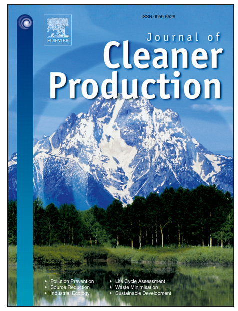

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Hao Yu, Wei Deng Solvang

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A Carbon-Constrained Stochastic Optimization Model with Augmented Multi-Criteria Scenario-Based Risk-averse Solution for Reverse Logistics Network Design under Uncertainty

Hao Yu and Wei Deng Solvang*

Dearpment of Industrial Engineering, UiT—The Arctic University of Norway, Lodve Langesgate 2, 8514 Narvik, Norway

**Corresponding author, (+47) 76966328*

Email: hao.yu@uit.no; wei.d.solvang@uit.no

Abstract: With the increase of the concern from the public for environmental pollution and waste of resources, the value recovery through reuse, repair, remanufacturing and recycling from the end-of-use (EOU) and end-of-life (EOL) products have become increasingly important. Reverse logistics is the process for capturing the remaining value from the EOU and EOL products and also for the proper disposal of the non-reusable and non-recyclable parts. A well-designed reverse logistics system will yield both economic and environmental benefits, so the development of an advanced decision-making tool for reverse logistics system design is of significant importance. The paper presents a novel multi-product multi-echelon stochastic programming model with carbon constraint for sustainable reverse logistics design under uncertainty. Compared with the previous stochastic optimization models in reverse logistics system design, which mainly focuses on the expectation of the optimal value, this paper, however, emphasizes on both optimal value expectation and its reliability in decision-making. Due to this reason, a multi-criteria scenario-based risk-averse solution method is developed based on a latest research in order to obtain the optimal solution with high level of confidence. Later in this paper, the application of the model and the augmented solution method is illustrated and the managerial implications are discussed through the numerical experiment and sensitivity analysis. The result of the study shows that the model can be used for providing decision-makers with a deep insight into the relationship between profit and carbon emission requirement, understanding and resolution of the infeasibility caused by capacity limitation, the use of flexible manufacturing system in reverse logistics, and proper use of the government subsidy as a leverage in reverse logistics design.

Key word: reverse logistics; network design; optimization; stochastic programming; sustainability; uncertainty; scenario-based solution, risk averse

1. Introduction

Logistics and supply chain network design is a complex decision-making problem in operational research, which aims mainly at determining the locations of different facilities and the material flows and transportation strategy among those facilities (Lee and Dong, 2009). Due to the complicated nature of the logistics and supply chain network design problem, it has never lost its appeal to both academic researchers and practitioners. In recent years, with the increasing focus on sustainable development and circular economy, the value recovery from the end-of-use (EOU) and end-of-life (EOL) products has been adopted by many enterprises all over the globe due to the economic incentives and stringent environmental regulations enforced. For example, the EU Directive 92/62/CE has set a compulsory requirement for the manufacturing companies to recover a percentage of the EOL, EOU as well as the packaging materials from the market (Gonzalez-Torre et al., 2004). Therefore, the design of an economically efficient and sustainable reverse logistics network has been increasingly focused in the recent literature (Nikolaou et al., 2013).

Reverse logistics is the entire process for effectively managing the material, information and cash flow in order to re-generate value from EOU and EOL products through repair, reuse, remanufacturing, recycling and re-introduction to the market, besides, it also involves the proper treatment of the non-reusable and non-recyclable parts (Rogers and Tibben‐Lembke, 2001, Yu and Solvang, 2016a). Reverse logistics network design is a long-term decision at strategic level, and when the supply chain network is configured, it could be extremely difficult and costly to alter it. A well-planned reverse logistics system will yield both economic and environmental benefits. However, an improperly designed reverse logistics system may reduce the profitability of the business while simultaneously cause more serious environmental and/or social impact. Due to this reason, it is of great importance to develop the advanced methods for resolving the complex decision-making problem of reverse logistics network design.

This paper formulates a new carbon-constrained mathematical model under stochastic environment for sustainable reverse logistics network design, and an augmented multi-criteria scenario-based risk-averse solution method is also developed for resolving the model. The remainder of the paper is organized as follows: Section 2 presents a comprehensive literature review of the recent research works in reverse logistics network design. Section 3 formulates the stochastic optimization model. Section 4 develops the augmented multi-criteria scenario-based risk-averse solution method based upon the research work given by Soleimani et al. (2016). The existed problems of the original method and the solution in the augmented method are explicitly discussed in this section. Section 5 presents the numerical experiment of the model and solution method. Section 6 summaries some generic managerial implications, i.e, the relationship between profit and carbon emission requirement, the use of flexible manufacturing system in reverse logistics, and proper use of the government subsidy as a leverage, etc. Section 7 concludes the paper and proposes directions for future research.

2. Literature review

During the past decade, reverse logistics network design problem has been extensively focused in operational research and mathematical optimization. Comprehensive literature review are given in Pokharel and Mutha (2009), Govindan et al. (2015), Agrawal et al. (2015), Mahaboob Sheriff et al. (2012) and Govindan and Soleimani (2017), and from the perspectives of sustainable development and uncertainties of decision-making, this paper presents a brief overview of some of the recent publications in this field.

The primary target of reverse logistics is the value recovery form EOU and EOL products, so economic benefit and sustainability have been widely formulated and emphasized in literature. Alumur et al. (2012) propose a mixed integer programming for a multi-period reverse logistics network design problem. The model aims at maximizing the total profits generated in the reverse logistics system through optimally locating different facilities and allocating the materials follows over several continuous periods. Demirel et al. (2016) develop a mixed integer linear programming for minimizing the reverse logistics costs for recycling the EOL vehicles in Turkey. Li and Tee (2012) formulate a mathematical model for reverse logistics network design with the consideration of both formal and informal channels. Sasikumar et al. (2010) formulate a mixed integer programming for reverse logistics network design, and a case study of truck tire remanufacturing is given in the paper.

Alshamsi and Diabat (2017) formulate a multi-period location-allocation model for reverse logistics network design, and a genetic algorithm is developed for resolving the large-scale optimization problems in an effective and efficient manner. Diabat et al. (2013b) combine both genetic algorithm and artificial immune system in the optimization problem of a product return system. Kumar et al. (2017) develop a mixed integer model for maximizing the profits generated in an integrated forward-reverse logistics system on a multi-period basis, and an evolutionary algorithm is developed for resolving the optimization problem. Das and Chowdhury (2012) propose an optimization model for the reverse logistic network design considering the collection and recycling of multiple types of EOU and EOL products. Zhou and Zhou (2015) formulate a cost-minimization model for the design of a multi-echelon reverse logistics network. Demirel and Gökçen (2008) propose a mathematical programming for designing a remanufacturing system.

Introduced in 2005 World Summit of the United Nations, sustainability framework includes economic, environmental and social dimensions (Chopra and Meindl, 2007). In order to account those dimensions simultaneously, reverse logistics network design becomes a complex decision-making problem which involves several objectives or criteria. Some research works focus on the optimal tradeoff among those conflicting objectives or criteria in decision-making. Diabat et al. (2013a) formulate a bi-objective optimization model for the optimal design of an integrated forward/reverse logistics system, and the model aims at simultaneously minimizing the costs and CO_2 emissions. Yu and Solvang (2016a) develop a bi-objective mixed integer linear programming for reverse logistics design considering both economic benefits and environmental impact, and in this paper, the environmental impact is evaluated by carbon emissions.

With the consideration of economic, environmental and social sustainability, Govindan et al. (2016a) investigates a multi-objective mixed integer programming of the design of a multi-product multi-period integrated forward/reverse logistics system. In this research, the environmental sustainability is measured by both cost saving from material recovery and CO_2 emission, while the social sustainability is evaluated by four indicators regarding the welfare, responsibilities and employment. Govindan et al. (2016b) formulated a fuzzy mathematical model for sustainable design of reverse logistics system. The model aims at simultaneously balancing the economic efficiency, environmental impact and social benefits in a sustainable reverse logistics system, and a customized multi-objective particle swarm optimization algorithm is developed to find out the optimal solution.

In the real world, decision-making is seldom done with all parameters exactly known in advance, but many important decisions have to be made even though the knowledge or information of some parameters is limited at the point of decision-making (King and Wallace, 2012). Reverse logistics network design is a long-term decision that involves great uncertainties, so some literature focuses on the uncertainty issues associated with reverse logistics network design. Lee and Dong (2009) develop a two-stage stochastic programming for designing a multi-period integrated forward-reverse logistics system under demand uncertainties. El-Sayed et al. (2010) formulate a stochastic optimization model for the design of a multi-period forward-reverse logistics network with the consideration of risk. Ramezani et al. (2013) develop a multi-objective stochastic optimization model for the optimal planning of an integrated forward-reverse logistics network, and the responsiveness and quality level of the EOU and EOL products are accounted in this model. Chu et al. (2010) propose a fuzzy chance-constrained model for the design of a reverse logistics system for household appliances recovery.

Considering both forward and reverse directions of the supply chain planning, De Rosa et al. (2013) formulate a robust optimization model for the network planning under supply uncertainties. Roghanian and Pazhoheshfar (2014) develop a stochastic programming for minimizing the opening and operating costs of a multi-period and multi-echelon reverse logistics system, and the capacities, customer demands for recycled products, and quantity of EOU and EOL products generated are considered as stochastic parameters. Soleimani and Govindan (2014) develop a multi-level multi-product two-stage stochastic programming for reverse logistics network design with the consideration of the risk minimization in the decision-making.

In some most recent literature, the consideration of both sustainability and uncertainty issues is focused in reverse logistics network design. Feitó-Cespón et al. (2017) investigate a stochastic optimization model for the redesign of reverse logistics system, and the model aims at simultaneously balancing the economic, environmental and social sustainability. Fonseca et al. (2010) formulate a two-stage bi-objective stochastic programming model for the facility location problem of reverse logistics. The model aims at simultaneously minimizing the costs and obnoxious effect of the reverse logistics system which is operated under uncertainties of the waste generation. Govindan et al. (2016b) develop a fuzzy multi-objective mixed integer programming for reverse logistics network design considering economic, environmental and social sustainability. Soleimani et al. (2017) formulate a fuzzy multi-objective mathematical model for the design of a sustainable closed-loop supply chain, and the model aims at maximizing the overall profit and satisfaction rate of customer demand while simultaneously minimizing the missed working days caused by occupational accidents.

Table 1 shows the literature classification. It has been shown from the literature review that many previous research works in reverse logistics network design only focus on the economic performance, but the other dimensions of sustainable development is not emphasized, and this is further proved by Govindan et al. (2015). There is no denying the fact that reverse logistics itself can be considered as a means to achieve circular economy and sustainable development through the value recovery from EOU and EOL products; however, an improperly planned reverse logistics network may cause both environment impact (e.g., excessive GHG emissions from long-distance and frequent transport (Sun, 2016), waste of resources and environmental pollutions from the implementation of low-tech recycling technologies (Liu et al., 2008), etc.) and negative influence on the social sustainability (e.g, threats to the health of the workers (Liu et al., 2008), threats to the local residents nearby the treatment facilities of hazardous materials (Yu and Solvang, 2016b), etc.). Besides, some mathematical models for sustainable reverse logistics network design are formulated under deterministic environment, which are incapable to deal with the uncertainties and market fluctuation.

The literature review shows there are very few research works on reverse logistics network design considering both uncertainty and sustainable issues, and exceptions are only given in some recent publications (Fonseca et al., 2010, Feitó-Cespón et al., 2017, Govindan et al., 2016b, Soleimani et al., 2017). Thus, there is a need to develop the advanced tool for a better decision-making of reverse logistics system design under market fluctuation and sustainable considerations. Furthermore, most mathematical models developed under uncertain environment focus only on the expectation of the objective value (e.g. min-cost, max-profit, etc.), and the risk of decision-making or the reliability of the achievement of the value expectation is rarely taken into account in reverse logistics network design. This problem has been identified and resolved by a multi-criteria scenario-based solution method developed in a latest research work (Soleimani et al., 2016). However, the method has a significant problem which may lead to sub-optimal solutions.

In order to fill the literature gap, the paper focuses on the following works:

- This paper formulates a novel two-stage stochastic mixed integer linear programming model with carbon emission constraint for sustainable reverse logistics network design. The model is formulated based on a generic multi-product three-echelon reverse logistics framework under uncertainty of the generation of different types of EOU and EOL products, and the price of recycled products and recovered energy.
- In addition to the contribution to the model formulation, an augmented multi-criteria scenario-based risk-averse solution method is also developed in this paper, and the method focuses on both optimal value expectation and level of confidence of the optimal result so that the solution of the stochastic optimization problem is more reliable. The problems existed in the original solution method are explicitly discussed and fixed in the augmented method.
- The proposed stochastic optimization model and augmented solution method are tested with experimental analysis with the changing parameters. Furthermore, deep managerial implications are obtained, and some of which, i.e., the use of flexible manufacturing system, economy of scale and role of government subsidy, etc., are discussed with mathematical programming approach for reverse logistics network design.

