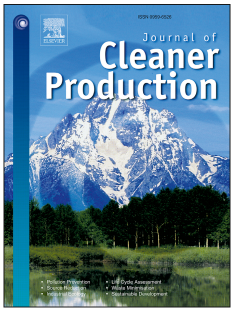

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PII: S0959-6526(18)31986-3

DOI: 10.1016/j.jclepro.2018.07.019

Reference: JCLP 13473

To appear in: *Journal of Cleaner Production*

Received Date: 2 March 2018

Revised Date: 23 June 2018

Accepted Date: 3 July 2018

Incorporating Flexible Capacity in the Planning of a Multi-Product Multi-Echelon Sustainable Reverse Logistics Network under Uncertainty

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Abstract: With the focus on sustainable development, the value recovery from End-of-Life (EOL) and End-of-Use (EOU) products has been given considerable attention by the whole society. Reverse logistics is the process for value recovery and re-creation through a series of activities, i.e., repair, remanufacturing, recycling and energy recovery. However, due to the stochastic reverse product flow, unstable quality of used products, and the price fluctuation of recycled and remanufactured products, the planning of a reverse logistics system is more complex compared with that of a forward supply chain. In this paper, we propose a two-stage stochastic bi-objective mixed integer programming model for the network design problem of a multi-product multi-echelon sustainable reverse logistics system under uncertainty, which aims at providing a set of Pareto solutions between profitability and environmental performance. Furthermore, due to the heterogeneous nature, the processing operations performed at remanufacturing and recycling centers for different products are by no means identical. Different from the previous modelling efforts derived from a genetic “capacitated location problem”, this paper considers the impact from the system flexibility on sustainable reverse logistics network design. Thus, the model is formulated in two parallel ways with either efficiency-focused non-flexible capacity or effectiveness-focused flexible capacity. The experimental analysis illustrates that increasing environmental requirement will decrease the profitability of the reverse logistics system, while, increasing flexibility may yield positive impacts on both economic and environmental performance when the efficiency loss is kept at a proper level.

Key words: reverse logistics; sustainable supply chain; facility locations; flexibility; sustainability

1. Introduction

In recent years, with the stringent environmental regulations enacted and ever increasing focus on sustainable development from the whole society, the value recovery from the End-of-Life (EOL) and End-of-Use (EOU) products has been given considerable attention by decision-makers, companies as well as academic researchers around the world (John et al., 2017). Not only from the perspective of landfill depletion and environmental pollution, but also from the economic perspective, the recovery of EOL and EOU products improves the utilization of recourses and also yields profits through some high value-added operations, i.e. remanufacturing (Guide Jr, 2000). Reverse logistics is the system dealing with the whole process and material flow for value recovery and re-creation from EOL and EOU products, and typical operations in a reverse logistics system include collection, transportation, inspection and disassembly, and distribution for reuse, remanufacturing, recycling, energy recovery and proper disposal of the EOL and EOU products (Rogers and Tibben‐Lembke, 2001).

Reverse logistics is believed to be one of the most important steps for circular economy and sustainable development. As defined by the Brundtland Commission of the United Nations (UN, 1987), sustainable development is "*development that meets the present without compromising the ability of future generations to meet their own needs*". Introduced in 2005 World Summit, sustainable development is supported by three dimensions: economic, environmental and social sustainability (Chopra and Meindl, 2015). Through implementing the reverse logistics activities in an effective and efficient manner, companies can significantly improve the use of materials and cost saving (Kannan et al., 2012), while simultaneously obtaining a higher customer loyalty and potential profitability in future (Kannan, 2009). Meanwhile, reverse logistics can also enhance the environmental and social dimensions of sustainable development through, for example, reduction on landfilled waste, improved resource recovery and job creation in the business (Govindan et al., 2016a).

However, on the other hand, the improper recovery activities and operations may reduce the economic benefits while simultaneously impose great environmental risks on the workers and local residents. For instance, the transcontinental shipment of waste electrical and electronic equipment (WEEE) and packaging waste to Southeast Asia results in increased shipping costs, fuel consumptions and carbon emissions. Meanwhile, the low-tech treatment for value recovery of WEEE and packaging waste used in those countries yields significant pollution on the environment and imposes risks on the health and lifestyles of the workers and nearby residents. Thus, in order to improve sustainability, not only economic benefits, but also the other dimensions of sustainable development should be taken into account in the decision-making of reverse logistics activities. Furthermore, due to the pressure from the public and stakeholder interests (Fahimnia et al., 2015b), practice-based studies have also revealed the top management of companies has paid more attention for the green practices and management of the supply chain (Vlachos et al., 2007).

The network planning of a reverse logistics system is one of the most important strategic decisions (Melo et al., 2009). It involves determination of the number and locations of new facilities to be opened, identification of the mode for transportation, and establishment of the distribution channels for the treatment of EOL and EOU products (Melo et al., 2014). Compared with the network design problem of a traditional forward supply chain, the planning of a reverse logistics system is more complex due to three reasons. First, reverse logistics involves more types of activities (e.g., collection, sorting and disassembly, transportation and distribution, reuse, remanufacturing, recycling, energy recovery and disposal) and the network structure is therefore more complicated. Second, reverse logistics involves more uncertainties in the returned flow in terms of both quantity and quality (Talaei et al., 2016). Further, in the long period of the lifecycle of a reverse logistics system, the price for the recovered products are heavily influenced by the market fluctuation and can hardly be predicted accurately (Soleimani et al., 2016). The third reason is that, due to the heterogeneous nature, the processing operations performed at remanufacturing and recycling centers of different products are by no means identical (Guide Jr, 2000). This further complicates the reverse logistics network design problem with the consideration of the trade-off between efficiency and flexibility (Yu and Solvang, 2017).

In order to solve those challenges, a great number of mathematical models and methods have been developed for helping with a better decision-making of reverse logistics network design. The earlier modelling efforts have been done with single objective function focusing only on the economic performance of the reverse logistics system under a deterministic environment (Govindan et al., 2015), the objective is either to maximize profits or minimize costs (Govindan et al., 2015, John et al., 2018). However, with more emphasis on the environmental and social dimensions of sustainable development, the trade-off between economic performance and sustainability-related measures of reverse logistics network design under an uncertain environment has been increasingly focused by recent research works (See Table 1). However, from the literature review, one of the most important decisions regarding the strategic network configuration has not been thoroughly investigated with the mathematical modelling approach, that is the flexibility of a reverse logistics system. Even if the flexibility issues have been formulated and focused in some activities related to sustainable supply chain management, e.g., supplier selection (Kaur et al., 2016), there is still a lack of decision-support models considering flexibility issues in the network design problem of a sustainable supply chain in existing literature (Gunasekaran et al., 2016). Due to the uncertainty related to the quantity and quality of the input materials, improving the system flexibility of a reverse logistics system may yield significant impacts on both economic and environmental performance. Furthermore, the network decisions at strategic level will influence the decisions on the plant planning, e.g., layout design, internal route planning, etc. At this point, a mathematical modelling approach can provide decision-makers and practitioners with quantitative analysis of the flexibility issues in the strategic planning of a multi-product sustainable reverse logistics system.

The modelling idea behind a product-specified non-flexible configuration is the traditional mass production system that maximizes the efficiency and takes advantage of economy of scale. While, on the other hand, implementing a flexible configuration or flexible manufacturing system aims at improving the effectiveness and taking advantage of economy of scope. However, the improvement on system flexibility usually leads to a compromise on the productivity. Therefore, in the context of a reverse logistics system, this paper aims to answer the following research questions.

1. What is the influence of flexibility on sustainable reverse logistics network design?
2. Does the increase on flexibility can always lead to an improvement on the performance of a multi-product reverse logistics system?
3. In which conditions a flexible configuration performs better than a non-flexible configuration in reverse logistics?

In order to answer the aforementioned questions, we propose a new two-stage stochastic bi-objective mixed integer programming model for the planning of a multi-product sustainable reverse logistics system, and the model aims at balancing the profitability and environmental performance. The goal of this research is, by using an optimization model, to understand the influence of the flexibility on both economic and environmental performances of a multi-product reverse logistics system under uncertainty. To our knowledge, this is the first research work focusing on the flexibility issues in sustainable reverse logistics network design under uncertainty.

The main contributions of this research are summarized as follows:

1. We developed a mathematical modelling approach incorporating the flexibility in sustainable reverse logistics network design under uncertainty.
2. Through the numerical experiments, we investigated the impact of flexibility on the performance of a multi-product reverse logistics system under both deterministic and stochastic environments.
3. Some generic managerial implications related to flexibility and efficiency in sustainable reverse logistics network design under different conditions are discussed based upon scenario analysis.
4. In addition, we also compared the effectiveness and computational efficiency of two solution methods in resolving a multi-objective optimization problem.

The remainder of the paper is organized as follows. Section 2 presents an extensive literature review on reverse logistics network design with a focus on recent publications, and the literature gap regarding the flexibility issues in sustainable reverse logistics network design is discussed. Section 3 gives the problem, method, notations as well as the mathematical model. Section 4 presents a brief introduction of the solution methods. In section 5, experimental analysis is given to illustrate the application of the model. Section 6 summarizes some generic managerial implications. Finally, section 7 concludes the paper and suggests directions for future study.

2. Literature Review

Quantitative modelling efforts for a logistics system aim at providing decision-makers with strategic analysis for an effective and efficient decision-making of logistics network design (Fahimnia et al., 2015a). Due to the complex nature of a reverse logistics system, the network design problem has been focused by both academic researchers and practitioners (Govindan et al., 2015), and numerous mathematical models have been developed for a large variety of industries and businesses (Alshamsi and Diabat, 2015). Comprehensive literature reviews related to reverse logistics problems have been given with different focuses, i.e., conceptual development and perspectives (Wang et al., 2017), industry focused studies (Campos et al., 2017), quantitative models and techniques (Govindan et al., 2015, Govindan and Soleimani, 2017), and modelling methods incorporating with sustainability (Eskandarpour et al., 2015).

Due to the quantitative nature of the current study, this section presents an overview of the recent development on the optimization models for reverse logistics network design. Based upon the characteristics of the models and methods, the literature can be categorized into four groups with their primary research focuses: (1) economic performance; (2) multi-criteria sustainable performance; (3) control of uncertainty; (4) development of efficient computational algorithms.

2.1 Economic performance focused reverse logistics network design

Value recovery from the EOL and EOU products are the primary concern of the planning of a reverse logistics system. Alshamsi and Diabat (2015) developed a mixed integer programming for maximizing the profits of a reverse logistics system, and the model formulates both in-house and outsourcing options of transportation. In order to maximize the profits generated from the recycling of used refrigerators, John et al. (2018) proposed an optimization model for the planning of a reverse logistics network over multiple periods. Budak and Ustundag (2017) proposed a multi-period model for minimizing the costs of the reverse logistics network of healthcare institutions.

