. For each component variant, the quantity of new items needed in each period (see Eq. (6)) to satisfy the product demand can be estimated by subtracting the sum of reused, and remanufactured component variants, and those made from recycled materials from the total demand for the corresponding component variants in that period. For any component variant, if there are more reusable, remanufacturable, and recyclable items collected than the demand of the corresponding component variant in that time period (i.e., over-collection), excess items are being sold to the third-party recyclers and not kept in inventory.

### 2.2. Estimation of economic and environmental performance measures

This study investigates the impact of uncertainty of product return rate on the economic and environmental performance measures of product configuration design considering the total lifecycle approach. The total lifecycle cost includes two cost components, fixed cost \( (c^{fix}) \), and variable cost. The variable cost includes assembly cost, setup cost, and all other overhead costs. The variable cost is the cost element affected by the selection of component variants for the product design configuration, and the usage of new, reused, and/or remanufactured components, as well as those made from recycled materials and the cost of collecting those EoL products. The components which are sold to third-party recyclers are also considered in the cost computation. Disposal cost is considered negligible and not included in the model. Hence, the total lifecycle cost can be estimated as follows:

\[
TLCC(i) = c^{fix} + \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} \delta_{it} (n_{nit}^{new} (i) c^{new} + n_{nit}^{rcy} (i) c^{rcy} + n_{nit}^{mf} (i) c^{mf} + n_{nit}^{sy} (i) c^{sy}) + D_{it} c^{uw} + R_{it} c^{ret}
\]

where \( TLCC(i) \) is the estimated total lifecycle cost in the \( i \)-th simulation run; \( \delta_{it} \) denotes the parameters for component variants equal to 1 if the \( t \)-th variant of the \( k \)-th component is selected and 0 otherwise; \( c^{new} \), \( c^{rcy} \), \( c^{mf} \), and \( c^{sy} \) represent the unit costs of the \( k \)-th variant of the \( k \)-th component that is new, reused, remanufactured components, and those made from recycled materials, respectively; \( n_{nit}^{new} (i) \) is the number of components sold for the \( t \)-th variant of the \( k \)-th component at time \( t \) in the \( i \)-th simulation run; \( c^{uw} \) is the unit revenue gained from selling the \( t \)-th variant of the \( k \)-th component to a third-party company; \( c^{uw} \) corresponds to the use cost (per unit) of a product; and \( c^{ret} \) is the unit cost of collecting used products in the \( t \)-th period.

The total energy use includes energy use during pre-manufacturing, manufacturing, use (if any) and post-use stages of the product, can be estimated as follows:

\[
TEU(i) = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} n_{nit}^{new} (i) e_{nit}^{new} + n_{nit}^{rcy} (i) e_{nit}^{rcy} + n_{nit}^{mf} (i) e_{nit}^{mf} + n_{nit}^{sy} (i) e_{nit}^{sy} + D_{it} e^{uw} + R_{it} e^{ret}
\]

where \( TEU(i) \) is the estimated total energy use at the \( i \)-th simulation run; \( e_{nit}^{new} \), \( e_{nit}^{rcy} \), \( e_{nit}^{mf} \), and \( e_{nit}^{sy} \) represent energy use of the \( t \)-th variant of the \( k \)-th new, reused, and remanufactured components, and those made from recycled materials, respectively; and \( e^{uw} \) is associated with the unit energy consumption during the use stage of a product.

The total water use includes water consumption during pre-manufacturing, manufacturing, use (if any) and post-use stages of the product, can be estimated as follows:

\[
GW(i) = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} n_{nit}^{new} (i) w_{nit}^{new} + n_{nit}^{rcy} (i) w_{nit}^{rcy} + n_{nit}^{mf} (i) w_{nit}^{mf} + n_{nit}^{sy} (i) w_{nit}^{sy} - n_{nit}^{new} (i) g_{nit}^{new} - D_{it} w^{uw} + R_{it} w^{ret}
\]

where \( GW(i) \) is the global warming potential estimated in the \( i \)-th simulation run; \( g_{nit}^{new} \) and \( g_{nit}^{sy} \) denote the global warming potential impacts of the \( t \)-th variant of the \( k \)-th new, reused, and remanufactured components, respectively; \( g_{nit}^{mf} \) is the global warming potential impact (per unit) by selling the \( t \)-th variant of the \( k \)-th component to a third-party company; and \( w^{uw} \) is associated with the unit global warming potential impact during the use stage of a product.