Table 1 Literature review of some research works in reverse logistics network design

Research works	Network structure		Criteria for decision-making				Product		Period		Parameter		Uncertain approach	Application
	Forward	Reverse	Economic	Environmental	Social	Other	Single	Multiple	Single	Multiple	Certain	Uncertain		
Alumur et al. (2012)		*	*					*		*	*		-	Case study
Demirel et al. (2016)		*	*				*			*	*		-	Case study
Li and Tee (2012)		*	*	*			*			*	*		-	Numerical study
Sasikumar et al. (2010)		*	*				*			*	*		-	Case study
Alshamsi and Diabat (2017)		*	*				*		*		*		-	Case study
Diabat et al. (2013b)		*	*				*		*		*		-	Numerical study
Kumar et al. (2017)	*	*	*				*			*	*		-	Numerical study
Das and Chowdhury (2012)		*	*					*	*		*		-	Numerical study
Zhou and Zhou (2015)		*	*				*		*		*		-	Case study
Demirel and Gökçen (2008)	*	*	*					*	*		*		-	Numerical study
Diabat et al. (2013a)	*	*	*	*				*	*		*		-	Case study
Yu and Solvang (2016a)		*	*	*				*	*		*		-	Numerical study
Govindan et al. (2016a)	*	*	*	*	*			*		*	*		-	Case study
Govindan et al. (2016b)		*	*	*	*		*			*		*	Fuzzy	Numerical study
Lee and Dong (2009)		*	*					*		*		*	Stochastic	Numerical study
El-Sayed et al. (2010)	*	*	*				*			*		*	Stochastic	Numerical study
Ramezani et al. (2013)	*	*	*			*		*	*			*	Stochastic	Numerical study
Chu et al. (2010)		*	*				*			*		*	Fuzzy	Numerical study
Feitó-Cespón et al. (2017)		*	*	*	*			*	*			*	Stochastic	Case study
De Rosa et al. (2013)		*	*				*			*		*	Robust	Case study
Roghanian and Pazhoheshfar (2014)		*	*					*	*			*	Stochastic	Numerical study
Fonseca et al. (2010)		*	*		*			*	*			*	Stochastic	Case study
Soleimani and Govindan (2014)		*	*					*	*			*	Stochastic	Numerical study
Soleimani et al. (2016)	*	*	*					*		*		*	Stochastic	Numerical and case study
Soleimani et al. (2017)	*	*	*		*			*		*		*	Fuzzy	Numerical study
Current study		*	*	*				*	*			*	Stochastic	Numerical study

3. Development of mathematical model

The proposed reverse logistics network structure is given in Figure 1. As illustrated in the figure, the reverse logistics network is comprised of the local collection centers for EOU and EOL products (*g*), central collection center (*c*), remanufacturing and recycling center (*p*), energy recovery plant (*r*), waste treatment facility and the market (*m*). First, the EOU and EOL products are collected at the local collection centers which are located closely to the customers, and this first-level collection could be either a spontaneous customer return of EOU and/or EOL products at the fixed depots or an organized return service performed by the local waste management companies. Then, the locally collected EOU and EOL products are sent to the central collection centers where they will be inspected and disassembled for further distribution. The disassembled parts will be sent for either remanufacturing/recycling or for energy recovery through incineration/bio-chemical treatment, and the non-reusable and non-recyclable parts will be sent for disposal at landfill.

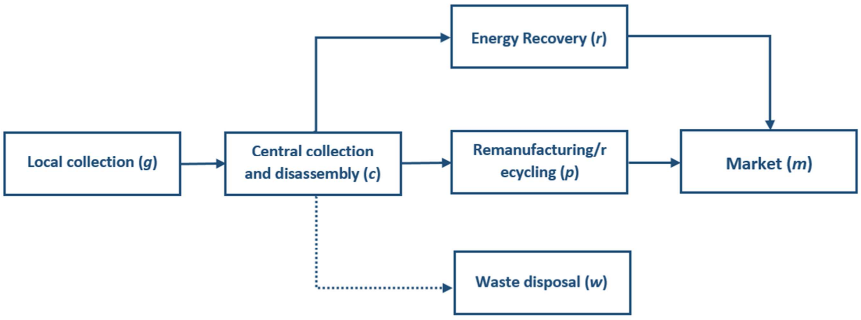


Figure.1 Reverse logistics network.

In this paper, the objective of the reverse logistics network design is to maximize the profit generated through value recovery of EOU and EOL products, and the reverse logistics system is subsidized in order to improve the profitability and enthusiasm of the companies for the reuse, recycling, remanufacturing and energy recovery of EOU and EOL products. The reverse logistics network design problem is formulated as a stochastic mixed integer programming, and the generation of different types of EOU and EOL products, and the price of recycled products and recovered energy are considered as uncertain parameters. Furthermore, the model also considers the environmental sustainability of the reverse logistics system, which is constrained by the carbon emissions of the reverse logistics activities.

It is a prerequisite that the locations of local collection centers, markets for recycled products and recovered energy, existing landfills for waste disposal, and the candidate locations of central collection centers, recycling center, energy recovery plants, as well as the relevant cost and carbon emissions associated with facility operation and the transportation of EOU and EOL products are known.

The definition of sets, indices, parameters and decision variables is first given as follows. Herein, the unit of the parameters are also suggested, but different measures of units may be used in case studies (Feitó-Cespón et al., 2017, Demirel et al., 2016, Fonseca et al., 2010, Soleimani et al., 2016, Alumur et al., 2012).

Set and indices:

G, *g*	Generation points of EOU and EOL product
C, *c*	Candidate locations of collection center
P, *p*	Candidate locations of remanufacturing/recycling plant
R, *r*	Candidate locations of energy recovery plant

W, w	Waste disposal facilities
M, m	Markets of recycled product and recovered energy
T, t	Types of EOU and EOF product
S, s	Scenarios

Parameters:

EP_{gt}^{s}	Generation of product *t* at location *g* in scenario *s* (unit/year)
Pen_{rt}^{s}	Benefit from the energy recovery from one unit product *t* at facility *r* in scenario *s* ($/unit)
Ppd_{pt}^{s}	Benefit from the recycling of one unit product *t* at facility *p* in scenario *s* ($/unit)
$Subr_t$, $Subp_t$	Government subsidy for recovering or recycling one unit product *t* ($/unit)
F_c, F_p, F_r	Fixed operating cost for collection center, recycling plant and energy recovery plant ($/year)
Po_{ct}, Po_{pt}, Po_{rt}	Unit processing cost at collection center, recycling plant and energy recovery plant ($/unit)
Po_w	Gate fee for landfilling one unit of EOU and/or EOL product ($/unit)
Ct_{gct}, Ct_{cpt}, Ct_{crt}, Ct_{cwt}, Ct_{pmt}, Ct_{rmt}	Unit transportation cost of product *t* among different facilities ($/unit)
Ruq_{ems}^{s}	Required maximum equivalent carbon emissions of the reverse logistics system in scenario *s* (kg)
∂_{tp}, ∂_{tr}	Conversion rate of product *t* at respective facilities
MCp_{ct}, MCp_{pt}, MCp_{rt}, MCp_w	Planned capacity of respective facilities (unit/year)
Q	A very large number
EP_{ct}, EP_{pt}, EP_{rt}, EP_w	Unit equivalent carbon emissions from the processing of product *t* at respective facilities (kg/unit)
Et_{gct}, Et_{cpt}, Et_{crt}, Et_{cwt}, Et_{pmt}, Et_{rmt}	Unit equivalent carbon emissions from the transportation of product *t* between respective facilities (kg/unit)

First-level decision variables

X_c^s,X_p^s,X_r^s	Binary decision variable determining if a new facility will be opened at respective candidate locations in scenario *s*

Second-level decision variables

Qcd_{ct}^{s}, Qpd_{pt}^{s}, Qen_{rt}^{s}, Qwm_{w}^{s}	Amount of different types of EOU and EOL products processed at respective facilities in scenario *s* (units)

Qt^s_{gct}, Qt^s_{cpt}, Qt^s_{crt}, Qt^s_{cwt}, Qt^s_{pmt}, Qt^s_{rmt}	Amount of different types of EOU and EOL products transported between respective facilities in scenario s (units)

The objective of the proposed model is to maximize the total profit of the reverse logistics system. As shown in Eq. (1), the total profit is determined by the total revenue generated and the overall costs for operating the system.

Maximize:

$$\text{Profit=Revenue-Cost} \tag{1}$$

Eqs. (2)-(4) calculate the total revenue of the reverse logistics system, which includes the total income obtained from selling the recycled products and energy and the governmental subsidy. It is noteworthy that the governmental subsidy is crucial to promote the reuse, remanufacturing and recycling of EOU and EOL products in some countries so as to improve the profitability of the companies in reverse logistics system (Jia et al., 2017, Cao et al., 2016). In addition, it is assumed that the parts and components from EOU and EOL products can be transformed into recycled products and energy at a fixed rate.

$$\text{Revenue=Income+Subsidy} \tag{2}$$

$$\text{Income=}\sum_{r\in R}\sum_{t\in T} Pen^s_{rt}Qen^s_{rt} + \sum_{p\in P}\sum_{t\in T} Ppd^s_{pt}Qpd^s_{pt} \quad \forall s\in S \tag{3}$$

$$\text{Subsidy=}\sum_{t\in T} Subr_t \sum_{r\in R} Qen^s_{rt} + \sum_{t\in T} Subp_t \sum_{p\in P} Qpd^s_{pt} \quad \forall s\in S \tag{4}$$

Eqs. (5)-(8) calculate the operating cost of the reverse logistics system, which is comprised of fixed cost, processing cost and transportation cost. When the non-recyclable EOU and EOL products sent to existing landfills, a gate fee will be charged depending on the volume of the waste products.

$$\text{Cost=Fixed operating cost + Processing cost+Transportation cost} \tag{5}$$

$$\text{Fixed operating cost=}\sum_{c\in C} F_c X^s_c + \sum_{p\in P} F_p X^s_p + \sum_{r\in R} F_r X^s_r \quad \forall s\in S \tag{6}$$

$$\begin{aligned}\text{Processing cost=}&\sum_{c\in C}\sum_{t\in T} Po_{ct}Qcd^s_{ct} + \sum_{p\in P}\sum_{t\in T} Po_{pt}Qpd^s_{pt} + \sum_{r\in R}\sum_{t\in T} Po_{rt}Qen^s_{rt} \\ &+ \sum_{w\in W} Po_w Qwm^s_w \quad \forall s\in S\end{aligned} \tag{7}$$

$$\begin{aligned}\text{Transportation cost=}&\sum_{g\in G}\sum_{c\in C}\sum_{t\in T} Ct_{gct}Qt^s_{gct} + \sum_{c\in C}\sum_{p\in P}\sum_{t\in T} Ct_{cpt}Qt^s_{cpt} + \sum_{c\in C}\sum_{r\in R}\sum_{t\in T} Ct_{crt}Qt^s_{crt} \\ &+ \sum_{c\in C}\sum_{w\in W}\sum_{t\in T} Ct_{cwt}Qt^s_{cwt} + \sum_{p\in P}\sum_{m\in M}\sum_{t\in T} Ct_{pmt}Qt^s_{pmt} \\ &+ \sum_{r\in R}\sum_{m\in M}\sum_{t\in T} Ct_{rmt}Qt^s_{rmt} \quad \forall s\in S\end{aligned} \tag{8}$$

The constraints of the model are formulated in Eqs. (9)-(24). Eq. (9) restricts that the reverse logistics system should be able to handle all the EOU and EOL products generated in the region through all different scenarios.

$$EP_{gt}^{s} = \sum_{c \in C} Qt_{gct}^{s}, \forall g \in G, \forall t \in T, \forall s \in S \tag{9}$$

Eqs. (10)-(14) guarantee the flow balance at the central collection center, remanufacturing/recycling plants and energy recovery plants.

$$Qcd_{ct}^{s} = \sum_{g \in G} Qt_{gct}^{s}, \forall c \in C, \forall t \in T, \forall s \in S \tag{10}$$

$$Qcd_{ct}^{s} = \sum_{p \in P} Qt_{cpt}^{s} + \sum_{r \in R} Qt_{crt}^{s} + \sum_{w \in W} Qt_{cwt}^{s}, \forall c \in C, \forall t \in T, \forall s \in S \tag{11}$$

$$Qpd_{pt}^{s} = \sum_{c \in C} Qt_{cpt}^{s}, \forall p \in P, \forall t \in T, \forall s \in S \tag{12}$$

$$Qen_{rt}^{s} = \sum_{c \in C} Qt_{crt}^{s}, \forall r \in R, \forall t \in T, \forall s \in S \tag{13}$$

$$Qwm_{w}^{s} = \sum_{c \in C} Qt_{cwt}^{s}, \forall w \in W, \forall t \in T, \forall s \in S \tag{14}$$

Eqs. (15)-(16) ensure that the dissembled parts and components from the EOU and EOL products cannot be more than the respective recyclable or recoverable fraction. It is noteworthy that the sum of ∂_{tp} and ∂_{tr} may be greater than 100% for some products due to the fact that some parts and components are suitable for both recycling and energy recovery, and the model is capable to generate the optimal allocation under different scenarios.

$$\sum_{p \in P} Qt_{cpt}^{s} \leq \partial_{tp} Qcd_{ct}^{s}, \forall c \in C, \forall t \in T, \forall s \in S \tag{15}$$

$$\sum_{r \in R} Qt_{crt}^{s} \leq \partial_{tr} Qcd_{ct}^{s}, \forall c \in C, \forall t \in T, \forall s \in S \tag{16}$$

Eqs. (17)-(20) restrict the maximum capacity of collection center, remanufacturing/recycling plant, energy recovery plant and disposal site are not exceeded.

$$Qcd_{ct}^{s} \leq MCp_{ct}, \forall c \in C, \forall t \in T, \forall s \in S \tag{17}$$

$$Qpd_{pt}^{s} \leq MCp_{pt}, \forall p \in P, \forall t \in T, \forall s \in S \tag{18}$$

$$Qen_{rt}^{s} \leq MCp_{rt}, \forall r \in R, \forall t \in T, \forall s \in S \tag{19}$$

$$Qwm_{w}^{s} \le MCp_{w}, \forall w \in W, \forall, \forall s \in S \tag{20}$$

Eqs. (21)-(23) restrict that the transportation of EOU and EOL products cannot happen from/to the candidate locations which are not selected.