Taking into account of disassembly line balancing, Kannan et al. (2017) developed a mixed integer nonlinear optimization model for planning a multi-product reverse logistics system from the third-part provider's perspective. The model aims at maximizing the profits from product recovery, and the market fluctuation is resolved with inventory balancing strategy. Kheirkhah and Rezaei (2016) proposed a single objective cost-minimization model for reverse logistics network design considering cross-docking operations. Alshamsi and Diabat (2017) investigate a mixed integer programming for profit-maximization of recovery activities, and a genetic algorithm was developed to efficiently resolve large problems. In order to provide optimal decisions on the biding price and facility operations, Capraz et al. (2015) proposed a mixed integer linear programming for the recycling system of waste electrical and electronic equipment (WEEE). Demirel et al. (2016) investigated a multi-period mixed integer programming for reverse logistics network design of EOL vehicles.

2.2 Multi-criteria sustainable reverse logistics network design

Due to the pressure from different stakeholders on sustainable development, environmental and social aspects of sustainability have been incorporated in supply chain design (Govindan et al., 2014), and the focus of the optimization problem becomes therefore the balance between economic incentives and ecological influence (Zhu and Sarkis, 2004). With the help of advanced mathematical models, a variety of policy mechanisms combined with economic incentives for the design of a sustainable reverse logistics network are tested, among which implementing different carbon policies for emission reduction has been extensively focused. At this point, the impact of carbon tax on the planning of a reverse logistics network is investigated by Diabat et al. (2013), Haddadsisakht and Ryan (2018), John et al. (2017),Kannan et al. (2012), and Yu and Solvang (2016a), while the implementation of a carbon cap under market fluctuation is tested by Soleimani et al. (2017) and Yu and Solvang (2017).

The most frequently used method for modelling sustainability-related concerns in reverse logistics network design is multi-objective programming. Yu and Solvang (2016b) developed a bi-objective model for balancing the costs and carbon emissions of a reverse logistics system. Considering the economic, environmental and social sustainability in reverse logistics, Govindan et al. (2016b) investigated a fuzzy multi-objective optimization model. In this study, the environmental performance is evaluated by Eco-indicator 99 and the social indicator is evaluated by the created job opportunities and working conditions. Feitó-Cespón et al. (2017) proposed a multi-objective stochastic model for balancing the trade-off among costs, environmental performance and level of service in the redesign of a multi-product reverse logistics system. Considering the decision-making at operational level, Ramos et al. (2014) developed a multi-objective optimization model for the routing problem in a reverse logistics system. The model simultaneously balances the costs, carbon emissions as well as working time.

With the implementation of extended producer responsibility (EPR) and other regulations, manufacturers are required to take responsibilities for the returned flow of their products. In this regard, the supply chain structure becomes more complex with the inclusion of reverse logistics activities. Significant efforts have been spent in order to develop advanced decision-making models for planning an integrated forward/reverse logistics system. Taking into account of both economic and environmental performance of an integrated forward/reverse supply chain, Ghayebloo et al. (2015) developed a bi-objective model for balancing the costs and greenness. Babaveisi et al. (2017) proposed a multi-objective programming for simultaneously minimizing the costs, risks as well as shortage of products in designing a closed-loop supply chain. Considering the economic, environmental and social sustainability, Govindan et al. (2016a) investigated a multi-objective model for planning a multi-product forward/reverse supply chain with hybrid production plants for both manufacturing and remanufacturing operations.

2.3 Reverse logistics network design under uncertainty

The network planning is a strategic decision that has a long-term impact on the performance of a reverse logistics system. Within the lifespan of a reverse logistics system, some parameters may exist significant uncertainties. However, some important decisions, i.e., facility location, have to be made with inexact information (King and Wallace, 2012). Thus, uncertainty control is another focus in reverse logistics network design (Talaei et al., 2016). In order to redesign a reverse logistics network for treating wood waste, Trochu et al. (2018) developed a mixed integer model with scenario-based extension for controlling the uncertainty. Govindan et al. (2016b) proposed a fuzzy multi-objective mathematical model for planning a sustainable reverse logistics system. The model aims at balancing the economic, environmental and social sustainability for reverse logistics network design under uncertainty. Yu and Solvang (2017) investigated a two-stage stochastic programming with carbon constraint for reverse logistics network design, and an augmented multi-criteria scenario-based risk-averse solution method was developed for maximizing the profits from reverse logistics activities while minimizing the risks from uncertainty.

Considering the network design of an integrated forward/reverse supply chain under uncertainty, El-Sayed et al. (2010) and Pishvaee et al. (2009) formulated mathematical models with stochastic parameters for cost minimization, while a robust optimization model was given by Pishvaee et al. (2011). In order to simultaneously maximize the profits, fill rate of customer demands and satisfaction level of stakeholders, Özkır and Başlıgil (2013) developed a fuzzy multi-objective model for planning a closed-loop supply chain with inexact parameters. Soleimani et al. (2017) formulated a fuzzy multi-objective programming for designing a sustainable closed-loop supply chain with carbon emission requirement, and the model aims to seek the optimal balance among profits, level of customer service and the missing working days due to occupational accident. Talaei et al. (2016) proposed a fuzzy robust optimization model for effectively managing the trade-off between total costs and carbon emissions in the design of an integrated forward/reverse logistics system.

2.4 Development of highly efficient computational algorithms

Reverse logistics network design is a complex decision-making problem, which involves a large amount of parameters, decision variables and constraints. With the increase on the size of the problem, computational time required for calculating the optimal solution will increase dramatically. Thus, the improvement on the computational efficiency is focused in previous research works. Several approximation methods, heuristics and meta-heuristics have been developed, i.e., genetic algorithm (Alshamsi and Diabat, 2017), particle swarm optimization (Guo et al., 2017a, Guo et al., 2017b), Lagrangian relaxation (Jabbarzadeh et al., 2018), Benders cuts (Haddadsisakht and Ryan, 2018), simulated annealing (Fattahi and Govindan, 2017), and non-dominated sorting genetic algorithm (Babaveisi et al., 2017, Ghezavati and Beigi, 2016).

In addition, some research works have been done with the development and implementation of new artificial intelligent methods for resolving large-sized planning problems. Li et al. (2017) developed a hybrid artificial bee colony algorithm for a cost-minimization model for reverse logistics network design. Zandieh and Chensebli (2016) proposed a water-flow-like algorithm for planning a single-period two-echelon reverse logistics system. Fard and Hajaghaei-Keshteli (2018) formulated a static *Stackelberg* game and a tri-level metaheuristic to manage the interactions among different players in a reverse logistics system.

2.5 Summary and literature gap

Table 1 presents a vis-à-vis comparison of the relevant literature in reverse logistics network design with respect to several criteria. Compared with the result from a comprehensive review by Govindan et al. (2015), it is observed the earlier modelling efforts focus primarily on economic benefits of reverse logistics system under a predictable environment. While, an increasing number of recent publications investigated models with inexact parameters and multiple objectives in order to incorporate environmental and social sustainability in decision-making under uncertainty. Besides, the value recovery of multiple types of products has attracted more attentions in recent mathematical models.

Considering the heterogeneous nature of different products, most of the modelling efforts for a multi-product reverse logistics system formulate a product-specified non-flexible capacity constraint, while the other models neglect the difference between the processing procedures for recycling different products. However, the impact of system flexibility on sustainable reverse logistics network design has not been thoroughly investigated in the existing literature. Modelling a sustainable reverse logistics network design problem under uncertainty based upon a generic “capacitated location problem” may neither be able to find out the optimal solution in strategic decision-making nor provide valuable suggestions for the plant planning decisions, i.e., layout planning, internal route planning.

The most significant problem of those models is the way they deal with the demand fluctuation. With a non-flexible capacitated model under uncertainty, an increased demand for managing used products and a more stringent regulation on emission reduction may lead to either a decision on facility expansion or a compromised service level on waste management. However, both decisions may not be the optimal solution in some cases. Facility expansion requires an additional investment, while at the same time; this decision may also cause a reduction on facility utilization and higher operating costs when the generation of used products is low. From the mathematical programming perspective, a reduction on service level is another option, for example, a more economically attractive solution may be found by incorporating a chance constraint in a stochastic optimization model in order to allow a certain probability of demands are not met. However, in practice, “leaving the garbage on the street” will result in a dramatically reduced satisfaction of the local residents. In addition, the plant planning of a flexible and a non-flexible configuration is of great difference, but the generic capacitated location models cannot provide implications for supporting the plant planning decisions.

A reverse logistics system is featured with significant uncertainty related to the quantity and quality of different returned products and a variety of processing procedures are required to recover them. Practical-based survey (Guide Jr, 2000) and computational-based analysis (Seebacher and Winkler, 2014, Feng and Shen, 2017) have both confirmed the profitability of a reverse logistics system can be improved through incorporating with flexible capacity. Furthermore, a recent quantitative modelling effort has revealed, by improving the system flexibility under an uncertain environment, both economic and environmental performance of a multi-product reverse logistics system may be improved without a large investment on facility expansion or a compromise on service level (Yu and Solvang, 2017).

Based on the discussion above, the raison d'être of this paper is to fill the literature gap by incorporating flexibility in sustainable reverse logistics network design. The problem is modelled in two parallel ways with both efficiency-focused non-flexible capacity and effectiveness-focused flexible capacity. Managerial implications regarding the sustainable reverse logistics network design under uncertainty with both capacity configurations are discussed through experimental analysis. Besides, as shown in Table 1, only 17% of the recent mathematical models considers the control of uncertainty in sustainable reverse logistics network design. Thus, we formulates a new two-stage stochastic bi-objective mixed integer programming model aiming at providing decision-makers and practitioners with robust optimal decisions on sustainable reverse logistics network design under an uncertain environment.

Table 1 Review of the recent research works on reverse logistics network design

Articles	Product flow		Capacity			Network		Objectives				Parameter	Modelling approach	Solution		Solver	Validation
	Single	Multiple	Non-flexible	Flexible	Unspecified	Forward	Reverse	Economic	Environmental	Social	Others			Exact	Approximation		
Pishvaee et al. (2009)	∨				∨	∨	∨	∨				Non-deterministic	Stochastic MIP	∨		LINGO	Experiment
El-Sayed et al. (2010)	∨				∨	∨	∨	∨				Non-deterministic	Stochastic MIP	∨		XpressSP	Experiment
Pishvaee et al. (2011)	∨				∨	∨	∨	∨				Non-deterministic	Robust MIP	∨		CPLEX	Experiment
Kannan et al. (2012)	∨				∨		∨	∨	∨			Deterministic	MIP	∨		LINGO	Experiment
Demirel et al. (2016)	∨				∨		∨	∨				Deterministic	MIP	∨		GAMS CPLEX	Case
Alshamsi and Diabat (2015)	∨				∨		∨	∨				Deterministic	MIP	∨		GAMS CPLEX	Case
Ghezavati and Beigi (2016)	∨				∨		∨	∨		∨		Deterministic	MOMIP		∨	MATLAB GAMS	Experiment
Yu and Solvang (2016b)	∨				∨		∨	∨	∨			Deterministic	MOMIP	∨		LINGO	Experiment
Govindan et al. (2016b)	∨				∨		∨	∨	∨	∨		Non-deterministic	Fuzzy MOMIP	∨	∨	MATLAB MINITAB	Experiment
Zandieh and Chensebli (2016)	∨				∨		∨	∨				Deterministic	MIP		∨	MATLAB	Experiment
Li et al. (2017)	∨				∨		∨	∨				Deterministic	MIP		∨	C++	Experiment
Silva et al. (2017)	∨				∨		∨	∨		∨		Deterministic	MOMIP	∨		CPLEX	Case
Guo et al. (2017a)	∨				∨		∨	∨				Deterministic	MIP		∨		Case
Guo et al. (2017b)	∨				∨	∨	∨	∨	∨			Deterministic	Two-stage MIP		∨		Case
Budak and Ustundag (2017)	∨				∨		∨	∨				Deterministic	MIP	∨		Xpress IVE	Case
Fard and Hajaghaei-Keshteli (2018)	∨				∨	∨	∨	∨				Deterministic	Game theoretic tri-level MIP		∨		Experiment
Rahimi and Ghezavati (2018)	∨				∨		∨	∨	∨	∨		Non-deterministic	Stochastic MOMIP	∨		GAMS	Experiment
Demirel and Gökçen (2008)		∨	∨			∨	∨	∨				Deterministic	MIP	∨		GAMS CPLEX	Experiment
Amin and Zhang (2012)		∨			∨	∨	∨	∨				Deterministic	MIP	∨		GAMS	Experiment
Diabat et al. (2013)		∨			∨	∨	∨	∨	∨			Deterministic	MIP	∨		GAMS CPLEX	Experiment
Özkır and Başlıgil		∨			∨	∨	∨	∨			∨	Non-	Fuzzy MOMIP	∨		GAMS	Experiment