The total water use includes water consumption during pre-manufacturing, manufacturing, use (if any) and post-use stages of the product, can be estimated as follows:

\[
TWU(i) = \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{i=1}^{I} n_{nit}^{new} (i) w_{nit}^{new} + n_{nit}^{rcy} (i) w_{nit}^{rcy} + n_{nit}^{mf} (i) w_{nit}^{mf} + n_{nit}^{sy} (i) w_{nit}^{sy} + D_{it} w^{uw} + R_{it} w^{ret}
\]

where \( TWU(i) \) is the total water use estimated at the \( i \)-th simulation run; \( w_{nit}^{new} \) and \( w_{nit}^{sy} \) represent water use of the \( t \)-th variant of the \( k \)-th new, reused, and remanufactured components, and those made from recycled materials, respectively; and \( w^{uw} \) is associated with the unit water consumption during the use stage of a product.

### 3. Industrial case study

To illustrate the applicability and effectiveness of the proposed methodology, an industrial case study is presented here for a toner cartridge configuration design. The OEM, headquartered in North America, manufactures laser printers and cartridges (company name not disclosed due to confidentiality). The company is planning to develop a new laser toner cartridge following a closed-loop material flow approach by recovering EoL products. However, there is uncertainty associated with the product returns which affects the number of reusable and remanufacturable components that can be used in manufacturing the toner cartridge in each time period of the demand cycle for the configuration design identified through the optimization model.
Our case company does not perform in-house recycling; instead all recyclable materials are sold to third-party recyclers that may return recycled materials to the same material flow.

In the industry case study, we assume that there is no cost incurred when the product return rate is below or equal to 0.5; a step-wise increasing cost will be incurred to achieve a product return rate higher than 0.5. In fact, the collection cost has already been considered as a reverse logistic cost and integrated into reuse and remanufacturing cost and offset against revenue for materials sold to recyclers. However, the company’s current reverse logistic system is able to collect about 50% of previously sold products in each period. As indicated by their engineers/managers, additional costs may have to be incurred to increase the return rate further. Hence the consideration of a step-wise increasing cost when return rate is above 0.5. Also, if the quantity of product returns in any period is higher than the product demand in that period (over-collection), we assume the excess quantity is sold by the company. The average water use for the minimum cost cartridge design is 49.84 m$^3$; a variation of -26% to +29% from average. The average GWP for the minimum cost cartridge design is 30.67 kg CO2eq (range 28.28 to 31.11 kg CO2eq); a variation of -3% to +16% from average. Thus, it is evident that there is potential for much larger variations in the GWP and water use for the minimum cost cartridge design, than the potential variation for total lifecycle cost and energy use, as the product return rate varies. While the step-wise increasing cost of higher product return rates gives rise to the somewhat skewed distribution of total lifecycle cost, other performance measures (GWP, energy and water use) are only dependent on the quantity of collecting items when the product return rate is below or equal to 0.5, the majority of total lifecycle cost scenarios obtained from the simulation model. In the charts, the x-axis shows the variation in the respective performance measure; the y-axis shows the frequency of obtaining a particular value for the performance measure.