$$\sum_{g \in G} Qt_{gct}^{s} \le X_{c}^{s} Q, \forall c \in C, \forall t \in T, \forall s \in S \tag{21}$$

$$\sum_{c \in C} Qt_{cpt}^{s} \le X_{p}^{s} Q, \forall p \in P, \forall t \in T, \forall s \in S \tag{22}$$

$$\sum_{c \in C} Qt_{crt}^{s} \le X_{r}^{s} Q, \forall r \in R, \forall t \in T, \forall s \in S \tag{23}$$

Eq. (24) ensures that the carbon emission requirement is fulfilled by the reverse logistics system. The excessive carbon emissions all over the globe has been tremendously acknowledged as one of the most important causes for climate change and global warming, so the requirement of carbon emissions is formulated in this model in order to set a threshold for the environmental performance of the reverse logistics system.

$$\begin{aligned} Ruq_{ems}^{s} \ge & \sum_{c \in C} \sum_{t \in T} EP_{ct} Qcd_{ct}^{s} + \sum_{p \in P} \sum_{t \in T} EP_{pt} Qpd_{pt}^{s} + \sum_{r \in R} \sum_{t \in T} EP_{rt} Qen_{rt}^{s} + \sum_{w \in W} EP_{w} Qwm_{w}^{s} \\ & + \sum_{g \in G} \sum_{c \in C} \sum_{t \in T} Et_{gct} Qt_{gct}^{s} + \sum_{c \in C} \sum_{p \in P} \sum_{t \in T} Et_{cpt} Qt_{cpt}^{s} + \sum_{c \in C} \sum_{r \in R} \sum_{t \in T} Et_{crt} Qt_{crt}^{s} \\ & + \sum_{c \in C} \sum_{w \in W} \sum_{t \in T} Et_{cwt} Qt_{cwt}^{s} + \sum_{p \in P} \sum_{m \in M} \sum_{t \in T} Et_{pmt} Qt_{pmt}^{s} \\ & + \sum_{r \in R} \sum_{m \in M} \sum_{t \in T} Et_{rmt} Qt_{rmt}^{s}, \forall s \in S \end{aligned} \tag{24}$$

In addition to the aforementioned constraints, the first-level decision variables X_c^s, X_p^s and X_r^s are binary variables, which belongs to the set of $\{0, 1\}$, and second-level decision variables Qcd_{ct}^s, Qpd_{pt}^s, Qen_{rt}^s, Qwm_w^s, Qt_{gct}^s, Qt_{cpt}^s, Qt_{crt}^s, Qt_{cwt}^s, Qt_{pmt}^s and Qt_{rmt}^s are non-negative variables.

4. Solution Method

In stochastic optimization, the uncertainty issues can be formulated and tackled by two different approaches. In the first approach, the uncertainty is described by the continuous distributed evens or outcomes, while, in the other approach, a set of discrete scenarios is used to represent the uncertainties. In this paper, the uncertainties related to the generation of EOU and EOL products, and the price of recycled products and recovered energy are formulated as discrete scenarios, and a new multi-criteria scenario-based solution method developed by Soleimani et al. (2016) is applied and further improved into an augmented method to resolve the stochastic optimization problem for reverse logistics network design.

Due to its effectiveness and simplicity, scenario-based solution method has been extensively used to formulate the stochastic optimization problems in many different industries (Soleimani et al., 2016, Chen et al., 2002, Papavasiliou et al., 2011). The basic idea for resolving a scenario-based stochastic optimization problem is not to find out the optimal solution of an individual scenario, but it is to determine the optimal solution through all the possible scenarios. Therefore, the optimal solution of a scenario-based stochastic optimization problem should be efficient while simultaneously with a great level of confidence and reliability. The method developed by Soleimani et al. (2016) takes into account of both issues, and the steps of the method is briefly introduced as follows.

1. *Scenario generation:* The uncertainties related to the generation of EOU and EOL products, and the price of recycled products and recovered energy are represented by several scenarios generated logically and efficiently, and the strategies and methods for scenario generation with high representativeness are given by Kaut and Wallace (2003), King and Wallace (2012) and Kouwenberg (2001).
2. *Finding out the candidate solutions:* For each individual scenario, the stochastic optimization problem is converted into a deterministic optimization problem and can be resolved. The optimal solutions of each individual scenario are considered the candidate solutions of the stochastic optimization problem.
3. *Testing the performance of the candidate solutions through all possible scenarios:* For obtaining the optimal solution with a high level of confidence, each candidate solution is tested with all the possible scenarios. In the test scenarios, the first-level decision variables (facility locations and network configuration) of each candidate solutions will remain the same, while the second-level decision variables (volume processed at each facility and transportation strategy) are optimized with respect to difference in the generation of EOU and EOL products, and the price of recycled products and recovered energy.
4. *Evaluating candidate solutions:* The performance of the candidate solutions through all the possible scenarios is evaluated through three indicators: Mean, standard deviation and the reciprocal of coefficient of variation. The mean is used for evaluating the optimal objective value of the candidate solution while standard deviation is used to measure the level of confidence, and the reciprocal of coefficient of variation is used as the indicator to evaluate the overall performance of each candidate solution in terms of both expected optimal value and the reliability.

$$\text{Standard deviation } \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{25}$$

$$\text{Coefficient of variation } CV = \frac{\sigma}{\mu} \tag{26}$$

Eqs. (25) and (26) are used for calculating standard deviation and coefficient of variation, and more introduction related to those concepts is provided in Lewontin (1966) and Brown (1998). With this method, the objective is to obtain the optimal solution with high profit and high level of confidence, so the reciprocal of coefficient of variation is used to evaluate the performance of the candidate solutions. The optimal solution is the one with the maximum value of the ratio of profit to the level of confidence ($\frac{1}{cv} = \frac{\mu}{\sigma}$), which are evaluated by the mean (μ) and standard deviation (σ), respectively. This means the optimal solution of the reverse logistics network design should be with high profit expectation (high mean) while simultaneously be robust and reliable in order to ensure a high possibility to achieve the expected profit (low standard deviation).

The advantage of this multi-criteria method is the emphasis on the minimization of risk and decision-making with high reliability, because the decision-making based only upon mean value regarding fluctuations cannot be with high level of confidence and reliability to deal with the uncertainties (Ogryczak, 2000). As shown in the Figure 2(A), solutions A and B are the candidate solutions of the stochastic optimization problem through scenarios s_1, s_2,…, s_n. and it is assumed that the dispersion of the optimal values of the different scenarios follows normal distribution, so the optimal values are spread within the range $\mu \pm 3\sigma$ (Hogg and Craig, 1995, Brownlee and Brownlee, 1965). In this example, solution A has a slightly higher profit expectation compared with solution B, so it will be the optimal solution if the mean is the only indicator for evaluating the candidate solutions as performed in many previous research works (Soleimani and Govindan, 2014). However, it is obvious that solution A has a larger standard deviation and the profit of different scenarios are broadly distributed compared that with that in solution B. This data dispersion reflects a greater possibility in solution A that the optimal profits in some scenarios will vary sharply compared with the profit expectation at the mean, and those are the weak-performance scenarios which significantly hinder the arrival of the optimal profitability of the reverse logistics system. With the help of the multi-criteria scenario-based solution approach developed by Soleimani et al. (2016), this problem is resolved through taking the reliability issue into decision-making, and in this case, solution B will be the optimal solution to the stochastic optimization problem due to its smaller standard deviation. As shown in the figure, even if the optimal profit expectation of solution B is slightly weaker, but the more concentrated data dispersion around the mean illustrates a higher level of confidence and reliability. This means the optimal value achieved in different scenarios is more close to the expectation, and solution B has a more stable and robust performance especially in weak-performance scenarios.

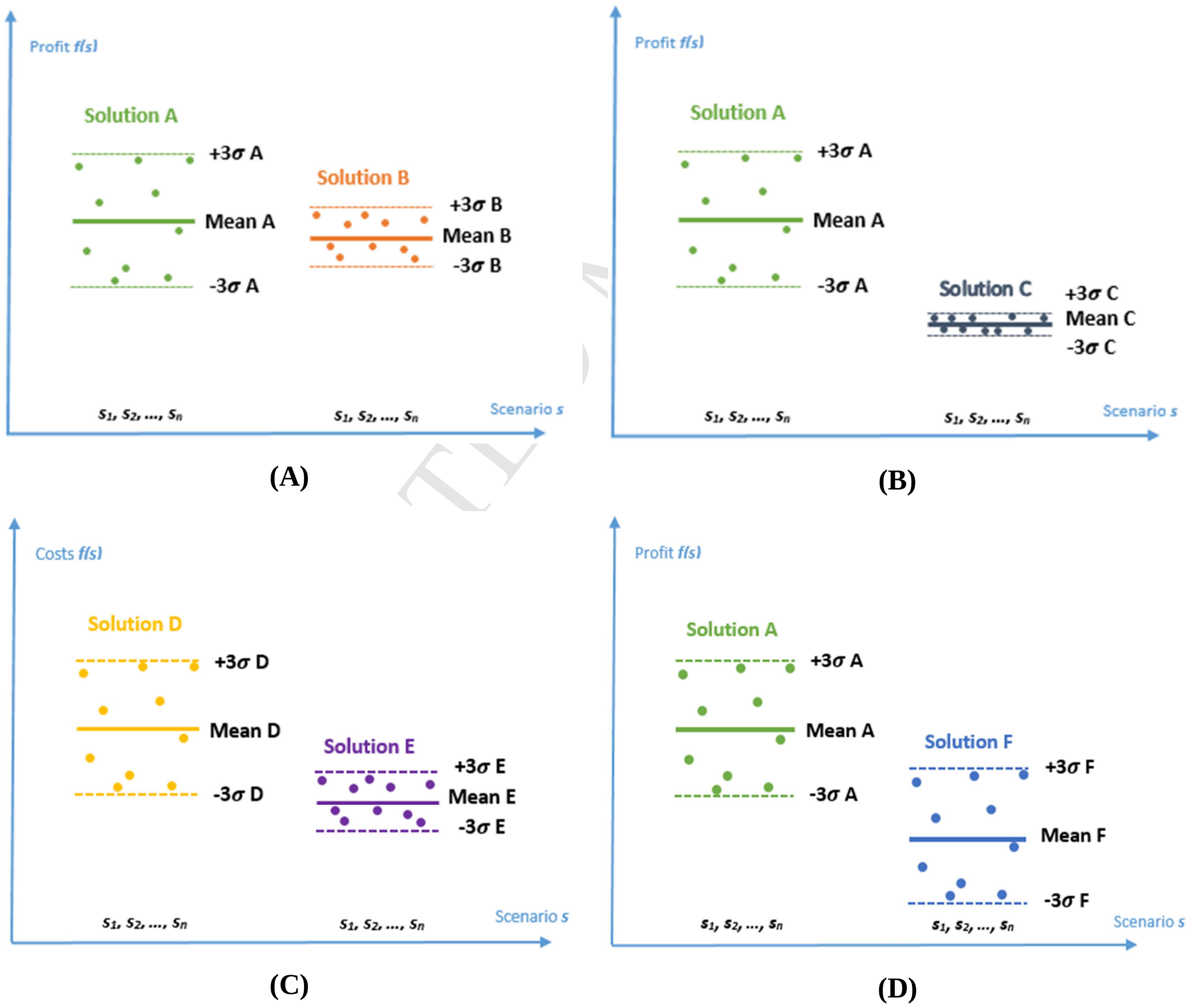


Figure.2 Schematic of the benefit and problems of the multi-criteria scenario-based solution method: **(A)** Typical max-mean and min-standard deviation problem; **(B)** The problem of weak-reliable solution; **(C)** The incapability to resolve cost-minimization problem; **(D)** The problem of performance evaluation of risk/reliability with standard deviation.

The theoretical foundation of the multi-criteria scenario-based solution method is to find out the optimal solution with high performance in both profit and reliability, but the performance evaluation through the reciprocal of coefficient of variance is inappropriate and with several problems. First, the simplified division relationships between the mean and standard deviation may lead to a weak-reliable solution, which is a low profitable network configuration but with high reliability. As shown in Fig. 2(B), solution C has lower economic performance, but the reliability of the optimal profits through different scenarios is extremely high, so it will be selected as the optimal solution with the evaluator of $\frac{1}{cv}$. However, it is obvious that the profit expectation of solution A is better compared with solution C even though the weak-performance scenario is arrived at. Therefore, it is not a good choice to combine the profit expectation and reliability in a simplified division relationship for performance evaluation of a stochastic optimization problem.

There is also another problem caused by the performance evaluation with the reciprocal of coefficient of variation. The indicator of $\frac{1}{cv}$ aims at maximizing the mean for improving the expected profit while simultaneously minimizing standard deviation for improving the reliability. However, the focus of many mathematical models developed in previous research works for reverse logistics network design is to minimize the overall costs (Diabat et al., 2013a, Govindan et al., 2016b, Kannan et al., 2012, Yu and Solvang, 2016a, Demirel and Gökçen, 2008, Demirel et al., 2016), and the simplified division relationship is not able to generate the optimal solution of the cost-minimization problem due to the same convergence direction of the mean and standard deviation. As shown in Figure 2(C), solution E (lower mean and lower standard deviation) may has similar performance as solution D (higher mean and higher standard deviation) with the performance evaluation by the indicator of $\frac{1}{cv}$. However, it is obvious that solution E has a lower expected cost with a higher reliability, so it should be much better than solution D, and this cannot be reflected through the simplified division relationship.