(2013)												deterministic					
Ramos et al. (2014)		∨			∨		∨	∨	∨	∨		Deterministic	MOMIP	∨		CPLEX	Case
Garg et al. (2015)		∨			∨	∨	∨	∨	∨			Deterministic	MOMIP	∨		LINGO	Experiment
Ghayebloo et al. (2015)		∨			∨	∨	∨	∨	∨			Deterministic	MOMIP	∨		GLPK	Experiment
Capraz et al. (2015)		∨			∨		∨	∨				Deterministic	MIP	∨		CPLEX	Case
Govindan et al. (2016a)		∨			∨	∨	∨	∨	∨	∨		Deterministic	MOMIP	∨		LINGO	Experiment
Yu and Solvang (2016a)		∨	∨				∨	∨	∨			Non-deterministic	Stochastic MIP	∨		LINGO	Experiment
Kheirkhah and Rezaei (2016)		∨	∨				∨	∨				Deterministic	MIP	∨		GAMS	Experiment
Talaei et al. (2016)		∨	∨			∨	∨	∨	∨			Non-deterministic	Robust fuzzy MIP	∨			Experiment
Entezaminia et al. (2017)		∨	∨			∨	∨	∨				Non-deterministic	Robust MIP	∨		CPLEX	Case
Keshavarz Ghorabaee et al. (2017)		∨	∨			∨	∨	∨	∨			Non-deterministic	Fuzzy MOMIP	∨			Experiment
Jindal and Sangwan (2017)		∨	∨			∨	∨	∨	∨			Non-deterministic	Fuzzy MOMIP	∨		LINGO	Experiment
John et al. (2017)		∨	∨				∨	∨	∨			Deterministic	MIP	∨		LINGO	Experiment
Yilmaz et al. (2017)		∨			∨		∨	∨		∨		Deterministic	MOMIP	∨		OPL	Case
Kannan et al. (2017)		∨	∨				∨	∨				Deterministic	MIP	∨		LINGO	Experiment
Temur and Bolat (2017)		∨			∨		∨	∨	∨			Deterministic	MOMIP	∨		GAMS CPLEX	Case
Fattahi and Govindan (2017)		∨	∨			∨	∨	∨				Non-deterministic	Stochastic MIP		∨	GAMS CPLEX	Experiment
Feitó-Cespón et al. (2017)		∨	∨				∨	∨	∨	∨		Non-deterministic	Stochastic MOMIP	∨		MATLAB	Experiment
Babaveisi et al. (2017)		∨	∨			∨	∨	∨		∨	∨	Deterministic	MOMIP		∨		Experiment
Soleimani et al. (2017)		∨			∨	∨	∨	∨	∨	∨	∨	Non-deterministic	Fuzzy constrained MOMIP		∨	LINGO	Experiment
Alshamsi and Diabat (2017)		∨			∨		∨	∨				Deterministic	MIP		∨	CPLEX	Case
Yu and Solvang (2017)		∨	∨				∨	∨	∨			Non-deterministic	Stochastic constrained MIP	∨		LINGO	Experiment
Coelho and Mateus (2017)		∨			∨		∨	∨				Deterministic	MIP		∨	CPLEX	Experiment
John et al. (2018)		∨	∨				∨	∨				Deterministic	MIP	∨		LINGO	Case

Trochu et al. (2018)		∨			∨		∨	∨				Non-deterministic	Stochastic MIP	∨			Case
Jabbarzadeh et al. (2018)		∨	∨			∨	∨	∨				Non-deterministic	Robust MIP		∨	GAMS	Case
Haddadsisakht and Ryan (2018)		∨			∨	∨	∨	∨				Non-deterministic	Stochastic robust MIP		∨	CPLEX	Experiment
This research		∨	∨	∨			∨	∨	∨			Non-deterministic	Stochastic MOMIP	∨		LINGO	Experiment

Note: MIP=Mixed integer programming; MOMIP=Multi-objective mixed integer programming

3. Model development

3.1 Problem description

As illustrated in Figure 1, the main operations in a generic reverse logistics system include customer return and local collection, central collection for quality inspection, sorting and disassembly, value recovery operations including remanufacturing, recycling and energy recovery, and disposal for non-recyclable products. The material flow of the reverse logistics starts from the customer return to the retailers or local collection centers for EOL and EOU products, and then those products will be collected at the central collection centers where quality inspection, sorting and disassembly will be conducted. In accordance with the type of product and quality level, different value recovery operations will be performed and then the recovered products will be sold in the market.

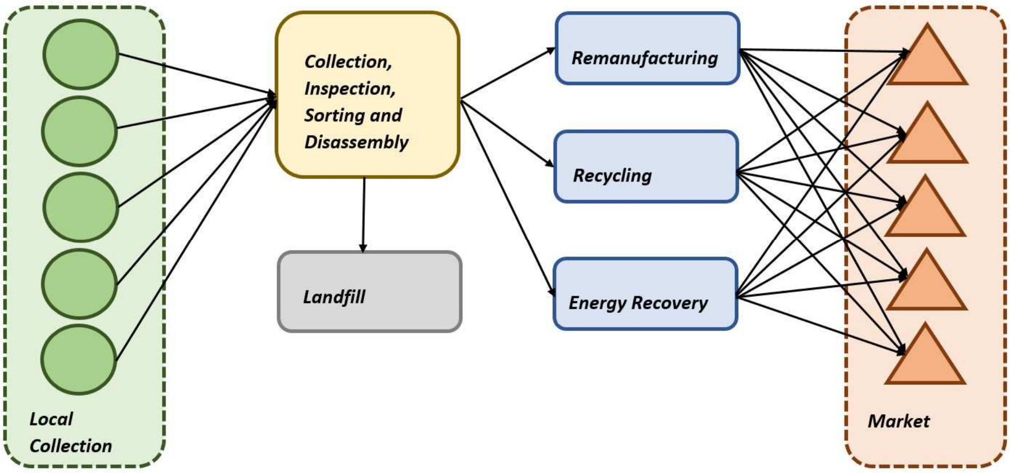

Figure 1. Structure of a generic reverse logistics system.

3.2 Modelling methods

For decision-support of sustainable reverse logistics network design under uncertainty, the model developed in this paper combines three modelling methods: (1) mixed integer programming; (2) multi-objective programming; and (3) stochastic programming.

- ***Mixed integer programming:*** As shown in Table 1, mixed integer programming is the basic modelling method for supply chain network design problems. It involves two types of decision variables: Binary integer variable and continuous variable. The binary integer variables determine whether a candidate location is selected to open a new facility, while the continuous variable provide decisions on facility operations and transportation strategy.
- ***Multi-objective programming:*** Sometimes, decision-making involves several objectives that are usually in conflict with one another. In sustainable reverse logistics network design, multi-objective programming is used to balance the trade-off between economic benefits and sustainability-related measures (e.g. environmental impacts).
- ***Two-stage stochastic programming:*** In this paper, the quantity and quality of used products as well as the price for the recovered products and energy are formulated as stochastic parameters. As many argues (King and Wallace, 2012), a two-stage stochastic programming provides decisions at two levels with different characteristics:

robust or flexible. The first stage decisions are made before the realization of uncertain parameters and should be robust to withstand random events, while the second stage decisions can be made after the realization of scenarios with more certain information and should be flexible to cope with the change of external environment in order to maximize benefits.

Table 2 Modelling methods in sustainable reverse logistics network design.

Modelling methods	Functions in sustainable reverse logistics network design
Mixed integer programming	Fundamental technique for a location-allocation problems
Multi-objective programming	Trade-off analysis with multiple objectives
Two-stage stochastic programming	Control of uncertainty

Table 2 shows the functions of those modelling methods in sustainable reverse logistics network design under uncertainty. With the consideration of sustainability and control of uncertainty, the proposed model supports decision-making of at both levels:

1) First stage decisions:
    - Number and locations of central collection centers
    - Number and locations of remanufacturing plants
    - Number and locations of recycling plants
    - Number and locations of energy recovery plants
2) Second stage decisions:
    - Amount of used products processed at each facility
    - Transportation strategy among different facilities

It is obvious the first stage decisions have long-term impacts on the performance of a reverse logistics system and should be featured with robustness, while even if the model can also determine the optimal values for the second stage decisions, they can be easily altered after the realization of uncertain parameters due to their flexible nature.