The average total lifecycle cost for the minimum cost cartridge design is $9.37 M (range $8.80 M to 11.44 M; a variation of -6% to +22% from average). Because there are no additional costs of collecting items when the product return rate is below or equal to 0.5, the majority of total lifecycle cost scenarios obtained from the simulation model fall into the $8.80 M to $9.5 M range. The average GWP for the minimum cost cartridge design is 30.67 kg CO2eq (range 22.81 M to 39.53 kg CO2eq; a variation of -26% to +29% from average). The average water use for the minimum cost cartridge design is 49.84 M m$^3$ (range 37.87 M to 62.60 M m$^3$; a variation of -24% to +26% from average). Similarly, the average energy use for the minimum cost cartridge design is 646.7 T J (range 558.8 T J to 764 T J; a variation of -14% to +18% from average). Thus, it is evident that there is potential for much larger variations in the GWP and water use for the minimum cost cartridge design, than the potential variation for total lifecycle cost and energy use, as the product return rate varies. While the step-wise increasing cost of higher product return rates gives rise to the somewhat skewed distribution of total lifecycle cost, other performance measures (GWP, energy and water use) are only dependent on the quantity of product returns leading to more symmetrical distributions.

Fig. 6 shows the variation of economic and environmental performance measures for the minimum cost cartridge design obtained following the simulation model. In the charts, the x-axis shows the variation in the respective performance measure; the y-axis shows the frequency of obtaining a particular value for the performance measure.

4. Results and discussion

In this section, the results of the industrial case study based on the proposed methodology is presented. The Monte Carlo simulation model was formulated and coded with the Matlab software. The model was run 100 K times and took 359 s. Fig. 6 shows the product return rates generated based on the normal distribution, where the mean and standard deviation are 0.5 and 0.1, respectively. The return rate varies between 0.075 and 0.93, but as can be observed from Fig. 4, the product return rate seems to vary between 0.4 and 0.6 in the majority of situations.

Fig. 5 shows the variation of economic and environmental performance measures for the minimum cost cartridge design obtained following the simulation model. In the charts, the x-axis shows the variation in the respective performance measure; the y-axis shows the frequency of obtaining a particular value for the performance measure.

The average total lifecycle cost for the minimum cost cartridge design is $9.37 M (range $8.80 M to 11.44 M; a variation of -6% to +22% from average). Because there are no additional costs of collecting items when the product return rate is below or equal to 0.5, the majority of total lifecycle cost scenarios obtained from the simulation model fall into the $8.80 M to $9.5 M range. The average GWP for the minimum cost cartridge design is 30.67 kg CO2eq (range 22.81 M to 39.53 kg CO2eq; a variation of -26% to +29% from average). The average water use for the minimum cost cartridge design is 49.84 M m$^3$ (range 37.87 M to 62.60 M m$^3$; a variation of -24% to +26% from average). Similarly, the average energy use for the minimum cost cartridge design is 646.7 T J (range 558.8 T J to 764 T J; a variation of -14% to +18% from average). Thus, it is evident that there is potential for much larger variations in the GWP and water use for the minimum cost cartridge design, than the potential variation for total lifecycle cost and energy use, as the product return rate varies. While the step-wise increasing cost of higher product return rates gives rise to the somewhat skewed distribution of total lifecycle cost, other performance measures (GWP, energy and water use) are only dependent on the quantity of product returns leading to more symmetrical distributions.

Fig. 6 shows the variation of economic and environmental performance measures for the minimum environmental impact cartridge design.

The average total lifecycle cost for the environmental impact design is $9.93 M (range $9.61 M to 11.53 M; a variation of -3% to +16% from average). The majority of total lifecycle cost scenarios obtained
from the simulation fall into the $9.61 \text{ M}$ to $10 \text{ M}$ range. The average GWP for the minimum cost cartridge design is $28.28 \text{ M kg CO}_2\text{eq}$ (range $21.50 \text{ M}$ to $35.71 \text{ M kg CO}_2\text{eq}$; a variation of $-24\%$ to $+26\%$ from average). The average water use for the minimum cost cartridge design is $47.56 \text{ M m}^3$ (range $36.44 \text{ M}$ to $59.17 \text{ M m}^3$; a variation of $-23\%$ to $+24\%$ from average). Similarly, the average energy use for the minimum cost cartridge design is $634.8 \text{ TJ}$ (range $566.5 \text{ TJ}$ to $727.4 \text{ TJ}$; a variation of $-11\%$ to $+15\%$ from average). Thus, it is evident that there is potential for much larger variations in the GWP and water use for the minimum environmental impact cartridge design, than the

![Fig. 4. Product return rate distribution.](image4)

![Fig. 5. Variation of performance measures for minimum cost cartridge design.](image5)
potential variation for total lifecycle cost and energy use, as the product return rate varies. From Figs. 5 and 6, it can be observed that the variation of performance measures for the minimum environmental impact cartridge design is less than that for the minimum cost cartridge design.