In addition to the problem with performance evaluation, the measurement of risk/reliability with standard deviation may lead to inappropriate managerial interpretations, because standard deviation is an absolute measurement of data dispersion, which is heavily affected by the mean. Figure 2(D) presents an example including two solutions (A and F) to a stochastic optimization problem. The mean of the two solutions vary significantly, but the standard deviation is the same, so solutions A and F should be at the same level of risk/reliability. However, from the perspective of statistic theory, the probability of data dispersion around the mean is different with respect to the different magnitude even if they have the same standard deviation (Barlow and Proschan, 1996). As shown in the figure, the optimal solution in the weak-performance scenarios of solution F deviates from its mean in more percentage due to its smaller mean, and this reflects a more spread date dispersion. Therefore, it is preferred to use a relative measurement to evaluate the level of risk/reliability in the multi-criteria scenario-based solution method for stochastic optimization problems.

In order to resolve the aforementioned problems, the multi-criteria scenario-based risk-averse solution method is further developed into an augmented method in this paper, and figure 3 illustrates the procedures of the solution method. First, the absolute measurement of risk/reliability with standard deviation is replaced by the relative measurement of data dispersion by coefficient of variation, and this enables meaningful comparisons between two or more magnitude of variation with different means (Green et al., 1993). Then, the performance evaluation of candidate solutions with the indicator of $\frac{1}{cv}$ is replaced by the new indicators based upon a normalized weighted-sum formula that has been extensively used in combining several different objective functions in the multi-objective optimization problems (Sheu, 2007, Sheu, 2008, Yu and Solvang, 2016a). The benefit of weighted-sum method in resolving multi-objective optimization is its simplicity (Marler and Arora, 2004), and it also enables the interaction between objective performance measurement indicator and subjective allocation of weights in order to find out the optimal solutions under different circumstances. Therefore, the normalized weighted-sum method is used to combine the performance evaluations of the mean and coefficient of variation for comparing the different candidate solutions in an effective manner.

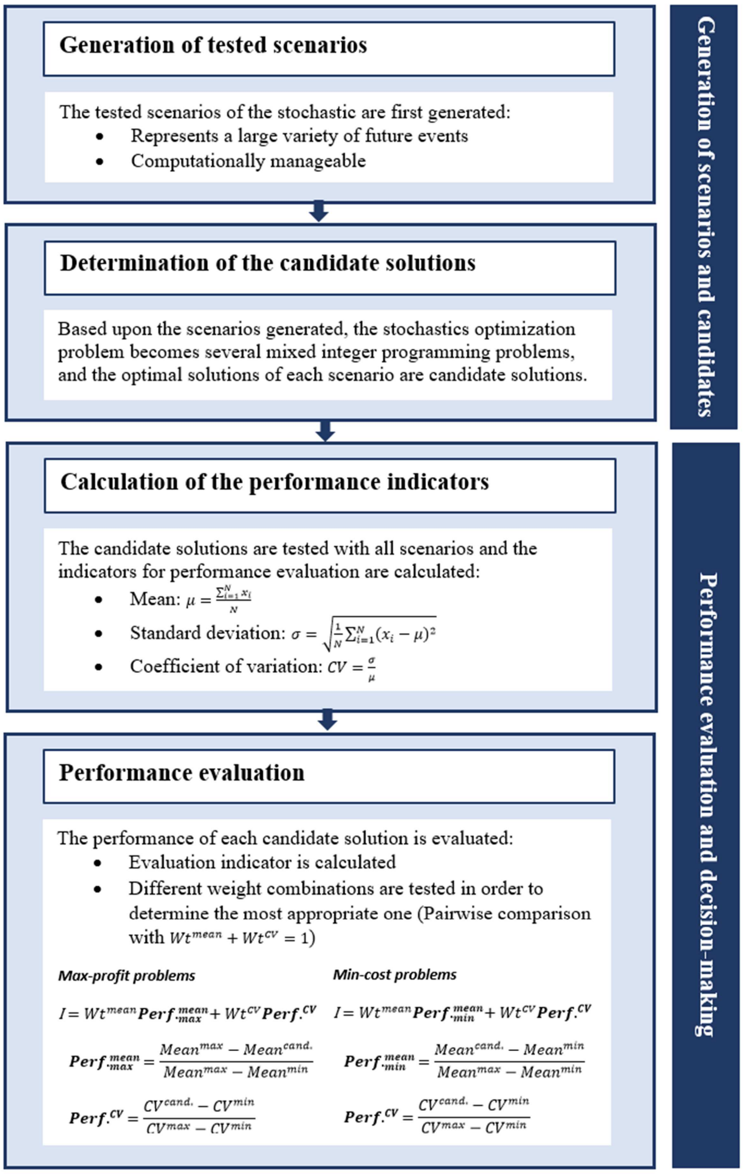


Figure.3 Augmented multi-criteria scenario-based risk-averse solution method.

The normalized weighed-sum method formulated in Eqs.(27)-(32) is capable to resolve both profit-maximization and cost-minimization problems. Eqs. (27), (29), (31) and (32) are used to evaluate the performance of a profit-maximization problem, while Eqs. (28), (30), (31) and (32) are applied in the performance measurement of a cost-minimization problem. Herein, $\boldsymbol{Perf}_{\cdot max}^{mean}$, $\boldsymbol{Perf}_{\cdot min}^{mean}$, $\boldsymbol{Perf}_{\cdot}^{CV}$, Wt^{mean} and Wt^{CV} represent the performance measurement value and weight of the mean and coefficient of variation in both profit-maximization and cost minimization problems. $Mean^{max}$, $Mean^{min}$, CV^{max} and CV^{min} are the maximum and minimum values of the mean and coefficient of variation throughout all the candidate solutions, and $Mean^{cand.}$ and $CV^{cand.}$ represent the mean and coefficient of variation of each candidate solution, respectively. In the performance evaluation of the mean and coefficient of variation of each candidate solution, the benchmark is their maximum difference determined by the respective maximum and minimum values throughout all the candidate solutions, and those are the denominators in Eqs. (29)-(31). The numerators of those equations reveal how far the candidate solution deviates from the best solution throughout all the candidates, and the numerator equals to 0 when the candidate solution has the best performance. The benchmark denominators are used to normalize the performance evaluation of the mean and coefficient of variation due to their different measures of units, and $\boldsymbol{Perf}_{\cdot max}^{mean}/\boldsymbol{Perf}_{\cdot min}^{mean}$ and $\boldsymbol{Perf}_{\cdot}^{CV}$ can then be combined in a weighted-sum for the decision-making. The candidate solution with the smallest weighted-sum is the optimal solution, which means the performance of the mean and coefficient of variation is close to the best performance across all the candidate solutions. This method can effectively resolve the weak-reliable problem through distributing a larger weight to $\boldsymbol{Perf}_{\cdot\boldsymbol{max}}^{\boldsymbol{mean}}/\boldsymbol{Perf}_{\cdot\boldsymbol{min}}^{\boldsymbol{mean}}$ so that the importance of the performance in profit/cost expectation will be dramatically improved. On the other hand, when the mean of the candidate solutions are slightly differentiated from each other, a larger weight will be given to $\boldsymbol{Perf}_{\cdot}^{\boldsymbol{CV}}$ in order emphasize the reliability in the decision-making.

$$\text{Evaluation indicator}_{max} = Wt^{mean}\boldsymbol{Perf}_{\cdot\boldsymbol{max}}^{\boldsymbol{mean}} + Wt^{CV}\boldsymbol{Perf}_{\cdot}^{\boldsymbol{CV}} \quad (27)$$

$$\text{Evaluation indicator}_{min} = Wt^{mean}\boldsymbol{Perf}_{\cdot\boldsymbol{min}}^{\boldsymbol{mean}} + Wt^{CV}\boldsymbol{Perf}_{\cdot}^{\boldsymbol{CV}} \quad (28)$$

$$\boldsymbol{Perf}_{\cdot\boldsymbol{max}}^{\boldsymbol{mean}} = \frac{Mean^{max} - Mean^{cand.}}{Mean^{max} - Mean^{min}} \quad (29)$$

$$\boldsymbol{Perf}_{\cdot\boldsymbol{min}}^{\boldsymbol{mean}} = \frac{Mean^{cand.} - Mean^{min}}{Mean^{max} - Mean^{min}} \quad (30)$$

$$\boldsymbol{Perf}_{\cdot}^{\boldsymbol{CV}} = \frac{CV^{cand.} - CV^{min}}{CV^{max} - CV^{min}} \quad (31)$$

$$Wt^{mean} + Wt^{CV} = 1 \quad (32)$$

From the discussion above, the augmented multi-criteria scenario-based risk-averse solution method can effective resolve the problems of the original method, and it also provides the decision-makers with more flexibility between the profitability (or costs) and reliability in reverse logistics network design under stochastic environment.

5. Experimental analysis

5.1 Numerical experiment

In order to illustrate the application of the stochastic optimization model and the effectiveness of the augmented multi-criteria scenario-based risk-averse solution method, a numerical experiment of a mid-sized problem is tested. The reverse logistics system includes two types of EOU and EOL products (A and B), fifteen generation points, eight candidate locations for central collection center, five candidate locations for recycling/remanufacturing plant, and five candidate locations for energy recovery plant. In the numerical experiment, the generated volume and conversion fractions of products A and B, and the cost parameters related to the facility operation and transportation are generated based upon uniform distribution, as shown in Table 2.

Table 2 Parameters of the numerical experiment

Parameters	Uniform distribution	
	Product A	Product B
Generation of EOU and EOL products (EP_{gt}^{s})	4000-6000	2000-6000
Fixed cost of central collection center (F_c)	0.8-1.5 million	0.8-1.5 million
Unit processing cost at central collection center (Po_{ct})	50-80	50-80
Fraction can be remanufactured and recycled (∂_{tp})	50%	40%
Fraction can be sent for energy recovery (∂_{tr})	30%	40%
Fixed cost of recycling/remanufacturing plant (F_p)	1.2-2 million	1.2-2 million
Unit processing cost at recycling/remanufacturing plant (Po_{pt})	100-200	100-200
Unit profit at recycling/remanufacturing plant (Ppd_{pt}^{s})	500-1000	200-400
Fixed cost of energy recovery plant (F_r)	1.5-2 million	1.5-2 million
Unit processing cost at energy recovery plant (Po_{rt})	200-300	200-300
Unit profit at energy recovery plant (Pen_{rt}^{s})	500-1000	300-500

Government subsidy for treating one unit product ($Subr_t$, $Subp_t$)	200-300	100-200
Gate fee at landfill for disposing one unit product (Po_w)	50-100	50-100
Unit transportation costs (Ct_{gct}, Ct_{cpt}, Ct_{crt}, Ct_{cwt}, Ct_{pmt}, Ct_{rmt})	50-200	50-200

Some assumptions are made in the numerical experiment in order to maintain a high rationality. First, the capacity is directly proportional to the fixed costs of each facility, because more equipment and personnel are required for an increased capacity. Second, the unit carbon emissions are inversely proportional to the variable processing costs and transportation costs due to the fact that more money has to be invested for improving the technological level in order to reduce the carbon emissions (Wang et al., 2011). Multipliers generated randomly in the certain intervals are used to estimate the values of those parameters in the numerical experiment. All the parameters used in the numerical experiment are given in the supplementary file.

After the parameters have been given, eleven test scenarios are generated in a logically sensible and computationally efficient manner. In accordance with the scenario generation performed in Soleimani et al. (2016), we first define three benchmark scenarios, namely, best-case scenario, worst-case scenario and basic scenario. In the best-case scenario, the upper limits of the parameter intervals of the generation of EOU and EOL products, price of recycled products and recovered energy are used (EP_{ga}^{s}=6,000, EP_{gb}^{s}=6,000, Pen_{ra}^{s}=1,000, Pen_{rb}^{s}=400, Ppd_{pa}^{s}=1,000, Ppd_{pb}^{s}=500), while in the worst-case scenario, the lower limits of them are reached (EP_{ga}^{s}=4,000, EP_{gb}^{s}=2,000, Pen_{ra}^{s}=500, Pen_{rb}^{s}=200, Ppd_{pa}^{s}=500, Ppd_{pb}^{s}=300). In the basic scenario, the mean values of the stochastic parameters are used (EP_{ga}^{s}=5,000, EP_{gb}^{s}=4,000, Pen_{ra}^{s}=750, Pen_{rb}^{s}=300, Ppd_{pa}^{s}=750, Ppd_{pb}^{s}=400). Then, we generate two scenarios of each stochastic parameter on both positive side and negative side around the mean. With the combination of different scenarios of the stochastic parameters, eight different test scenarios are generated as shown in Figure 4.