3.3 Notations

Sets and indices:

W	Set of customers, indexed by *w*
I	Set of candidate locations for central collection centers, indexed by *i*
M	Set of candidate locations for remanufacturing centers, indexed by *m*
C	Set of recycling centers, indexed by *c*
R	Set of energy recovery centers, indexed by *r*
D	Set of landfills, indexed by *d*
Q	Set of products, indexed by *q*
S	Set of scenarios, indexed by *s*
V	Set of candidate locations for remanufacturing centers, recycling centers and energy recovery centers $V = \{M, C, R\}$, indexed by *v*
X	Set of all candidate locations $X = \{I, V\}$, indexed by *x*
U(yz)	Set of all routes between different facilities $U(y,z) = \{(w,i),(i,m),(i,c),(i,r),(i,d) \mid \forall w \in W,\ i \in I, m \in$

$M, c \in C, r \in R, d \in D\}$, indexed by *yz*

Parameters:

Pt_{vq}^{s}	Price of the products or energy generated from recovering one unit of product *q* at facility *v* in scenario *s*
Su_{vq}	Government subsidy for recovering one unit of product *q* at facility *v* in scenario *s*
F_x	Fixed operating costs for opening a facility at candidate location *x*
Oc_{xq}	Processing costs for treating one unit of product *q* at facility *x*
Gf_{dq}	Gate fee for sending one unit of product *q* to landfill *d*
Tc_{qyz}	Transportation cost for shipping one unit of product *q* between different facilities within the reverse logistics system
Car_{xq}	CO_2 emissions for treating one unit of product *q* at facility *x*
Car_{dq}	CO_2 emissions for landfilling one unit of product *q* at facility *d*
$CarT_{qyz}$	CO_2 emissions of the transportation of one unit of product *q* between different facilities within the reverse logistics system
P_s	Probability of the realization of scenario *s*
Pd_{wq}^{s}	Amount of product *q* collected at customer *w* in scenario *s*
Cap_{xq}	Capacity for dealing with product *q* at facility *x*
Rep_{xq}	Required rate of utilization for treating product *q* at facility *x*
γ_q^{rm}	Fraction of product *q* suitable for remanufacturing
γ_q^{ry}	Fraction of product *q* suitable for recycling
γ_q^{rc}	Fraction of product *q* suitable for energy recovery
π_q^{s}	Quality level of product *q* in scenario *s*
En_q	Environmental policy requirement presenting the minimum recovered percentage from the recoverable fraction of product *p*
A_q	Percentage of the recoverable fraction if product *q* is at good quality, $A_q = \text{Percentage of set } \{\gamma_q^{rm} \cup \gamma_q^{ry} \cup \gamma_q^{rc}\} \leq 100\%$ It is noted that, $\sum(\gamma_q^{rm}, \gamma_q^{ry}, \gamma_q^{rc}), \forall q \in Q$ may be more than 100% due to the overlap fraction suitable for multiple treatments.
A_q^{C}	Percentage of the non-recoverable fraction if product *q* is at good quality, $A_q^C = \text{Percentage of the complement set of } \{\gamma_q^{rm} \cup \gamma_q^{ry} \cup \gamma_q^{rc}\}$, and $A_q^C + A_q = 100\%$
Cap_x^{Flex}	Flexible capacity of facility *x*
ϑ_{xq}^{Flex}	Conversion rate of the usage of flexible capacity for processing product *q* at facility *x*

Ef_i^{Loss}	Rate of the efficiency loss for implementing flexible capacity at facility *x*
Rep_i^{Flex}	Required rate of utilization of facility *x* with flexible capacity

Decision variables

Loc_x	Binary decision variables determining if a new facility is open at candidate location *x*
Qn_{xq}^s	Quantity of product *q* treated at facility *x* in scenario *s*
Qtn_{qyz}^s	Quantity of product *q* transported via route *yz* in scenario *s*

3.4 Mathematical model for sustainable reverse logistics network design with non-flexible capacity

The model is formulated as follows:

$$
\begin{aligned}
\text{Max Obj1} = \sum_{s\in S} P_s \Bigg(& \sum_{q\in Q}\sum_{m\in M} \left(Pt_{mq}^s + Su_{mq}\right) Qn_{mq}^s \\
& + \sum_{q\in Q}\sum_{c\in C} \left(Pt_{cq}^s + Su_{cq}\right) Qn_{cq}^s + \sum_{q\in Q}\sum_{r\in R} \left(Pt_{rq}^s + Su_{rq}\right) Qn_{rq}^s \Bigg) \\
& - \Bigg(\Bigg(\sum_{i\in I} F_i Loc_i + \sum_{m\in M} F_m Loc_m + \sum_{c\in C} F_c Loc_c + \sum_{r\in R} F_r Loc_r \Bigg) \\
& + \sum_{s\in S} P_s \Bigg(\sum_{q\in Q}\sum_{i\in I} Oc_{iq} Qn_{iq}^s + \sum_{q\in Q}\sum_{m\in M} Oc_{mq} Qn_{mq}^s \\
& + \sum_{q\in Q}\sum_{c\in C} Oc_{cq} Qn_{cq}^s + \sum_{q\in Q}\sum_{r\in R} Oc_{rq} Qn_{rq}^s + \sum_{q\in Q}\sum_{d\in D} Gf_{dq} Qn_{dq}^s \\
& + \sum_{q\in Q}\sum_{w\in W}\sum_{i\in I} Tc_{qwi} Qtn_{qwi}^s + \sum_{q\in Q}\sum_{i\in I}\sum_{m\in M} Tc_{qim} Qtn_{qim}^s \\
& + \sum_{q\in Q}\sum_{i\in I}\sum_{c\in C} Tc_{qic} Qtn_{qic}^s + \sum_{q\in Q}\sum_{i\in I}\sum_{r\in R} Tc_{qir} Qtn_{qir}^s \\
& + \sum_{q\in Q}\sum_{i\in I}\sum_{d\in D} Tc_{qid} Qtn_{qid}^s \Bigg) \Bigg)
\end{aligned}
\tag{1}
$$

$$\begin{aligned}\text{Min Obj2}= \sum_{s\in S} P_s \Bigg(& \sum_{q\in Q}\sum_{i\in I} Car_{iq}Qn_{iq}^{s} + \sum_{q\in Q}\sum_{m\in M} Car_{mq}Qn_{mq}^{s} + \sum_{q\in Q}\sum_{c\in C} Car_{cq}Qn_{cq}^{s} \\ & + \sum_{q\in Q}\sum_{r\in R} Car_{rq}Qn_{rq}^{s} + \sum_{q\in Q}\sum_{d\in D} Car_{dq}Qn_{dq}^{s} \\ & + \sum_{q\in Q}\sum_{w\in W}\sum_{i\in I} CarT_{qwi}Qtn_{qwi}^{s} + \sum_{q\in Q}\sum_{i\in I}\sum_{m\in M} CarT_{qim}Qtn_{qim}^{s} \\ & + \sum_{q\in Q}\sum_{i\in I}\sum_{c\in C} CarT_{qic}Qtn_{qic}^{s} + \sum_{q\in Q}\sum_{i\in I}\sum_{r\in R} CarT_{qir}Qtn_{qir}^{s} \\ & + \sum_{q\in Q}\sum_{i\in I}\sum_{d\in D} CarT_{qid}Qtn_{qid}^{s} \Bigg)\end{aligned} \tag{2}$$

Subject to:

(1) Demand satisfaction

$$Pd_{wq}^{s} = \sum_{i\in I} Qtn_{qwi}^{s}, \forall s \in S, w\epsilon W, q \in Q \tag{3}$$

(2) Flow balance

$$\sum_{w\in W} Qtn_{qwi}^{s} = Qn_{iq}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{4}$$

$$\sum_{i\in I} Qtn_{qim}^{s} = Qn_{mq}^{s}, \forall s \in S, m\epsilon M, q \in Q \tag{5}$$

$$\sum_{i\in I} Qtn_{qic}^{s} = Qn_{cq}^{s}, \forall s \in S, c\epsilon C, q \in Q \tag{6}$$

$$\sum_{i\in I} Qtn_{qir}^{s} = Qn_{rq}^{s}, \forall s \in S, r\epsilon R, q \in Q \tag{7}$$

$$\sum_{i\in I} Qtn_{qid}^{s} = Qn_{dq}^{s}, \forall s \in S, d\epsilon D, q \in Q \tag{8}$$

$$Qn_{iq}^{s} = \sum_{m\in M} Qtn_{qim}^{s} + \sum_{c\in C} Qtn_{qic}^{s} + \sum_{r\in R} Qtn_{qir}^{s} + \sum_{d\in D} Qtn_{qid}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{9}$$

(3) Capacity constraints

$$Qn_{iq}^{s} \le Cap_{iq}Loc_{i}, \forall s \in S, i\epsilon I, q \in Q \tag{10}$$

$$Qn_{mq}^{s} \le Cap_{mq}Loc_{m}, \forall s \in S, m\epsilon M, q \in Q \tag{11}$$

$$Qn_{cq}^{s} \le Cap_{cq}Loc_{c}, \forall s \in S, c\epsilon C, q \in Q \tag{12}$$

$$Qn_{rq}^{s} \le Cap_{rq}Loc_{r}, \forall s \in S, r\epsilon R, q \in Q \tag{13}$$

(4) Utilization requirements

$$Qn_{iq}^{s} \ge Rep_{iq}Cap_{iq}Loc_{i}, \forall s \in S, i\epsilon I, q \in Q \tag{14}$$

$$Qn_{mq}^{s} \ge Rep_{mq}Cap_{mq}Loc_{m}, \forall s \in S, m\epsilon M, q \in Q \tag{15}$$

$$Qn_{cq}^{s} \ge Rep_{cq}Cap_{cq}Loc_{c}, \forall s \in S, c\epsilon C, q \in Q \tag{16}$$

$$Qn_{rq}^{s} \ge Rep_{rq}Cap_{rq}Loc_{r}, \forall s \in S, r\epsilon R, q \in Q \tag{17}$$

(5) Conversion constraints

$$\pi_{q}^{s}\gamma_{qm}Qn_{iq}^{s} \ge \sum_{m\in M} Qtn_{qim}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{18}$$

$$\pi_{q}^{s}\gamma_{qc}Qn_{iq}^{s} \ge \sum_{c\in C} Qtn_{qic}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{19}$$

$$\pi_{q}^{s}\gamma_{qr}Qn_{iq}^{s} \ge \sum_{r\in R} Qtn_{qir}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{20}$$

$$\sum_{d\in D} Qtn_{qid}^{s} \ge \left(A_{q}^{C} + \left(1 - \pi_{q}^{s}A_{q}\right)\right) Qn_{iq}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{21}$$

(6) Environmental policy

$$\sum_{m\in M} Qtn_{qim}^{s} + \sum_{c\in C} Qtn_{qic}^{s} + \sum_{r\in R} Qtn_{qir}^{s} \ge \pi_{q}^{s}A_{q}En_{q}Qn_{iq}^{s}, \forall s \in S, i\epsilon I, q \in Q \tag{22}$$

(7) Requirements for decision variables

$$Loc_{i}, Loc_{m}, Loc_{c}, Loc_{r} \in \{0,1\}, \forall i\epsilon I, m \in M, c \in C, r \in R \tag{23}$$

$$Qn_{iq}^{s}, Qn_{mq}^{s}, Qn_{cq}^{s}, Qn_{rq}^{s}, Qn_{dq}^{s}, Qtn_{qwi}^{s}, Qtn_{qim}^{s}, Qtn_{qic}^{s}, Qtn_{qir}^{s}, Qtn_{qid}^{s} \ge 0, \forall s \in S, q \in Q, w \in W, i\epsilon I, m \in M, c \in C, r \in R, d \in D \tag{24}$$

The objective function (1) maximizes the total profits of reverse logistics system, which is the surplus between income and costs. The income includes both sales revenue and subsidies from government for waste management. The costs include fixed costs (e.g. salary, bank interests, return of investment, etc.), processing costs and transportation costs. The second objective function (2) minimizes the environmental impact of reverse logistics activities, which is evaluated by carbon emissions. The carbon emissions related to facility operation and processing of used products can be estimated from material and energy consumption (Fahimnia et al., 2015b), while the carbon emissions from transportation is determined by the travelled distance, speed, load and fuel efficiency (Bektaş and Laporte, 2011, Tongwane et al., 2015).

The model also includes seven sets of constraints. Constraint (3) guarantees the customer demands for the treatment of used products are met. Constraints (4)-(9) specify the flow balance at each facility and each route. Inequalities (10)-(13) restrict the non-flexible capacity for each facility with respect to each type of product. Inequalities (14)-(17) restrict a minimum level of utilization for the facilities, which aim to avoid inefficient use of facilities. Constraints (18)-(21) require the percentage of used products sent for remanufacturing, recycling, energy recovery and disposal should comply with the quality and proportion requirements. Constraint (22) is the environmental policy requirement that specifies the maximum amount of the recoverable fraction can be landfilled. Constraints (23) and (24) are requirements for decision variables.