Fig. 7 shows the economic and environmental performance variation for different cartridge designs as the product return rate changes. These performance results also reinforce the observations shown in

Fig. 6. Variation of performance measures for minimum environmental impact cartridge design.

Fig. 7. Comparison of alternate cartridge performance measure variation with return rate.
Table 1 for the relative performance of the minimum cost and minimum environmental impact toner cartridge designs, in comparison to the baseline design. Both the minimum cost and minimum environmental impact designs perform better than the baseline toner cartridge design with respect to all measures. As can be observed, the total life cycle cost for the cartridge designs decreases with an increase in the product return rate until it is around 0.75. The minimum total cost can be achieved when the return rate is between 0.7 and 0.8. However, the total cost begins to increase when the product return rate is around 0.8. Thus, it is evident from the total lifecycle cost variation that there exists an optimal value (or range) for the product return rate that will help minimize the cost of any toner cartridge configuration design.

As can also be observed from the charts in Fig. 7, the energy use, water use and GWP all decrease as the product return rate increases. However, given there is an optimal value (range) for the product return rate that enables achieving the lowest cost, the case company would benefit most by implementing strategies to maintain the product return rate within that optimal range.

As shown in the total lifecycle cost chart, there will be an increase in the cost as the product return rate increases. This is partly due to having to spend more to collect the EoL products (step-wise cost structure presented earlier). Another factor that also leads to a lower marginal benefit from the increase in product return rate is likely due to over-collection. That is, the situations where the product return quantity is greater than the product demand. In such cases, though expenses are incurred in collecting the EoL products, the company will not be able to use the components from those products to offset costs. This is another reason for observing less marginal cost savings as the product return rate increases. Other impacts of over-collection can also be seen in the total energy use and GWP variations. As the product return rate increases, the total energy use decreases due to savings offered by reusing/remanufacturing components from those products. However, as product return rate increases and results in over-collection, no further savings in energy consumption are possible. Thus, energy consumption reaches a minimum value as product return rate increases and levels off as it results in over-collection of items which are sold off. The GWP computation shows a slightly different pattern of variation as the product return rate increases. This is because GWP savings from the over-collected items that are sold to other parties is off-set against the total GWP consumption for the case company’s product. Hence the continuous decline of GWP, though at lower rate, as the product return rate increases.

5. Conclusions

In this study, we examined the effect of uncertainty and variation in product return rate on the economic and environmental performances resulting from product configuration designs using a Monte Carlo simulation-based methodology. The proposed methodology is implemented on an industrial case study to demonstrate the applicability and effectiveness of the proposed approach. The results show that the uncertainty of product return rate would cause wide variations in economic and environmental performance measures for two cartridge designs with minimum cost and minimum environmental impact, respectively.

However, this study has some assumptions and limitations. First, demands for products were known throughout the entire lifecycle. The uncertainty in the demand for remanufactured products was not examined. A dynamic demand model could be integrated into the proposed model while considering the uncertainty in the demand. Second, the quality of product returns which involves high uncertainty was not investigated in this study. The proposed methodology can be extended considering the uncertainty in the quality of product returns that may have an impact on both economic and environmental performances of products. Third, the return rate is considered constant throughout the entire demand cycle. The future work could involve modeling varying return rates in different phases of the demand cycle. It is also possible to further assess the robustness of alternate product designs by scenario analysis, for example, considering different cost structures to implement product return strategies.

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References