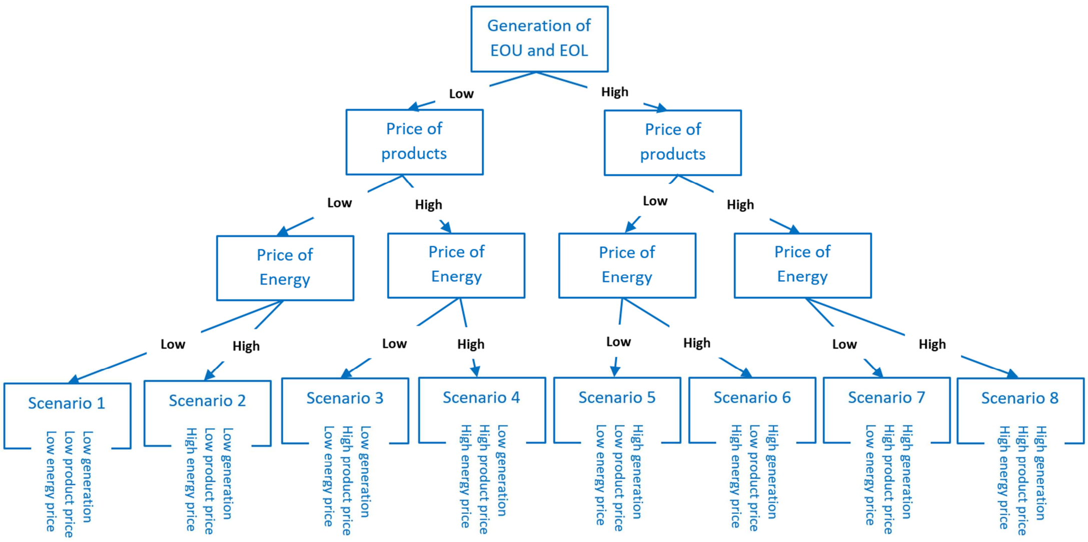


Figure.4 Scenario tree related to the numerical experiment.

5.2 Result and discussion

The model is coded and computed with Lingo 15.0 optimization package on a personal computer with Intel Core i5-6400T 2.20GHz processor and 8 GB memory under Window 10 operating system, and the carbon emissions requirement is not taken into account in the initial stage. Each test scenario is first resolved independently as a mixed integer optimization problem, and less than 10 s computation time needed to find out the optimal solution of each independent scenario due to the small size of the problem. The profit, carbon emissions and facility selection of each candidate solution is given in Table 3, and Figures 4 and 5 illustrate the composition of the profit and carbon emissions.

Scenario-based solution method is a powerful and efficient approach to solve stochastic optimization problem, and it is of great importance to generate appropriate scenarios to represent the fluctuate situations. The increase of scenarios generated may have a better representation of the uncertainty, but the benefit of doing this seems quite limited while the required computational time will increased significantly (Pishvaee et al., 2009, El-Sayed et al., 2010). Therefore, in this numerical experiment, we aims at generating sufficient test scenarios to effectively represent the uncertainty while simultaneously accounting the computational efficiency. As shown in Table 3, the mean value of all the candidate solutions is 39,775,718, and 5 scenarios have better performance while the other scenarios have lower performance, which presents a fair distribution of both optimistic and pessimistic expectations of the market fluctuation. Throughout all the candidate solutions, the highest profit is 75,439,570 obtained at best-case scenario and the lowest profit is 12,085,710 achieved at worst-case scenario, and the range is 159% of the mean value. When the extreme benchmark scenarios are excluded, the highest profit becomes 56,168,960 achieved at scenario 8 and the lowest profit becomes 24,621,660 obtained at scenario 1, and the range becomes 79% of the mean value. This proves the diversification of the generated scenarios. Taking into account of the aforementioned discussion, the diversification and fair distribution of optimistic and pessimistic expectation can prove the test scenarios generated cover a large variety of the market fluctuations.

Table 3 Profit, carbon emissions and facility selection of each candidate solution (results are normalized by dividing by10^4)

Scenario	Profit (10^4)	Carbon emissions (10^4)	Network configuration		
			Collection	Recycling	Recovery
Best-case	7544	27454	1, 2, 4, 6, 7, 8	2, 4, 5	1, 2, 3, 5
Basic	3724	20284	1, 2, 4, 6, 7	4, 5	2, 3, 5
Worst-case	1208	13047	1, 2, 6, 7	4, 5	3, 5
s1	2462	15570	2, 4, 6, 7, 8	3, 4	3, 4
s2	3506	15192	1, 2, 6, 7, 8	3, 4	4, 5
s3	3397	15718	2, 5, 6, 7, 8	4, 5	3, 4
s4	4387	15614	1, 2, 6, 7, 8	4, 5	2, 4
s5	3098	22502	2, 4, 6, 7, 8	2, 3, 4	1, 3, 4
s6	4510	22825	1, 2, 4, 6, 7, 8	2, 3, 4	2, 4, 5
s7	4299	22567	2, 4, 6, 7, 8	1, 4, 5	1, 3, 4
s8	5617	22405	2, 4, 6, 7, 8	1, 4, 5	2, 4, 5

It is shown from Table 3 that the carbon emissions and facility selection vary in different scenarios. In general, more facilities have to be opened and operated with the increase of EOU and EOL products generated, and this will increase the overall costs and carbon emissions of the reverse logistics system. As illustrated in Figures 5 and 6, the change of the total costs and carbon emissions is similar. It is also observed that the government subsidy generally increases with the increase of EOU and EOL recycled and recovered, while the revenue and profit are also heavily affected by the prices of the recycled products and recovered energy. For example, in scenario 5, even if the generation of EOU and EOL products is high, but the profitability is heavily and negatively affected by the low price for the recycled products and recovered energy, and the total costs for operating the reverse logistics system are more than the revenue it generates. In this case, the government subsidy plays an important role in compensating and promoting the reverse logistics activities. Furthermore, it is also observed that the facility operation takes more share in the overall costs, while the transportation of EOU and EOL products has a more important role in the carbon emissions of the reverse logistics system.

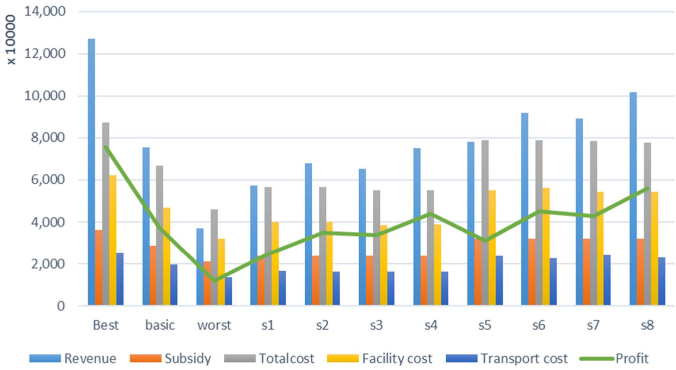


Figure.5 Comparison of the revenue, profit and cost compenents of the candidate solutions (results are normalized by dividing by10^4).

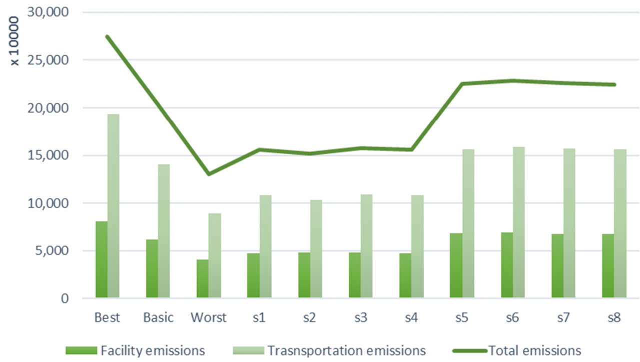


Figure.6 Comparison of the total emissions, facility emisions and transport emissions of the candidate scenarios (results are normalized by dividing by10^4).

The objective of the stochastic programming is to find out the optimal solution with the best profit expectation and high reliability, so each candidate solution is tested through all the scenarios generated. The facility selection of the candidate solution is the fixed, but the allocation of EOU and EOL products and transportation strategy will be changed with respect to the changing parameters, and the problem becomes therefore a linear optimization problem and can be resolved within 5 s. In total, 121 rounds of calculation are performed, and the result is presented in Table 4.

It is noteworthy that some candidate solutions may cause infeasible solutions in some test scenarios due to the insufficient capacities of the selected first-level facilities. For instance, the overall capacities of the central collection centers selected in candidate solution 1 for products A and B are 86,296 and 136,561, respectively, and this leads to infeasible solution in the best-case scenario at which 90,000 capacities for each type of product is required. In order to resolve this problem, two types of adjustments can be done either to reduce the service level or to increase the facility capacity. With the first option, the facility capacity will remain the same, but Eq. (9) should be relaxed to allow the EOU and EOL products may not be totally treated, as shown in Eq. (34), while in this case, another objective (Eq. (33)) should also be introduced in order to maximize the EOU and EOL products treated with the limited capacity. The reformulation is given as follows, which becomes a bi-objective model focusing on the tradeoff between profit and service level under carbon constraint. Further, a penalty may also be incorporated into the first objective function in order to account the influence of the reduced service level (King and Wallace, 2012).

$Obj1 = \max \text{Profit, Eqs. (1)-(8)}, \forall s \in S$

$$Obj2 = \max \sum_{g\in G} \sum_{t\in T} \frac{\sum_{c\in C} Qt^{s}_{gct}}{EP^{s}_{gt}}, \forall s \in S \tag{33}$$

Subject to:

$$EP^{s}_{gt} \geq \sum_{c\in C} Qt^{s}_{gct}, \forall g \in G, \forall t \in T, \forall s \in S \tag{34}$$

Eqs. (10)-(24)

The other option to treat the infeasibility is to increase the capacity of facility without the compromise on the service level of reverse logistics system. In this example, we adopt this option to treat the problem and perform reasonable comparison of the candidate solutions, and the increase on facility capacity is to fulfill the requirement for the treatment of EOU and EOL products with the minimum adjustment of the original planning. In addition, it is also observed from the infeasible solutions that the violation of the capacity constraint is usually caused by one product. For instance, the network configuration determined in the basic scenario is not able to handle the EOU and EOL products in the best-case scenario due to the insufficient capacity. In this scenario, the violation of capacity constraint is only caused by product A, however on the other hand, excessive capacity is planned for product B. Thus, from strategic perspective, the increase on facility capacity may also interpreted as the capacity conversion between different products without incurring additional costs, i.e., the uses of flexible manufacturing system.

Table 4 Performance of the candidate solutions through all the test scenarios (results are normalized by dividing by10^4)

Scenarios	Candidate solutions										
	c-1	c-2	c-3	c-4	c-5	c-6	c-7	c-8	c-basic	c-best	c-worst
s1	2462	2302	2374	2222	2401	2139	2137	1936	2180	2074	2318
s2	3342	3506	3249	3368	3154	3252	2928	3126	3179	3001	3154
s3	2946	2812	3397	3248	3000	2740	3249	3048	3208	3026	3347
s4	3833	4012	4247	4387	3747	3814	3999	4135	4158	3918	4168
s5	1870	2005	2146	1664	3098	2839	2832	2565	2414	2816	1664
s6	2896	3488	3172	3025	4211	4510	3889	4269	3830	4080	2579
s7	2426	2596	3248	2767	3800	3540	4299	4040	3523	4065	2772
s8	3452	4079	4274	4128	4913	5199	5347	5617	4938	5299	3687
Basic	2908	3158	3362	2918	3431	3463	3437	3525	3724	3524	3154
Best	4372	4830	5043	4606	6886	7325	7287	7506	6277	7544	4529
Worst	945	966	1056	1041	716	721	727	798	1003	707	1208
Mean	2859	3069	3234	3034	3578	3595	3648	3688	3494	3641	2962
Standard deviation	895	1036	1048	1055	1463	1629	1622	1716	1339	1678	954
CV	31.32%	33.78%	32.43%	34.78%	40.89%	45.31%	44.46%	46.54%	38.32%	46.09%	32.21%

As shown in Table 4, each candidate solution represents the best profit expectation in its own scenario. The best profit expectation through all the test scenarios is 36,877,352 achieved with candidate solution 8, while the worst expected profit is 28,591,958 obtained with candidate solution 1. However, considering the reliability issue, candidate solution 1 outperforms other candidate solutions with the smallest value on both standard deviation and coefficient of variation. The gap between the best and worst performance on the profit expectation and reliability are 29% and 49%, and this illustrates the performance of the candidate solutions varies significantly under market fluctuation. Due to the large gap of the expected profit, the performance evaluation of the candidate solutions should prioritize the profit expectation in order to avoid the weak-reliable solutions. Therefore, several weight combinations with incremental Wt^{mean} from 0.5 are tested, and the weight combination of Wt^{mean}=0.7 and Wt^{CV}=0.3 is used for the performance evaluation in this numerical experiment.