3.5 Model extension incorporating flexible capacity

Compared with designing a forward supply chain, planning a reverse logistics system is more difficult due to the uncertainties from the unstable flow of used products, stochastic condition and quality, and market fluctuation. From the modelling perspective, those uncertainties can be managed with either to permit a certain probability of infeasibility (King and Wallace, 2012) or relax the capacity constraint to accommodate increased demands (Yu and Solvang, 2017). While from the practical perspective, the interpretation of those techniques is to either reduce the service level of waste management or increase the investment for facility expansion, both of which are not easy ones for decision-makers to undertake. A reduction on service level will decrease the satisfaction of local residents, while facility expansion may lead to a low facility utilization when the generation of EOL and EOU products are low.

However, research works have revealed uncertainties may be tackled with an increase on the flexibility of reverse logistics system for treating multiple types of used products (Guide Jr, 2000, Yu and Solvang, 2017). The process flexibility has been considered as an effective solution for the mismatch between demand and capacity (Feng and Shen, 2017), and it has been investigated by practitioners for several decades in some reverse logistics activities, i.e., remanufacturing (Goodall et al., 2014, Nasr et al., 1998). Flexibility is defined as the capability to rapidly response to the change with little penalty on costs, efforts and performance (Upton, 1994). Compared with the traditional mass production system that emphasizes predominantly on productivity, the increase on process flexibility will, with a compromise on efficiency, lead to an improvement on the effectiveness under an uncertain environment. Therefore, the incorporation with flexibility in planning a multi-product sustainable reverse logistics system is important and may yield a great impact on both economic and environmental performance.

(8) Conversion to flexible capacity

$$Cap_i^{Flex} = (1 - Ef_i^{Loss}) \sum_{q \in Q} \vartheta_{iq}^{Flex} Cap_{iq}, \forall i \in I \tag{25}$$

$$Cap_m^{Flex} = (1 - Ef_m^{Loss}) \sum_{q \in Q} \vartheta_{mq}^{Flex} Cap_{mq}, \forall m \in M \tag{26}$$

$$Cap_c^{Flex} = (1 - Ef_c^{Loss}) \sum_{q \in Q} \vartheta_{cq}^{Flex} Cap_{cq}, \forall c \in C \tag{27}$$

$$Cap_r^{Flex} = (1 - Ef_r^{Loss}) \sum_{q \in Q} \vartheta_{rq}^{Flex} Cap_{rq}, \forall r \in R \tag{28}$$

For incorporating flexibility in decision-making, Equations (25)-(28) are first formulated in order to convert the non-flexible capacity into flexibility capacity at different facilities in the reverse logistics system. It is noteworthy that, due to the reconfiguration required and change of in-plant operations, there will be a loss of productivity when converting an efficiency-focused process to a flexibility-focused process (Ghemawat and Ricart Costa, 1993), so Ef_i^{Loss} is introduced for compensating the capacity loss.

(9) Capacity constraints under flexible capacity

$$\sum_{q\in Q} Qn_{iq}^{s} \leq Cap_i^{Flex} Loc_i, \forall s \in S, i \in I \tag{29}$$

$$\sum_{q\in Q} Qn_{mq}^{s} \leq Cap_m^{Flex} Loc_m, \forall s \in S, m \in M \tag{30}$$

$$\sum_{q\in Q} Qn_{cq}^{s} \leq Cap_c^{Flex} Loc_c, \forall s \in S, c \in C \tag{31}$$

$$\sum_{q\in Q} Qn_{rq}^{s} \leq Cap_r^{Flex} Loc_r, \forall s \in S, r \in R \tag{32}$$

(10) Utilization constraints under flexible capacity

$$\sum_{q\in Q} Qn_{iq}^{s} \geq Rep_i^{Flex} Cap_i^{Flex} Loc_i, \forall s \in S, i \in I \tag{33}$$

$$\sum_{q\in Q} Qn_{mq}^{s} \geq Rep_i^{Flex} Cap_m^{Flex} Loc_m, \forall s \in S, m \in M \tag{34}$$

$$\sum_{q\in Q} Qn_{cq}^{s} \geq Rep_i^{Flex} Cap_c^{Flex} Loc_c, \forall s \in S, c \in C \tag{35}$$

$$\sum_{q\in Q} Qn_{rq}^{s} \geq Rep_i^{Flex} Cap_r^{Flex} Loc_r, \forall s \in S, r \in R \tag{36}$$

After the flexible capacity have been defined by Equations (25)-(28), the mathematical model is expanded through replacing the constraints (10)-(17) in the original model by the flexible capacity constraints (29)-(32) and utilization constraints (33)-(36).

4. Solution Method

The objective of the model is to provide decision-makers with a set of non-dominant Pareto optimal solutions. In this paper, the stochastic parameters are formulated with a scenario-based approach. For representing the uncertainties, different scenarios with respect to stochastic parameters are first generated. Each scenario represents a prediction of the uncertain parameters in the planning horizon, which includes the quantity of used products at different customer zones (Pd_{wq}^{s}), quality level (π_q^s) and market price (Pt_{vq}^{s}). With the combinations of different stochastic parameters, a set of scenarios (s) with the probability of occurrence (P_s) is then generated for representing the future conditions of the optimization problem. Therefore, the optimal solution of this stochastic optimization problem is not to seek the best solution for an individual scenario (sub-optimal solution), but it is to determine the most robust and optimal one throughout all the possible scenarios.

Sustainable reverse logistics network design is a multi-objective programming problem that aims at simultaneously balancing the tradeoff between profitability and environmental impact. Given by Sakawa et al. (2013), a generic form of a multi-objective minimization problem is presented in Equation (37). Herein, $z(\boldsymbol{x}) = \left(z_1(\boldsymbol{x}), z_2(\boldsymbol{x}), \dots, z_k(\boldsymbol{x})\right)^T$ is a k-dimensional vector and X is the set of feasible solutions in decision space. In a multi-objective optimization problem, the definition of Pareto optimal solution or efficient solution $\boldsymbol{x}^*$ is that if and only if it is impossible to find another $\boldsymbol{x} \in X$ such that $z_i(\boldsymbol{x}) \leq z_i(\boldsymbol{x}^*)$ for all i and $z_j(\boldsymbol{x}) \neq z_j(\boldsymbol{x}^*)$ for at least one j (Sakawa et al., 2013). It is obvious from the definition that, at a Pareto optimal point, the target objective value cannot be improved without a sacrifice on the performance of other objective functions, and also there may exist an infinite number of Pareto solutions. There is a weaker form of Pareto optimality, which is called weakly efficient or weak Pareto solution. The definition of weak Pareto optimal solution $\boldsymbol{x}^*$ is if and only if it is impossible to find another $\boldsymbol{x} \in X$ such that $z_i(\boldsymbol{x}) \leq z_i(\boldsymbol{x}^*)$ for all i (Sakawa et al., 2013), and it is easy to see that the set of Pareto optimal solutions is a subset of the set of weak Pareto optimal solutions.

$$\begin{aligned} \text{Min } & z(\boldsymbol{x}) = \left(z_1(\boldsymbol{x}), z_2(\boldsymbol{x}), \dots, z_k(\boldsymbol{x})\right)^T \\ \text{S.t. } & \boldsymbol{x} \in X \end{aligned} \tag{37}$$

Scalarization methods are well-developed techniques for determining the Pareto optimal solutions for a multi-objective optimization problem. The basic idea of scalarization methods is to convert a multi-objective programming problem into a set of single objective optimization problems with the introduction of indicators or constraints. In this paper, two well-known scalarization methods are employed and customized to resolve the multi-objective optimization problems: weighing method and augmented ε–constraint method.

4.1 Weighting method

The principle of weighting method is to convert the multi-objective problem into a weighted sum with the combination of objective value and weight, and the Pareto optimal solution can be determined through resolving the single objective weighted sum function (Zadeh, 1963). Equation (38) illustrates a generic form of the weighing method for resolving a minimization problem, and $\boldsymbol{w} = (w_1, w_2, \dots, w_k)$ is the weight vectors of each objective function, which indicates the relative importance in decision-making.

$$\text{Min } \boldsymbol{w}z(\boldsymbol{x}) = \sum_{i=1}^{k} w_i z_i(\boldsymbol{x}) \qquad (38)$$
$$\text{S.t.} \quad \boldsymbol{x} \in X$$

The equation above cannot be used directly to resolve the proposed bi-objective optimization problem, because different units are used in the objective functions. Thus, the objective value must be first normalized before the weighted sum is calculated, and the procedures are presented as follows.

1. Calculating the Maximum and Minimum values of each individual objective function with both capacity settings.
   Non-flexible Capacity: $Obj1_{nonf}^{Max}, Obj2_{nonf}^{Max}, Obj1_{nonf}^{Min}, Obj2_{nonf}^{Min}$
   Solve: Max $Obj1$, Max $Obj2$, Min $Obj1$ Min $Obj2$, s.t. (3)-(24)
   Flexible Capacity: $Obj1_{flex}^{Max}, Obj2_{flex}^{Max}, Obj1_{flex}^{Min}, Obj2_{flex}^{Min}$
   Solve: Max $Obj1$, Max $Obj2$, Min $Obj1$ Min $Obj2$, s.t. (3)-(9), (18)-(24), (25)-(36)
2. Determining the weight combinations between the two objective functions (wt), where $wt_{Obj1} + wt_{obj2} = 1$.
3. Determining the set of Pareto optimal solutions through calculating the weighted sum with different weight combinations (wt).
   Non-flexible Capacity: $Pareto_{nonf}^{wt}$
   Solve: Min $Pareto_{nonf}^{w} = w_{Obj1} \frac{Obj1_{nonf}^{Max} - Obj1_{nonf}}{Obj1_{nonf}^{Max} - Obj1_{nonf}^{Min}} + w_{obj2} \frac{Obj1_{nonf} - Obj2_{nonf}^{Min}}{Obj2_{nonf}^{Max} - Obj2_{nonf}^{Min}}$
   s.t. (3)-(24)
   Flexible Capacity: $Pareto_{flex}^{wt}$
   Solve: Min $Pareto_{nonf}^{w} = w_{Obj1} \frac{Obj1_{flex}^{Max} - Obj1_{flex}}{Obj1_{flex}^{Max} - Obj1_{flex}^{Min}} + w_{obj2} \frac{Obj1_{flex} - Obj2_{flex}^{Min}}{Obj2_{flex}^{Max} - Obj2_{flex}^{Min}}$
   s.t. (3)-(9), (18)-(24), (25)-(36)

As many argues (Das and Dennis, 1997), the benefits of using weighting method is the simplicity and efficiency, because the derived weighted sum is at the same level of computational complexity as the single objective function in the model. However, it also suffers from some well-known pitfalls in determining the set of Pareto solutions (Das and Dennis, 1997). One of them is the weighting method cannot generate a complete set of Pareto optimal solutions depicting all the features of the frontier. Weighting method only calculates the extreme efficient solutions (Mavrotas, 2009), but it cannot find out the non-convex solutions in the decision space. The other problems of weighting method include the generation of weakly non-dominant solutions, redundant calculations for the same Pareto optimal solutions with different weight combinations, and incapability for generating a set of evenly distributed Pareto optimal solutions (Das and Dennis, 1997). Therefore, the proposed model is also resolved with another scalarization method: augmented ε–constraint method.