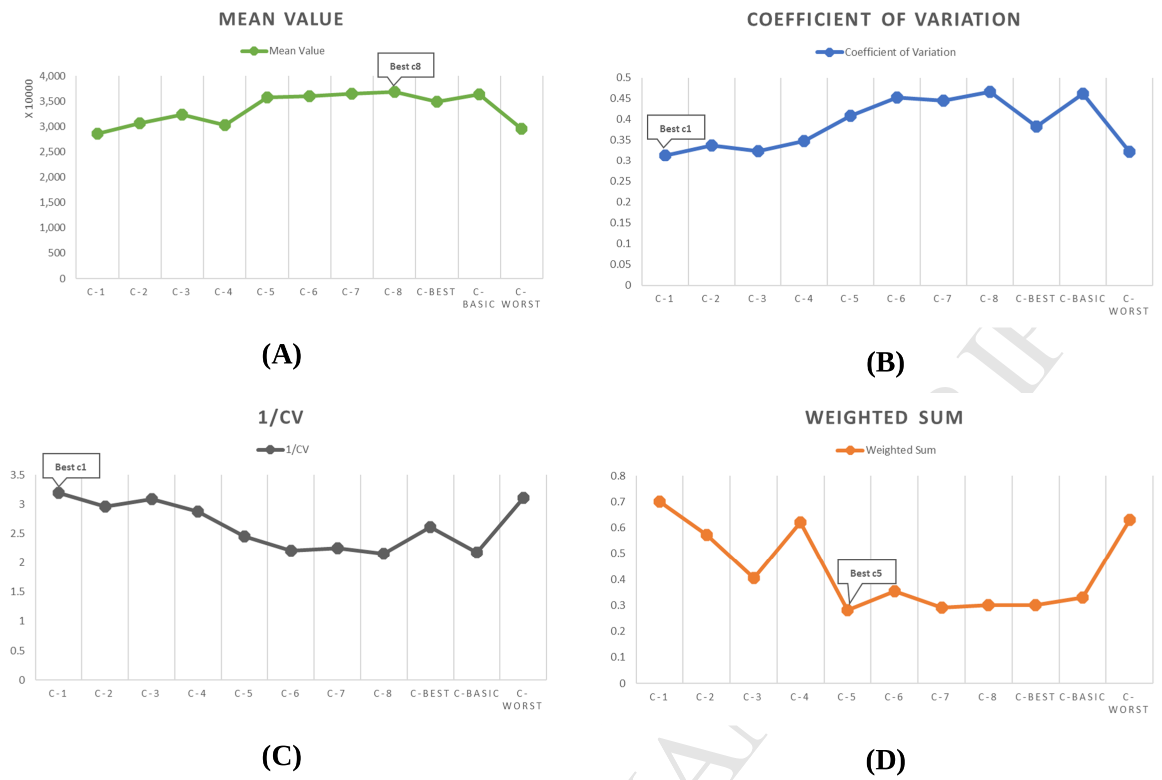
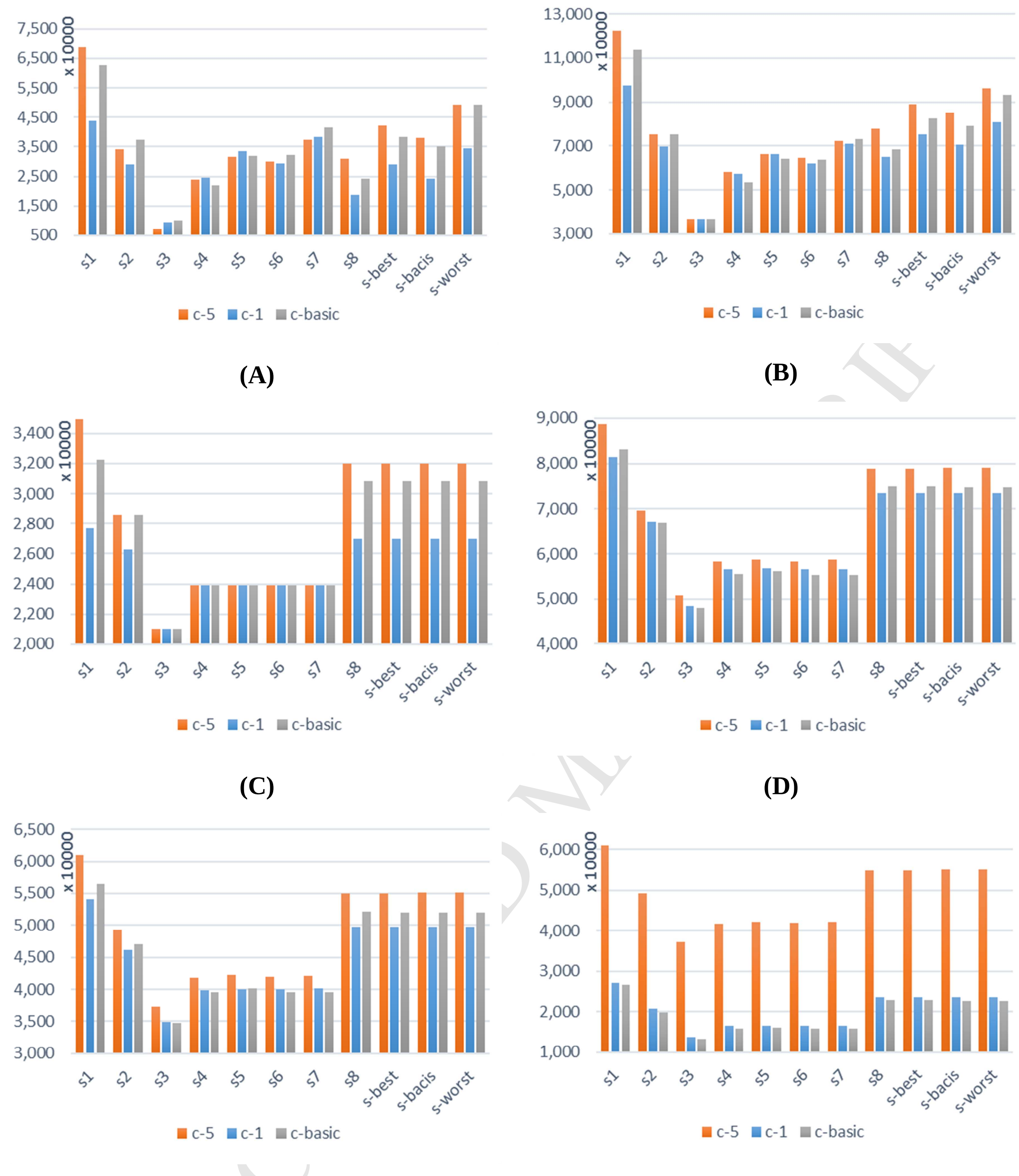


Figure.7 Performance of the candidate solutions through all the test scenarios: **(A)** Comparison of mean value; **(B)** Comparison of standard deviation; **(C)** Performance evaluation with $\frac{1}{cv}$; **(D)** Performance evaluation with the weighted sum.

The performance of the candidate solutions is evaluated through both $\frac{1}{cv}$ and weighted sum and the result is shown in Figure 7. As shown in the figure, candidate solution 1 is the optimal solution given by the evaluator $\frac{1}{cv}$, and the candidate solutions 2, 3 and 4 obtained with lower generation of EOU and EOL have better performance due to their outstanding performance in reliability. However, when the weighted sum is used for performance measurement, candidate solution 5 becomes the best choice, and the candidate solutions 6, 7 and 8 obtained with higher generation of EOU and EOL have better performance due to their better profit expectations. Comparing the candidate solutions 1 and 5, it is observed that candidate solution 1 has slightly better profit expectation in scenarios 1, 2, 4 and worst-case, but candidate solution 5 has much better performance in the other scenarios particularly when the generation of EOU and EOL products is high. The expected profit, total revenue, subsidy, total system operating costs, facility costs and transportation costs through all the test scenarios in candidate solutions 1, 5 and basic are compared and illustrated in Figure 8.

As shown in the figure, candidate solution 1 focuses on the efficiency of the reverse logistics system, which has less facility selected and the facility costs and transportation costs are much lower than that in the other scenarios. The benefit of this network structure is to have a high efficiency and utilization of facilities especially when the generation of EOU and EOL products is relatively low. However, even if candidate solution 1 has the most efficient network configuration and most reliable performance across all the test scenarios, it should not be considered as the optimal solution due to its much lower profit expectation, and the incapability and less profitability in dealing with the increased amount of EOU and EOL products.



(A) (B) (C) (D) (E) (F)

Figure.8 Comparison of candidate solutions 1 and 5 through all the scenarios (results are normalized by dividing by10^4): **(A)** Profit expectation; **(B)** Total revenue; **(C)** Subsidy; **(D)** Total costs; **(E)** Facility costs; **(F)** Transportation costs.

On the other hand, candidate solution 5 has much better performance when the generation of EOU and EOL products is high, but when the generation is low, the expected profit is slightly lower due to the increased costs for operating more facilities and the waste of capacity. Furthermore, comparing with other candidate solutions obtained from the scenarios with high generation of EOU and EOL products, candidate solution 5 has better performance in the reliability, which guarantees a higher level of confidence to achieve the expected profit. Therefore, based on the discussion, candidate solution 5 determined by the weighted sum is the optimal solution, and this proves the effectiveness of the augmented solution method for resolving stochastic optimization problem.

Furthermore, the performance of the basic scenario is also presented in the figure, and this can be considered as the optimal solution of a deterministic problem. As can be seen in Figure.8(A), the profit expectation is better than that in candidate solution 1 in most scenarios. This reveals that, even though many argues stochastic programming has much better performance in decision-making under uncertainty (King and Wallace, 2012), the effectiveness may not be better than a deterministic model if the value expectation and level of risk are not combined in an appropriate way for performance evaluation.

5.3 Model sensitivity

In this paper, we are interested in how the carbon requirement will affect the reverse logistics network design, so five sensitivity analysis are performed with the gradually increased carbon emission requirement by 10%, 20%, 30%, 40% and 50%, respectively. With the increased requirement on the carbon emissions of reverse logistic system, more infeasible solutions are found due to the capacity constraint, especially when the candidate solutions calculated in low generation scenarios are applied in the high generation scenarios. In order to have a reasonable and meaningful comparison, the capacity constraints are relaxed accordingly on the relevant facilities which cause infeasible solutions, and also the rule of minimum adjustment of the facility plan is applied when the relaxation is needed.

It is observed the limited facility capacities are the most significant bottleneck to fulfill the carbon emission requirements and to achieve a better profitability of the reverse logistics system, so another two scenarios are tested with the relaxation of the capacity constraints, say, the facilities are capable to deal with the increased amount of EOU and EOL products. However, more money has to be invested to purchase more equipment and recruit more personnel so as to improve the capacities of the facilities, so the fixed costs are increased by 100% and 200% in the tested problems, respectively. Therefore, seven different problems with changing parameters are generated and tested, and totally 847 rounds of calculation are performed in the sensitivity analysis.

Table 4 The optimal solution and network configuration of each test problem (results are normalized by dividing by10^4)

Test problems with changing parameters in sensitivity analysis	Optimal solution	Network configuration		
		Collection	Recycling	Recovery
Capacitated problem without requirement on carbon emissions	c-5	2, 4, 6, 7, 8	2, 3, 4	1, 3, 4
Capacitated problem with requirement of 10% reduction on carbon emissions	c-7	1, 2, 4, 6, 8	1, 4, 5	1, 3, 4
Capacitated problem with requirement of 20% reduction on carbon emissions	c-4	1, 2, 3, 8	4, 5	2, 4
Capacitated problem with requirement of 30% reduction on carbon emissions	c-4	1, 2, 3, 8	4, 5	2, 4
Capacitated problem with requirement of 40% reduction on carbon emissions	c-7	1, 2, 3, 6, 8	1, 4, 5	1, 3, 4
Capacitated problem with requirement of 50% reduction on carbon emissions	c-3	1, 2, 3, 7, 8	1, 5	3, 4
Uncapacitated problem with 100% increase on fixed facility costs (Uncapacitated s1)	c-5/c-best/c-basic	2, 6	4	3
Uncapacitated problem with 200% increase on fixed facility costs (Uncapacitated s2)	c-1/c-best/c-basic	6	4	3

Table 4 shows the optimal solution and network configuration of each test problem, and it is observed the optimal solution and network configuration are by no means identical with the change of carbon emission requirement and capacity constraint. Figures 9 and 10 present the comparison of the average cost expectation and average carbon emissions of the test problems. As shown in Figure 9, when the requirement on the reduction of carbon emissions increases from 10% to 30%, the decrease on the average profit expectation of the reverse logistics is extremely slight (0.4%, 1.2% and 2%). This reveals the implementation of the carbon emission requirement at this range will improve the environmental performance without compromising great economic benefits. However, the average expected profit reduces sharply by 20% and 54.5% when the carbon emissions requirement increases to 40% and 50%. This provides decision-makers with a clear relationship between the profitability and environmental sustainability of the reverse logistics system, and it also provides the reference for the policy-making on the carbon emission requirements.

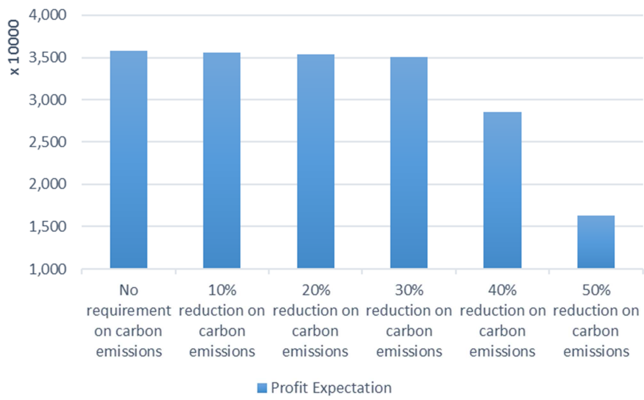
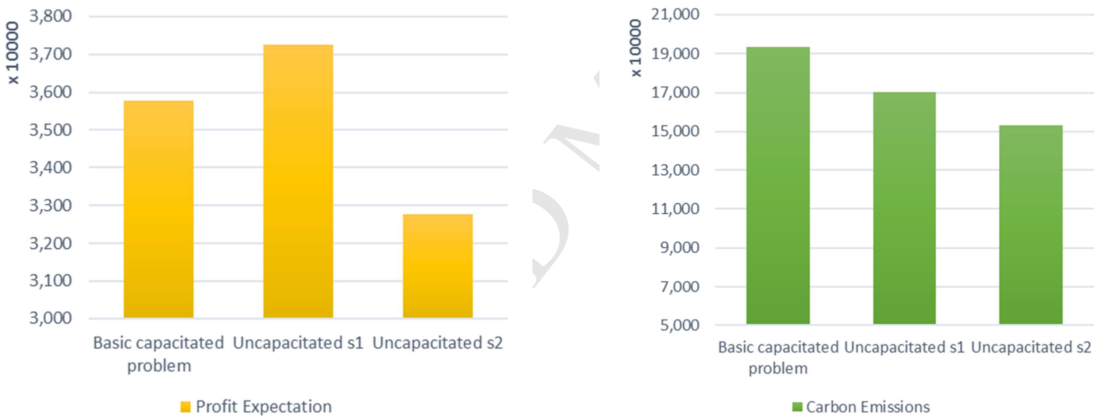


Figure.9 Average profit expectation over the incremental requirement for the reduction of carbon emissions (results are normalized by dividing by10^4).



(A) **(B)**

Figure.10 Comparison of the basic capacitated problem and uncapacited scenarios 1 and 2 (results are normalized by dividing by10^4): **(A)** Average profit expectation; **(B)** Average carbon emissions.

Figure 10 shows the comparison of the two uncapacitated sceanrios. As shown in the Figure 9(A), the average profit expectation increases by 4.1% with 100% increase on the fixed facility costs, while it is decreased by 8.4% with 200% increase on the fixed facility costs. This illustrates the larger facilities with more investment will improve the economic performance of the reverse logistics system only when the increase of the investment for facility expansion is maintained at a proper level, otherwise, the profitability will be negatively affected. Figure 9(B) shows the average carbon emissions reduce by 11.9% and 20.6% in the test problems, respectively. This illustrates that openning a smaller number of facilities with large capacity is another way to reduce the carbon emissions from the reverse logistics activities. Aslo, the result shows the facility expansion may improve both economic and environmental performance of the reverse logistis system, and the upper limit of the increased investment can be suggested to the decision-makers from the analysis.

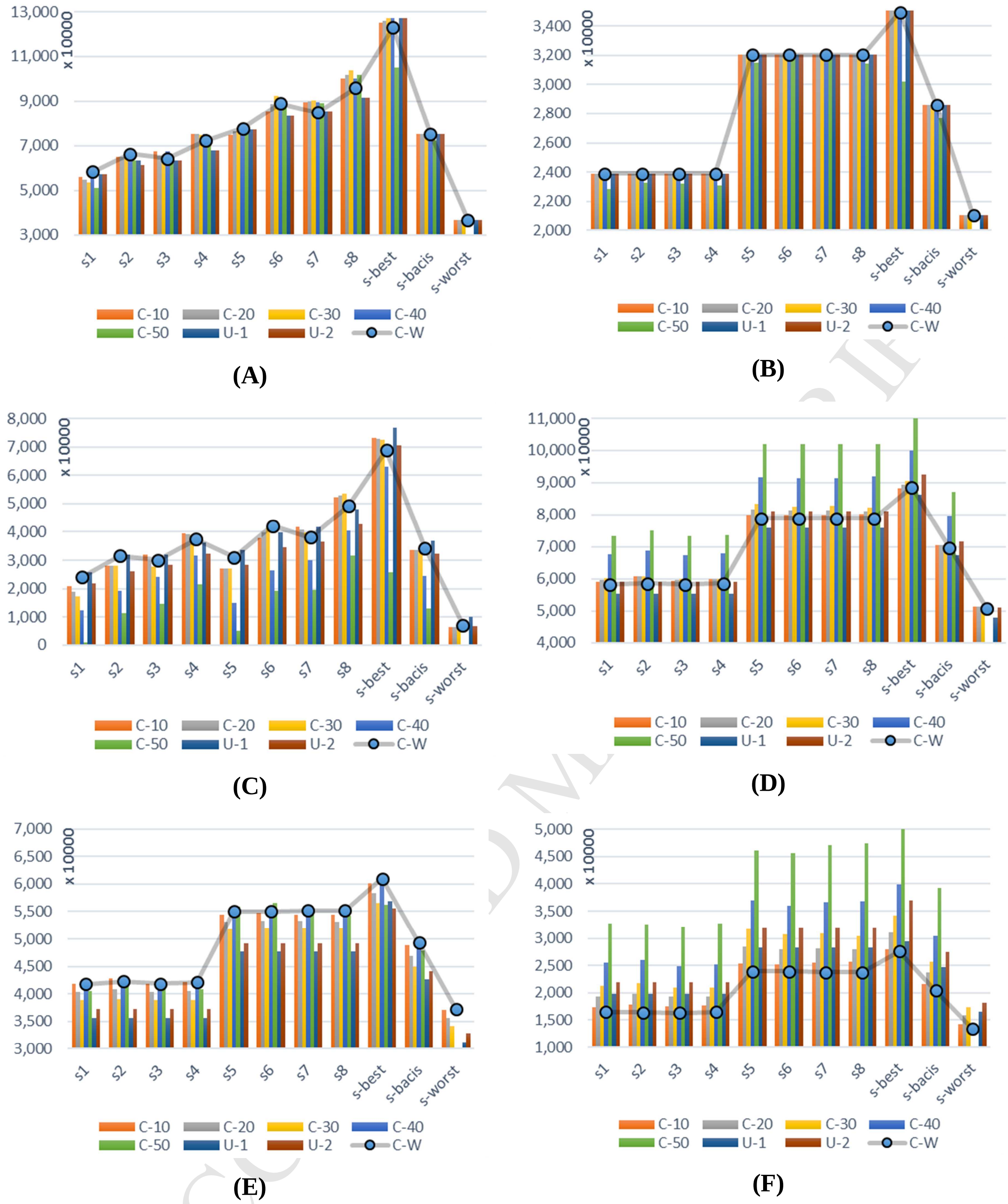
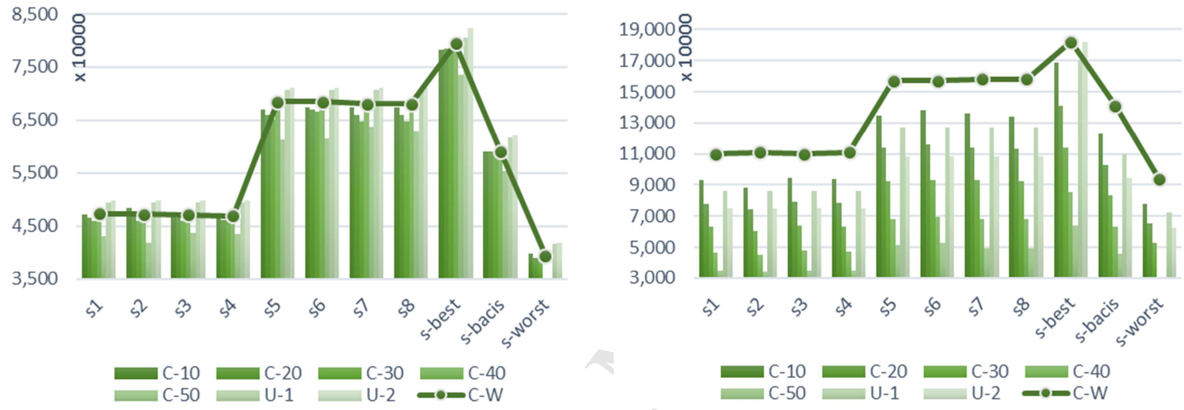


Figure.11 Comparison of the optimal solutions with respect to the changing parameters in the sensitivity analysis (results are normalized by dividing by10^4): **(A)** Profit expectation; **(B)** Total revenue; **(C)** Subsidy; **(D)** Total costs; **(E)** Facility costs; **(F)** Transportation costs.

Figures 11 and 12 illustrate the comparions of the optimal solutions of the test problems with respect to the expected profit, total revenue, subsidy, total costs, facility costs, transportation costs, and carbon emissions related to the facility operation and transportation through all the scenarios. As shown in figures, the total revenue and subsidy through all the scenarios change slightly in the differet test problems, but the total costs change drametically with the changing carbon emission requriement and capacity restriction. The more stringent requirement on the reduction of carbon emissions leads to higher costs particularly when 40% and 50% requirements are applied, and this is the main reason for the weak economic performance in those two scenarios. It is observed that the change of the total system operating costs and carbon emissions is caused by both facility operation and transportation of

EOU and EOL products. Compared with facility operation, a more sharper change can be observed on the transportation in both costs and carbon emissions, and this reveals the change of product allocation and transportation strategies with respect to different network configuaration has significant importance in determining both economic and environmental performance of the reverse logistics system.

In general, as observed from the sensitivity analysis, the reduction on carbon emissions of the reverse logistics system are determined by both facility operation and transportation of EOU and EOL products. Compared with facility operation, the transportation strategy plays a more important role in reducing carbon emissions, and this also leads to a sharper increase on the transportation costs of the reverse logistics system. When the range of the requirement on carbon emission reduction is no more than 30%, the negative influence on the profitability of the reverse logistics system is extremely slight, but with the implementation of more stringent requirement, the negative impact becomes significant. The model can help decision-makers with the evaluation of different regulatory mechanisms.



(A) **(B)**

Figure.12 Comparison of the optimal solutions with respect to the changing parameters in the sensitivity analysis (results are normalized by dividing by10^4): **(A)** Carbon emissions from the facility operations; **(B)** Carbon emissions from the transportation.

We are also interested in the role played by the government subsidy in determining the profitability of the reverse logistics system, so the ratio of subsidy/profit of the optimal solutions through all the scenarios in each test problem is calculated and compared, as shown in Table 5. The ratio of subsidy/profit illustrates the relative importance of the subsidy in the overal profit of the reverse logistics system, and if the ratio is more than less than 100%, that means the profit is contributed by both the suplus of the reverse logistics system (total revenue minus total costs) and government subsidy. If the ratio equals to 100%, that means the total revenue equals to the total costs, and the profit of the reverse logstics system is total contributed by the government subsidy. If the ratio is more than 100%, that means the total costs is higher than the total revenue obtainted from selling the recycled products and recovered energy, and the revere logstics system is not profitable without the government subsidy, so in this case, the government subsidy plays an extemely important role to promote the reuse, recycling and recovery of EOU and EOL products.

As shown in Table 5, the government subsidy is important to gaurantee the economic benefits for the companies in the reverse logistics system especially in the bad economies. In general, when the generation of EOU and EOL products are high, the profit of the reverse logistics system is contributed by both surplus and government subsidy, while more portion in the profit is taken by the government subsidy when the generation of EOU and EOL is low. Furthermore, with the increased requriement on the reduction of carbon emissions, the ratio of subsidy/profit increases gradually through all the scenarios, and this reveals that the government subsidy plays a more important role in maintaining the profitability of the reverse logistics system when the carbon emission requirement is implemented. In addtion, the contribution of government subsidy in the uncapacitated sceanrios is relatively smaller compared with that in other test problems particularly when the fixed facility costs are increased by 100%, and this shows a better profitatbility of the reverse logistics system.

Table 5 Ratio of subsidy/profit of the optimal solutions through all the scenarios in sensitivity analysis

Test problems with changing parameters in sensitivity analysis	Scenarios										
	s1	s2	s3	s4	s5	s6	s7	s8	best	basic	worst
Capacitated problem without requirement on carbon emissions	100%	76%	80%	64%	103%	76%	84%	65%	51%	83%	294%
Capacitated problem with requirement of 10% reduction on carbon emissions	115%	85%	75%	61%	119%	85%	77%	61%	49%	85%	319%
Capacitated problem with requirement of 20% reduction on carbon emissions	126%	85%	80%	61%	119%	81%	79%	61%	49%	85%	323%
Capacitated problem with requirement of 30% reduction on carbon emissions	139%	85%	86%	61%	119%	77%	81%	60%	50%	86%	328%
Capacitated problem with requirement of 40% reduction on carbon emissions	194%	125%	100%	76%	214%	121%	106%	79%	57%	118%	
Capacitated problem with requirement of 50% reduction on carbon emissions	2993%	202%	157%	108%	630%	164%	163%	100%	117%	211%	
Uncapacitated problem with 100% increase on fixed facility costs (Uncapacitated s1)	93%	75%	75%	66%	96%	81%	77%	67%	47%	78%	208%
Uncapacitated problem with 200% increase on fixed facility costs (Uncapacitated s2)	109%	91%	85%	74%	113%	93%	88%	75%	51%	89%	306%

6. Managerial Implication

One of the most important strategic decisions in a reverse logistics system is to determine the network structure in terms of the number and locations of facilities and the transportation strategy, which has significant influence on the long-term profitability and environmental sustainability. This is a complicated decision-making problem due to the balance between the economic benefits and environmental impact, and the uncertainties caused by market fluctuations. This research focuses on sustainable reverse logistics network design under stochastic environment, and the optimal solution emphasizes both profit expectation and reliability. Furthermore, the model is tested with seven scenarios with different carbon emissions constraint or capacity constraint.

From the numerical experiment and sensitivity analysis, the compulsory requirement is an effective way to reduce the carbon emissions from the reverse logistics system, but this will negatively affect the profitability due to the increased system operating costs. Further, the network configuration varies significantly with the changing carbon requirements. Also, the size of planned facilities can affect the network configuration, profitability and carbon emissions of the reverse logistics system. Due to the economy of scale from the larger facilities, both economic and environmental performance of the reverse logistics system may be improved if the increase of investment for facility expansion and aggregate transportation is maintained at a proper level. In addition, government subsidy plays an important role in determining the profitability of the reverse logistics. When a stringent requirement on carbon emission is implemented or the generation of EOU and EOL products is low and the facilities are not fully used, government subsidy significantly compensates the loss from the high costs for operating the reverse logistics system.

Considering the generic nature of reverse logistics network design, some managerial implications are summarized as follows.