4.2 Augmented ε–constraint method

The principle of ε–constraint method is to select one objective function from the original multi-objective optimization problem and convert the other objective functions into inequality constraints, and the Pareto optimal solution is determined through resolving the derived single objective constrained optimization problem (Haimes, 1971). Formula (39) shows a generic form of the ε–constraint method for a multi-objective minimization problem, and the Pareto optimal solutions can be generated through properly adjusting the value of the right hand side value of the added inequalities (ε_i).

$$\begin{aligned} &\text{Min } z_j(\boldsymbol{x}) \\ \text{S.t.} \quad & z_i(\boldsymbol{x}) \leq \varepsilon_i, i = 1, 2, \dots, k, i \neq j \\ & \boldsymbol{x} \in X \end{aligned} \tag{39}$$

Although, compared with weighting method, the ε–constraint method has several benefits in determining the Pareto optimal solutions, its original form suffers from two problems: (1) generation of dominant solutions in ranging the value of ε due to the possible dominant worst-case points found in the payoff matrix by the conventional method; (2) generation of weakly efficient solutions (Mavrotas, 2009). Efforts have been spent in resolving those problems (Ehrgott and Ryan, 2002). In this paper, the augmented ε–constraint method developed by Mavrotas (2009) is employed. With the augment ε–constraint method, the payoff matrix is first calculated through a lexicographic approach in order to eliminate the dominant solutions in ranging the value of ε. For overcoming the weakly efficient solution problem, a slack variable is introduced to transform the inequality constraints of the original method into equality constraints, as illustrated in Equation (40), where s_i is the slack variable and ϑ is a sufficiently small number (10^{-3}-10^{-6}).

$$\begin{aligned} &\text{Min } z_j(\boldsymbol{x}) - \vartheta \times \sum_{i=1,..,k,i\neq j} s_i \\ \text{S.t.} \quad & z_i(\boldsymbol{x}) + s_i = \varepsilon_i, i = 1, 2, \dots, k, i \neq j \\ & \boldsymbol{x} \in X \end{aligned} \tag{40}$$

The procedures for implementing augmented ε–constraint method for resolving the proposed bi-objective programming problem are given as follows.

1. Calculating the payoff matrix through a lexicographic approach with both capacity settings. It is noted, compared with conventional method, the lexicographic method eliminates the dominant solutions related to the worst-case point.
   Non-flexible capacity: $Obj1_{nonf}^{Max}, Obj2_{nonf}^{Max-lex}, Obj1_{nonf}^{Min-lex}, Obj2_{nonf}^{Min}$
   Solve:
   a) $Obj1_{nonf}^{Max}$ = Max $Obj1$, s.t. (3)-(24)
   b) Min $Obj2$, s.t. $Obj1 = Obj1_{nonf}^{Max}$, (3)-(24)
   c) Repeating the same procedures for $Obj2$
   Flexible capacity: $Obj1_{flex}^{Max}, Obj2_{flex}^{Max-lex}, Obj1_{flex}^{Min-lex}, Obj2_{flex}^{Min}$
   Solve:
   a) $Obj1_{flex}^{Max}$ = Max $Obj1$, s.t. (3)-(9), (18)-(24), (25)-(36)
   b) Min $Obj2$, s.t. $Obj1 = Obj1_{flex}^{Max}$, (3)-(9), (18)-(24), (25)-(36)
   c) Repeating the same procedures for $Obj2$

2. Calculating the range for $Obj2$ with both capacity settings, because the $Obj1$ is considered at higher priority.
   Non-flexible capacity: $Range_{nonf}^{Obj2} = Obj2_{nonf}^{Max-lex} - Obj2_{nonf}^{Min}$
   Flexible capacity: $Range_{flex}^{Obj2} = Obj2_{flex}^{Max-lex} - Obj2_{flex}^{Min}$
3. Setting the values of ε_{Obj2}. In this step, the number of grids (*ng*) is first determined, and the variation of ε_{Obj2} is the calculated: $\Delta\varepsilon_{Obj2} = \frac{Range^{Obj2}}{ng}$.
4. Determining the set of Pareto optimal solutions through resolving the derived constrained optimization problem.
   Non-flexible capacity: $Pareto_{nonf}^{\varepsilon}$
   Solve: Max $Obj1 + \vartheta \times s_2$
   s.t. $Obj2 + s_2 = \varepsilon_{Obj2}$, (3)-(24)
   Flexible capacity: $Pareto_{flex}^{\varepsilon}$
   Solve: Max $Obj1 + \vartheta \times s_2$
   s.t. $Obj2 + s_2 = \varepsilon_{Obj2}$, (3)-(9), (18)-(24), (25)-(36)

5. Computational Experiments

In this section, computational experiments are given to test model and solution methods. The problem includes twelve generation points of used products, five candidate points for central collection center, five candidate points for remanufacturing center, five candidate points for recycling center, three candidate points for energy recovery center, one landfill, and two types of products. The test parameters are generated randomly based upon uniform distribution as illustrated in Table 3, and all the other parameters are given in Appendix. **(Data in Excel)**

Table 3 Some of the parameter intervals used in the computational experiments.

Parameters	Uniform distribution	
	Product q_1	Product q_2
Amount of EOL and EOU products generation Pd_{wq}^{s}	4,000-12,000	6,000-20,000
Fixed costs of collection centers F_i	3-5 million	3-5 million
Processing costs at collection centers Oc_{iq}	50-80	50-80
Fixed costs of remanufacturing centers F_m	5-9 million	5-9 million
Processing costs at remanufacturing centers Oc_{mq}	100-120	100-120
Price of remanufactured products Pt_{mq}^{s}	800-1200	800-1200
Government subsidy of remanufactured products Su_{mq}	200-300	200-300

Table 4 Scenario generation for the problem.

Scenarios	Probability of occurrence	Stochastic parameters		
		Amount of EOL and EOU products collected	Price of the recovered products	Quality level
1 (Deterministic)	20%	Mean	Mean	Mean
2	10%	Low	Low	Low
3	10%	Low	Low	High
4	10%	Low	High	Low
5	10%	Low	High	High
6	10%	High	Low	Low
7	10%	High	Low	High
8	10%	High	High	Low

9	10%	High	High	High

The problem considers the scenario-based uncertainties related to the amount of the used products (Pd_{wq}^{s}), price of recovered products or energy (Pt_{vq}^{s}) and quality level (π_q^s). As discussed by previous authors (Pishvaee et al., 2009), the increase on the number of test scenarios in a stochastic model achieves limited improvement on the optimal solution with a huge sacrifice on computational efficiency. Therefore, considering both performance and efficiency, the scenario generation method used by Soleimani et al. (2016) is employed in this paper to generate nine scenarios. As shown in Table 4, the mean values of the given intervals of stochastic parameters are used for the deterministic scenario with the highest probability of occurrence at 20%. With the combinations of the stochastic parameters, another eight scenarios are generated with equal probability at 10%.

The calculation is performed with Lingo 16.0 optimization solver on a PC with 2.20 GHz CPU and 8 GB RAM under Windows 10 operating system.

5.1 Effect of flexible capacity on economic performance

The model is first solved with only profit-maximization objective, and the rate of efficiency loss is tested with Ef_i^{Loss}=0% and Ef_i^{Loss}=15%. The calculation results are presented in Tables 4 and 5, respectively. We first compared the network performance and structure under both deterministic and stochastic environments. When non-flexible capacity is implemented, the profit achieved under deterministic environment is 6.7% higher than that of the stochastic scenario. However, when flexible capacity is implemented with Ef_i^{Loss}=0%, the profit obtained under stochastic environment is 2.2% higher. When the rate of efficiency loss increases to 15%, the deterministic scenario achieves a 1% higher profit. In addition, more facilities are opened under a stochastic environment in order to deal with the market fluctuation, and this will lead to an increase on the overall system costs due to the low facility utilization under low demand scenarios. It is observed, under market fluctuation, a highly flexible reverse logistics system may achieve a better profitability than that under a stable environment.

Table 5 Computational results of the components in the objective functions with non-flexible/flexible capacity under deterministic/stochastic environment (results in 10^4).

Components in the objective functions	Non-flexible capacity		Flexible capacity (Ef_i^{Lost}=0%)		Flexible capacity (Ef_i^{Lost}=15%)	
	Deterministic	Stochastic	Deterministic	Stochastic	Deterministic	Stochastic
Profit	7436	6941	8173	8354	8096	8009
Revenue	17244	17124	17244	17901	17244	17551
Subsidy	6896	6640	7162	7228	7168	7238
Total costs	16704	16823	16233	16774	16316	16780
Facility costs	8696	8551	8027	8406	7970	8396
Transportation costs	8008	8272	8206	8368	8346	8384
Total emissions	28428	30484	28682	29066	29176	29292
Facility emissions	13409	15496	13952	14228	14760	14485
Transportation emissions	15019	14988	14730	14837	14415	14806

Table 6 Selection of facilities in different scenarios.

Selection of facilities	Non-flexible capacity	Flexible capacity (Ef_i^{Lost}=0%)	Flexible capacity (Ef_i^{Lost}=15%)

	Deterministic	Stochastic	Deterministic	Stochastic	Deterministic	Stochastic
Central collection centers	(1,0,1,1,0)	(0,0,1,1,1)	(0,0,1,1,0)	(1,0,1,1,0)	(0,0,1,1,0)	(1,0,1,1,0)
Remanufacturing centers	(1,0,0,1,0)	(0,1,0,1,0)	(1,0,0,1,0)	(0,1,0,1,0)	(1,0,0,1,0)	(0,1,0,1,0)
Recycling centers	(0,1,0,1,0)	(0,0,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)
Energy recovery centers	(1,0,0)	(1,1,0)	(1,0,0)	(0,1,0)	(0,1,0)	(0,1,0)

Under a stochastic environment, comparted with the non-flexible configuration, the profit expectation with flexible capacity increases by 20.4% (Ef_i^{Loss}=0%) and 15.4% (Ef_i^{Loss}=15%). Besides, we also conduct a sensitivity analysis of eight scenarios with Ef_i^{Loss}=0%, 5%, 10%, 15%, 20%, 25%, 30%, 35% and 40%, respectively. Figure 2 presents the comparison of profit expectation, overall income, total costs and total carbon emissions of the different scenarios. With the increase of the rate of efficiency loss in implementing a flexible capacity, the profit expectation gradually decreases and eventually becomes lower than that of the non-flexible configuration when Ef_i^{Loss}=35% and 40%. In contrast, the total costs remain stable until Ef_i^{Loss} increases to 20% from which a sharp increase is observed. The change of the overall income and carbon emissions does not show a consistent monotonicity over the test scenarios. In general, the performance of the two indicators decreases with the increase of Ef_i^{Loss}, but it is better than that of the non-flexible configuration over all the test scenarios. The result has illustrated that the flexible configuration is an effective tool for improving the economic performance of a reverse logistics system under market fluctuation, but the effectiveness is affected by the rate of efficiency loss in the transformation. Furthermore, the profit expectation may become worse with the flexible capacity when $Ef_i^{Loss}$is large enough.

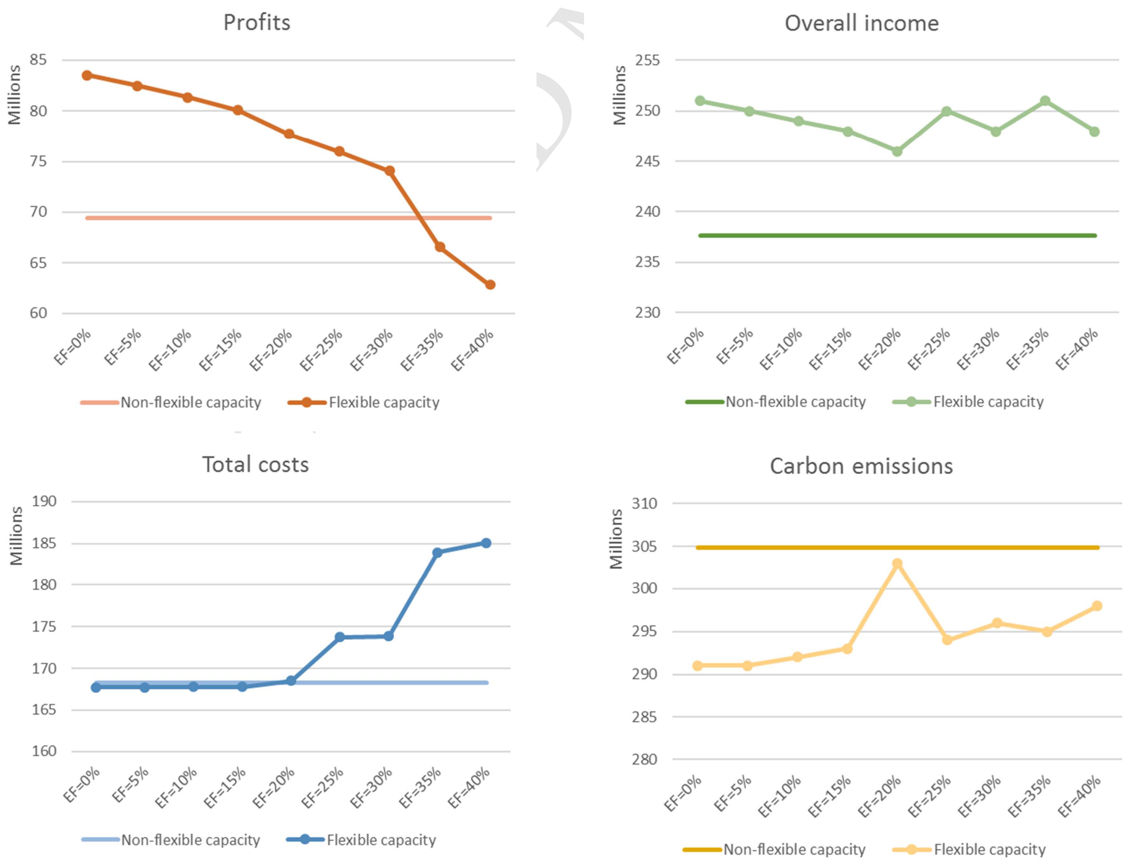

Figure 2. Comparison of profits, overall income, total costs and carbon emissions of the different scenarios under stochastic environment.

Figures 3 and 4 present the comparison of the performance on facility operations and transportation of the test scenarios. As shown, with the increase of Ef_i^{Loss}, the change of facility costs is in consistency with the change of the total costs with a variation at 22%, while the change of the transportation costs is not monotonic with a much smaller variation at 1.5%, so the change of the total costs is the result from facility operations. The carbon emissions related to facility operations and transportation show the similar pattern even if the difference on the variation is not that big compared with that of the costs. The result illustrates the effectiveness of facility operation is the most important consideration for implementing a flexible configuration.

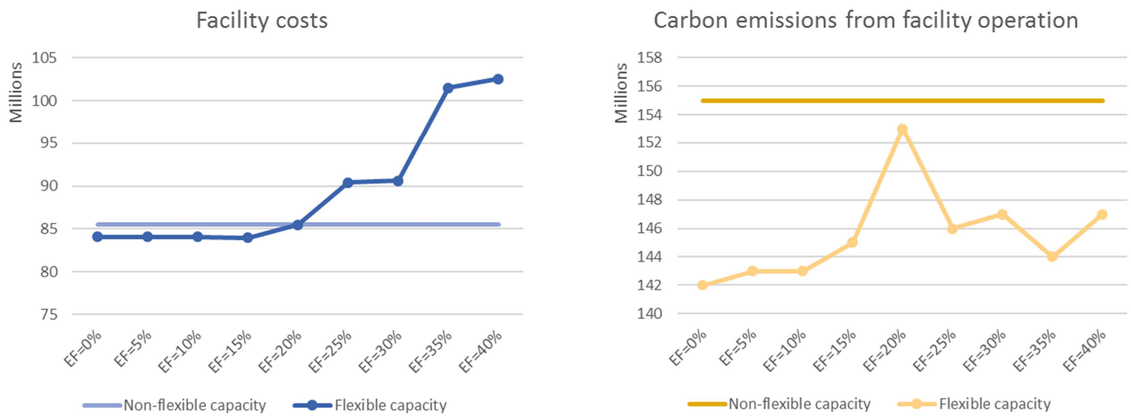

Figure 3. Comparison of costs and carbon emissions related to facility operations of different scenarios under stochastic environment.

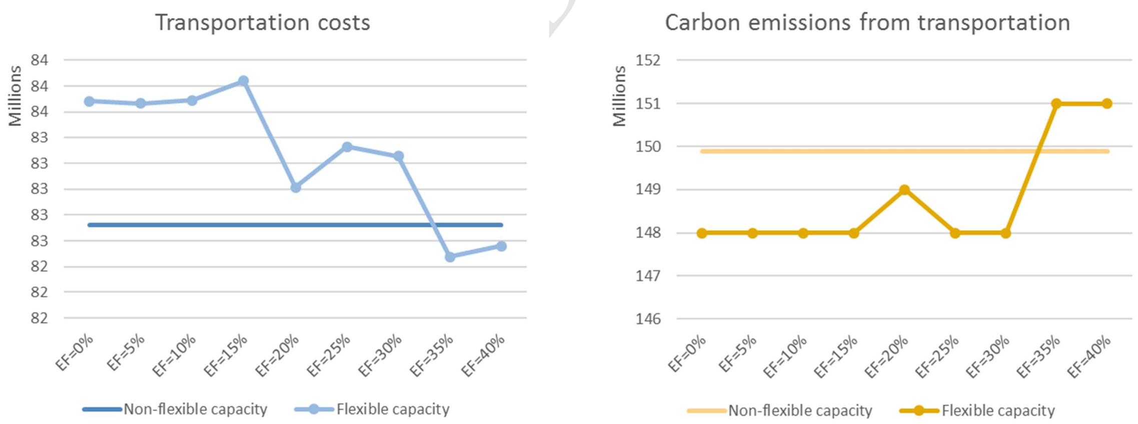

Figure 4. Comparison of costs and carbon emissions related to transportation of different scenarios under stochastic environment.

5.2 Effect of flexible capacity on economic and environmental performance

In this section, the model is tested with both objective functions. First, the bi-objective stochastic optimization model is solved by weighting method, and 11 Pareto optimal solutions are obtained with respect to the changing w_{Obj1} from 1 to 0 with a step at 0.1 each. Then, the problem is resolved by augmented ε –constraint method in order to generate another 11 Pareto optimal solutions accordingly. Table 7 presents the computational results, which includes the generation of Pareto solutions, computational performance and information on the slacks. Figures 5 and 6 present the Pareto frontiers between profits and carbon emissions of the reverse logistics system with both non-flexible capacity and flexible capacity.

Table 7 Computational results of the Pareto optimal solutions by both weighting method and augmented ε-constraint method.

Points	Weighting method							Augmented ε-constraint method							
	w_{Obj1}	Non-flexible capacity			Flexible capacity			Non-flexible capacity				Flexible capacity			
		Time	Profit (10^4)	Carbon (10^4)	Time	Profit (10^4)	Carbon (10^4)	Time	Profit (10^4)	Carbon (10^4)	Slack	Time	Profit (10^4)	Carbon (10^4)	Slack
1	1	11	6941	30484	13	8354	29066	53	6941	30484	0	71	8354	29066	0
2	0.9	90	6927	30150	61	8349	28939	75	6849	29655	0	117	8223	28349	0
3	0.8	84	6907	29988	163	8330	28744	116	6710	28826	0	102	8053	27632	0
4	0.7	146	6464	27549	140	8272	28495	185	6550	27998	0	121	7799	26915	0
5	0.6	77	6158	26816	80	7491	26166	121	6359	27169	0	88	7506	26198	0
6	0.5	52	5653	25426	70	7026	25339	108	6089	26341	0	103	7116	25482	0
7	0.4	55	4817	24321	84	5918	24054	61	5702	25512	0	109	6553	24765	0
8	0.3	26	4220	23803	24	5024	23374	62	5106	24683	0	71	5912	24048	0
9	0.2	31	766	22225	13	1934	21924	41	4292	23855	0	39	4950	23331	0
10	0.1	12	702	22205	6	1846	21900	40	2677	23026	0	13	3590	22614	0
11	0	9	639	22198	4	1147	21898	25	639	22198	0	10	1831	21898	0

We first compared the performance of the two solution methods in calculating the Pareto frontier of a multi-objective optimization problem. Due to the convex nature of the test problem, the shape of the Pareto frontier determined by both methods is similar. However, weighting method can only find the Pareto optimal solutions at the extreme points of the curve, while augmented ε–constraint method is able to generate evenly distributed Pareto optimal solutions and a smoother curve. Furthermore, augmented ε–constraint method can effectively eliminate the dominant solutions, but weighing method is incapable with that. For example, it is easy to see in Figure 5, point 11 is a dominant solution of point 10 in the Pareto curve with flexible configuration, and it is eliminated by augmented ε–constraint method. Thus, augmented ε–constraint method has a better performance in the effectiveness; while on the other hand, the computational time required by weighting method is less in most cases, so the weighting method has a better performance in terms of computational efficiency.

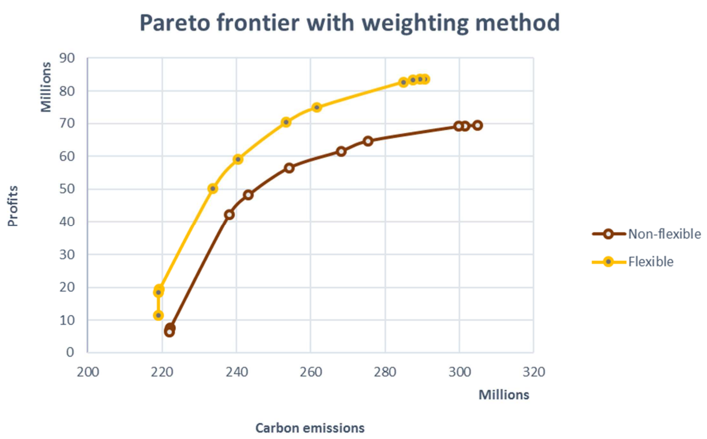

Figure 5. Pareto frontier determined by weighting method.

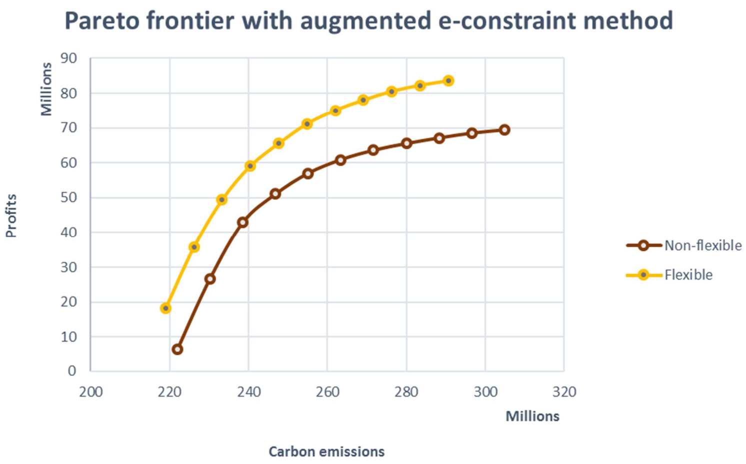

Figure 6. Pareto frontier determined by augmented ε-constraint method.

We then compared the performance of the reverse logistics system in terms of both profit expectation and environmental impact with the incorporation of flexible capacity. It is observed that the carbon emissions from reverse logistics activities increase with the increase of the profit expectation. In order to reduce the carbon emissions, some economic benefits will be lost, so Pareto frontier provides a set of the optimal trade-offs between the profits and environmental influence. As can be seen, the reduction on carbon emissions at the beginning stage from the profit-maximization scenario is more effective without a significant compromise on the economic benefits compared with that on the latter stage. It is also observed the implementation of a flexible configuration in the reverse logistics system improves both profit expectation and environmental performance.

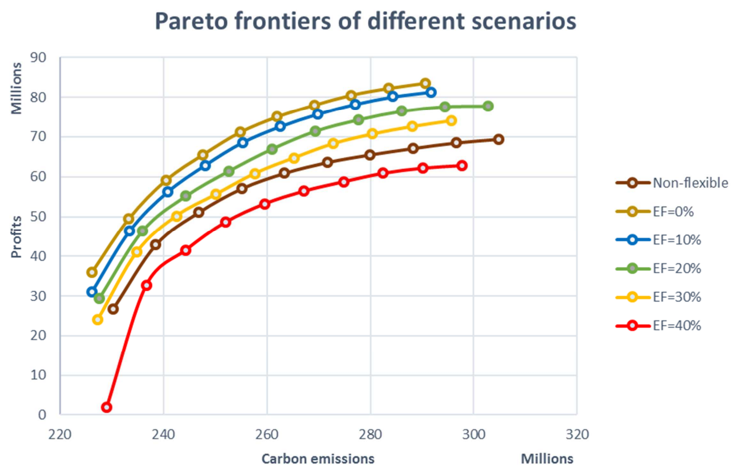

Figure 7. Pareto frontiers determined by augmented ε-constraint method of different scenarios (Ef_i^{Loss}=0%, 10%, 20%, 30% and 40%).

The transformation from a non-flexible system to a flexible system without a compromise on efficiency is hardly to achieve in reality, so sensitivity analysis is performed with an adjustment on Ef_i^{Loss} from 0% to 40% with 10% step each, and the result is given in Figure 7. With the increase of the rate of efficiency loss from 0% to 30%, both economic and environmental performance of the Pareto optimal solutions decrease gradually, but they still have a better performance than the Pareto optimal solutions obtained with a non-flexible configuration. However, when the rate of efficiency loss reaches 40%, the reverse logistics system with a flexible capacity achieves much lower profits and has more carbon emissions in most cases.

Thus, it is of interest to "take a closer look at" the model behavior in the segment where the performance of a flexible reverse logistics system is close to a non-flexible one. Figure 8 illustrates the comparison of the Pareto frontiers between non-flexible configuration and flexible configuration with Ef_i^{Loss}=30%, 32.5% and 35%, respectively. When Ef_i^{Loss}=32.5%, the performance of the reverse logistics system with both capacity settings is very close to each other. In this case, the flexible reverse logistics system favors more on profit-focused scenarios. While, on the other hand, the non-flexible configuration has a slightly better performance on the emission-focused scenarios.

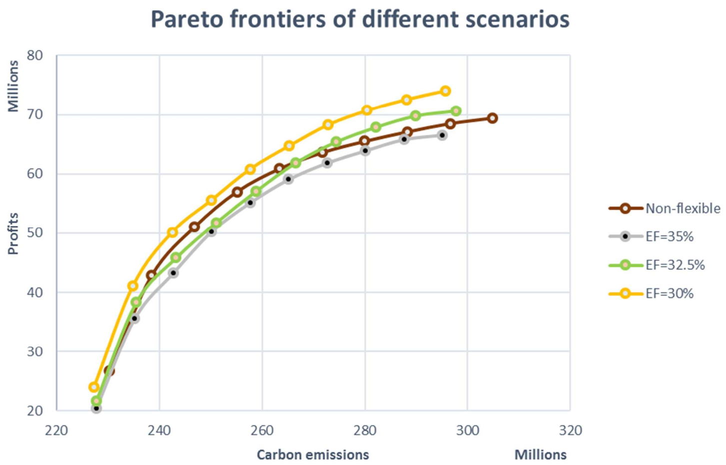

Figure 8. Pareto frontiers determined by augmented ε-constraint method of different scenarios (Ef_i^{Loss}=30%, 32.5% and 35%).

6. Managerial Implications

The planning of a sustainable reverse logistics system is a complex decision-making problem that aims at optimizing the trade-off between economic benefits and environmental influence. Furthermore, in the planning horizon of a reverse logistics system, there are many uncertainties related the quantity and quality of the reverse flow, and market fluctuation, which make the problem becoming more complicated. The latest modelling efforts and computational analysis on sustainable reverse logistics network design under uncertainty have shown a significant improvement on the understanding of the trade-offs among economic, environmental and social sustainability (Feitó-Cespón et al., 2017, Talaei et al., 2016), implications from the customer satisfaction (Özkır and Başlıgil, 2013), on-site/off-site separations (Rahimi and Ghezavati, 2018), as well as computational performance (Govindan et al., 2016b, Soleimani et al., 2017). In this paper, the managerial implications regarding the impact of flexibility on sustainable reverse logistics network design under uncertainty is focused.

The uncertainty in reverse logistics network design may either result in a lower utilization of resources in low demand scenarios or lead to an insufficient capacity to treat all the EOL and EOU products. In the latter case, the decision-maker may either implement a reduction on the service level or put more investment on facility expansion (Yu and Solvang, 2017). However, in the planning of a multi-product reverse logistics system, the transformation from an efficiency-focused non-flexible configuration to an effectiveness-focused flexible system may be the third option, which may improve both economic and environmental performances. The results of the computational experiments have shown the flexible reverse logistics system has a better performance in both economic benefits and environmental influence under a stochastic environment when the rate of efficiency loss is maintained at lower than 32.5%. Otherwise, the focus of the reverse logistics network design should be on efficiency.

Taking into account of the nature of the sustainable reverse logistics network design problem, some generic managerial implications are given as follows:

1. The implementation of a flexible configuration for a reverse logistics system dealing with multiple heterogamous products may improve both economic and environmental performance when the efficiency loss is kept in a proper level. In another words, if the companies in the reverse logistics system have to spend significant efforts to achieve a high flexibility, the benefits gained may be negligible or even negative.
2. When reverse logistics system is operated under an uncertain environment, a highly flexible configuration may provide a better chance to generate higher profits while simultaneously reduces carbon emissions.
3. When reverse logistic system is operated under a relatively stable environment, the efficiency-focused non-flexible configuration has a better performance.
4. The reduction on carbon emissions from the reverse logistics activities results in a compromise on the profit expectation, and a Pareto frontier can describe such a trade-off.
5. For calculating the Pareto frontier of the problem, augmented ε-constraint method is more effective in generating evenly distributed non-dominant efficient solutions, while weighting method requires less computational time.

7. Conclusion

Reverse logistics network design is a complex decision-making problem that involves conflicting objectives and uncertain parameters. In this paper, we develop a new two-stage stochastic bi-objective programming model for sustainable planning of a multi-product multi-echelon reverse logistics system under uncertainty. Considering the different processing operations for the recovery of multiple types of products with heterogeneous nature, the model is formulated in two parallel ways equipped with either an efficiency-focused non-flexible capacity or an effectiveness-focused flexible capacity. For resolving the multi-objective optimization problem, two solution approaches: weighting method and augmented ε-constraint method are employed to calculate the non-dominant efficient Pareto optimal solutions.

Compared with the modelling efforts in existing literature, the contribution of this paper is the consideration of flexibility in sustainable reverse logistics network design. Due to a lack of system flexibility, the trade-off analysis with previous mathematical models may lead to an excessive capacity installed with low utilization under an uncertain environment. The paper provides a decision-support model for performance evaluation, under different environments, between the flexible and non-flexible configurations in sustainable reverse logistics network design. The experimental analysis illustrates implementing a flexible configuration may improve the overall performance of a sustainable reverse logistics system under an uncertain environment. However, the result also suggests when the market environment is stable or significant efforts are needed to improve the system flexibility, implementing a non-flexible configuration is more favorable in order to maintain the efficiency. Furthermore, the strategic decision-making on flexibility or efficiency will also affect the decisions on plant planning, i.e., internal routing, layout design, etc.

The paper has provided important insights into incorporating flexible capacity in sustainable reverse logistics network design. Nevertheless, the research is not without limitations and many research directions are still worthy for future investigation.

1. Incorporating flexible capacity in remanufacturing and recycling will result in an increase on the costs for collection, separation, storage and pre-processing of the heterogeneous EOL and EOU products. The future modelling efforts may consider the cost increase on those operations.
2. Future works may be conducted to include more uncertain parameters in sustainable reverse logistics network design.
3. The inclusion of more uncertain parameters will lead to an increased computational complexity, so more effective and efficiency solution methods and algorithm should be developed.
4. For future research, focus may be given to the social sustainability in sustainable reverse logistics network design, and the selection of proper indicators for quantifying the social sustainability is of interest.

Acknowledgement

The authors would like to express their gratitude to the four anonymous reviewers and associate editor for their valuable comments. The research is supported by TARGET project financed by EU Northern Periphery and Arctic (NPA) Programme and OptiLog 4.0 project (Project No. 283084) financed by the Research Council of Norway under Transport 2025 Programme.

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Highlights

- Incorporating flexibility in sustainable reverse logistics network design
- Formulating mathematical model for decision support under uncertainty
- Different solution methods were tested, compared and discussed
- Results were analyzed for providing managerial implications