- First of all, when the generation of EOU and EOL products is high, the capacity of reverse logistics system may not be able to deal with all the waste products generated. The decision-maker has to determine either to reduce the service level or to have more investment on capacity expansion. It is a wise choice for decision-maker to consider the future capacity expansion at the initial stage of the reverse logistics network design.
- In a multi-product reverse logistics system, the violation of the capacity constraint may be caused by one or some of products, but for the other products, the waste or insufficient use of capacity may be observed. Thus, another effective and efficient way to resolve the capacity limitation is to improve the flexibility of the facilities in order to enable the conversion of capacity of different products. The concept of flexible manufacturing system has been well introduced and extensively applied in the forward supply chain, but the implementation in the reverse logistics system should also be focused so that the flexibility and resource utilization can be dramatically improved.
- In general, the inclusion of carbon requirement may result in a decrease on the profitability of reverse logistics system. In order to balance the economic benefits and environmental impact, government subsidy may be used as an important leverage for compensating the economic loss from the carbon requirement. For example, the rate of government subsidy may be optimally changed with the changing requirement on the carbon emissions, and the model is able to support this decision.

7. Conclusion

In this paper, we develop a stochastic optimization model for network design of a multi-product multi-echelon carbon-constrained reverse logistics system. The stochastic optimization problem is resolved with an augmented multi-criteria scenario-based risk-averse solution method, which guarantees a well profit expectation with a high level of confidence and reliability. In order to show the application of the model, numerical experiment with the changing constraints on carbon emission requirement and facility capacity, and some deep managerial implications are drawn from the analysis of the results. The main contribution of the research is summarized as follows.

- We develop a new stochastic optimization model for reverse logistics network design with the consideration of both economic benefits and environmental impact.
- We develop an augmented multi-criteria scenario-based solution risk-averse method based upon the result of a latest research, and through the use of normalized weighed sum in decision-making, the problems existed, i.e., weak-reliable solution, inability to solve the cost-minimization problem, etc., can be effectively resolved with the augmented method.
- We use the augmented multi-criteria scenario-based solution method to resolve the stochastic optimization problem, which emphasizes both the optimal value and the reliability to achieve the optimal value.
- We get deep managerial implications from the numerical example and sensitivity analysis, i.e., the relationship between profit and carbon emission requirement, understanding and resolution of the infeasibility caused by capacity limitation, the use

of flexible manufacturing system in reverse logistics, proper use of the government subsidy as a leverage, etc. Furthermore, the managerial implications are obtained in a stochastic environment, and this will improve the reliability and robustness of the decision-making under market fluctuation.

For future development of the research, some suggestions are given. First, the environmental sustainability is only evaluated by carbon emissions, and more environmental indicators, i.e., water pollution, land pollution, etc. should be included in the model formulation. Besides, the social aspects of sustainability, i.e., employment, working environment, etc., should be also accounted in the sustainable reverse logistics design, as discussed by Govindan et al. (2016b) and Feitó-Cespón et al. (2017). Second, a further research should be taken for developing a systematic framework in order to suggest the weight combination or the range of weight combination with respect to the variation of the mean. For example, when the variation of the best value and worst value of the mean is 45%, a suggested range of weight combination should be immediately suggested for the performance evaluation. This will significantly improve the effectiveness and efficiency of the augmented multi-criteria scenario-based risk-averse solution method for stochastic optimization problems. Last but not the least, the capacity conversion of different types of products achieved by flexible manufacturing system in reverse logistics should be focused and further discussed in order to improve both economic and environmental sustainability.

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Highlights:

- We develop a new stochastic optimization model for reverse logistics network design with the consideration of both economic benefits and environmental impact.
- We develop an augmented multi-criteria scenario-based solution risk-averse method based upon the result of a latest research, and through the use of normalized weighed sum in decision-making, the problems existed, i.e., weak-reliable solution, inability to solve the cost-minimization problem, etc., can be effectively resolved with the augmented method.
- We use the augmented multi-criteria scenario-based solution method to resolve the stochastic optimization problem, which emphasizes both the optimal value and the reliability to achieve the optimal value.
- We get deep managerial implications from the numerical example and sensitivity analysis, i.e., the relationship between profit and carbon emission requirement, understanding and resolution of the infeasibility caused by capacity limitation, the use of flexible manufacturing system in reverse logistics, proper use of the government subsidy as a leverage, etc. Furthermore, the managerial implications are obtained in a stochastic environment, and this will improve the reliability and robustness of the decision-making under market fluctuation.

GTT	A	B
1	3446	7716
2	4137	5785
3	1744	5190
4	4010	5386
5	4354	3515
6	3110	7866
7	4853	6596
8	2448	7111
9	4895	7762
10	2839	6260
11	3894	5892
12	1969	3428
13	1322	4848
14	4972	3847
15	2825	6485
Total	50818	87687
	3455624	

Sorting	FC	VC		CAC		CQ		CR		EMSC	
Candidate		A	B	A	B	A	B	A	B	A	B
1	835406	68	58	17464.16	26139.85	0.5	0.4	0.6	0.5	147.0588	172.4138
2	967775	57	69	12631.88	28096.44	0.5	0.4	0.6	0.5	175.4386	144.9275
3	1294303	59	73	24499.54	51438.19	0.5	0.4	0.6	0.5	169.4915	136.9863
4	934621	72	58	23057.1	33625.79	0.5	0.4	0.6	0.5	138.8889	172.4138
5	1044252	60	58	13829.81	22075.49	0.5	0.4	0.6	0.5	166.6667	172.4138
6	828307	51	66	14865	26760.94	0.5	0.4	0.6	0.5	196.0784	151.5152
7	960029	51	76	21310.24	29430.65	0.5	0.4	0.6	0.5	196.0784	131.5789
8	828923	65	71	14431.55	18647.45	0.5	0.4	0.6	0.5	153.8462	140.8451

Recycling	FT	VT		CAT		PFC		SUBC		EMST	
Candidate		A	B	A	B	A	B	A	B	A	B
1	1720394	123	172	12795.43	30013.99	788	268	300	105	162.6016	116.2791
2	1307807	172	138	8796.637	17699.86	962	312	300	105	116.2791	144.9275
3	1886380	160	174	12501.98	34388.71	902	335	300	105	125	114.9425
4	1352402	122	163	15381.88	25235.82	986	303	300	105	163.9344	122.6994
5	1845360	129	156	16513.67	25277.74	786	207	300	105	155.0388	128.2051

Disposal	VD		PD		EMSD		CAD	
	A	B	A	B	A	B	A	B
1	64	97	0	0	312.5	206.1856	30000	50000

Recovery	FR	VR		CAR		PFR		SUBR		EMSR	
Candidate		A	B	A	B	A	B	A	B	A	B
1	1638332	292	209	10948.15	10866.58	544	470	300	119	342.4658	478.4689
2	1659473	240	245	10680.78	16452.56	541	430	300	119	416.6667	408.1633
3	1506705	246	235	16308.2	12598.79	935	398	300	119	406.5041	425.5319
4	1863060	281	248	23190.44	18558.85	959	375	300	119	355.8719	403.2258
5	1653003	247	253	19131.44	13451.4	587	443	300	119	404.8583	395.2569

Collection	1		2		3		4		5		6		7		8	
Generatior	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
1	198	149	89	53	163	166	55	166	110	51	62	89	136	180	159	154
2	50	71	115	162	194	163	147	200	117	60	166	60	148	176	183	130
3	173	77	154	83	64	100	93	195	102	98	57	128	61	76	133	111
4	198	184	100	163	144	187	103	126	148	114	169	152	166	77	116	82
5	191	181	131	73	195	141	113	152	183	88	176	189	119	153	108	178
6	122	83	58	107	136	172	180	176	142	113	189	75	132	135	186	194
7	95	159	57	61	149	200	60	107	132	80	102	169	189	200	135	109
8	133	175	166	72	83	101	152	61	112	55	58	188	134	117	149	121
9	168	87	186	176	89	134	183	103	121	121	131	119	52	127	134	148
10	106	62	106	171	142	137	130	98	76	50	94	141	57	133	122	192
11	133	125	165	194	160	178	191	70	84	65	144	94	58	55	76	161
12	121	76	188	167	157	126	136	195	98	84	173	99	81	163	58	98
13	69	131	188	70	88	125	102	78	67	60	170	58	174	150	60	162
14	157	156	136	125	95	116	189	129	195	54	136	71	194	62	83	53
15	157	144	61	172	139	80	176	181	130	63	149	113	61	148	93	197

Collection	1		2		3		4		5		6		7		8	
Generatior	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B
1	50.50505	134.2282	561.7978	754.717	122.6994	240.9639	909.0909	240.9639	363.6364	784.3137	645.1613	449.4382	367.6471	166.6667	125.7862	324.6753
2	400	563.3803	260.8696	123.4568	257.732	122.6994	340.1361	200	427.3504	333.3333	120.4819	833.3333	337.8378	170.4545	163.9344	153.8462
3	173.4104	649.3506	259.7403	602.4096	312.5	400	322.5806	102.5641	392.1569	408.1633	350.8772	390.625	491.8033	657.8947	375.9398	360.3604
4	151.5152	217.3913	400	122.6994	277.7778	213.9037	194.1748	158.7302	202.7027	350.8772	177.5148	197.3684	120.4819	519.4805	258.6207	609.7561
5	104.712	110.4972	229.0076	273.9726	102.5641	283.6879	176.9912	263.1579	218.5792	340.9091	113.6364	264.5503	336.1345	196.0784	462.963	224.7191
6	245.9016	481.9277	517.2414	186.9159	220.5882	290.6977	111.1111	113.6364	281.6901	265.4867	105.8201	533.3333	378.7879	148.1481	107.5269	206.1856
7	315.7895	188.6792	350.8772	819.6721	201.3423	100	333.3333	373.8318	378.7879	250	490.1961	295.858	211.6402	150	148.1481	366.9725
8	150.3759	114.2857	180.7229	277.7778	361.4458	396.0396	328.9474	491.8033	178.5714	363.6364	517.2414	212.766	223.8806	341.8803	134.2282	247.9339
9	119.0476	344.8276	268.8172	284.0909	337.0787	149.2537	109.2896	291.2621	247.9339	165.2893	152.6718	420.1681	961.5385	393.7008	373.1343	337.8378
10	188.6792	806.4516	377.3585	116.9591	211.2676	291.9708	384.6154	510.2041	263.1579	600	531.9149	212.766	701.7544	150.3759	245.9016	208.3333
11	75.18797	400	303.0303	154.6392	250	168.5393	157.0681	428.5714	595.2381	307.6923	208.3333	212.766	517.2414	545.4545	657.8947	124.2236
12	247.9339	526.3158	159.5745	299.4012	191.0828	396.8254	220.5882	153.8462	408.1633	476.1905	173.4104	303.0303	617.284	306.7485	517.2414	510.2041
13	434.7826	381.6794	212.766	714.2857	454.5455	160	392.1569	512.8205	298.5075	833.3333	235.2941	689.6552	229.8851	333.3333	833.3333	123.4568
14	127.3885	320.5128	147.0588	320	421.0526	258.6207	211.6402	387.5969	102.5641	370.3704	294.1176	704.2254	257.732	483.871	240.9639	754.717
15	127.3885	208.3333	491.8033	290.6977	359.7122	500	170.4545	165.7459	307.6923	476.1905	201.3423	353.9823	819.6721	202.7027	430.1075	203.0457

TC2	Recycling 1		2		3		4		5	
Collection	A	B	A	B	A	B	A	B	A	B
1	194	149	158	110	82	101	83	122	69	104
2	145	116	163	102	188	196	67	75	149	129
3	175	98	83	173	141	111	94	126	130	81
4	113	58	122	116	52	167	52	104	60	91
5	190	174	182	159	176	145	200	122	170	115
6	98	129	51	194	125	186	58	93	147	154
7	193	138	58	186	144	104	55	189	53	188
8	177	184	144	55	91	129	88	147	63	166

EMS2	Recycling 1		2		3		4		5	
Collection	A	B	A	B	A	B	A	B	A	B
1	51.54639	201.3423	126.5823	363.6364	609.7561	396.0396	361.4458	327.8689	434.7826	384.6154
2	206.8966	431.0345	245.3988	392.1569	265.9574	255.102	746.2687	266.6667	335.5705	310.0775
3	57.14286	306.1224	481.9277	231.2139	354.6099	360.3604	212.766	317.4603	153.8462	370.3704
4	265.4867	689.6552	327.8689	431.0345	769.2308	179.6407	961.5385	384.6154	666.6667	549.4505
5	52.63158	114.9425	274.7253	251.5723	284.0909	206.8966	250	245.9016	117.6471	260.8696
6	306.1224	387.5969	784.3137	103.0928	160	107.5269	344.8276	322.5806	340.1361	129.8701
7	103.6269	144.9275	862.069	161.2903	138.8889	288.4615	727.2727	264.5503	943.3962	159.5745
8	169.4915	108.6957	138.8889	363.6364	549.4505	387.5969	340.9091	340.1361	317.4603	120.4819

TC3	Disposal	1
Collection	A	B
1	169	62
2	179	121
3	60	147
4	144	152
5	52	178
6	175	88
7	66	77
8	113	151

EMS3	Disposal	
Collection	A	B
1	177.5148	806.4516
2	167.5978	247.9339
3	166.6667	136.0544
4	208.3333	131.5789
5	192.3077	112.3596
6	57.14286	454.5455
7	454.5455	519.4805
8	176.9912	264.9007

TC4	Recovery	1		2		3		4		5
Collection	A	B	A	B	A	B	A	B	A	B
1	145	125	130	55	122	154	145	182	161	51
2	193	118	117	104	186	59	128	50	67	71
3	94	196	55	153	108	157	161	106	166	68
4	117	181	65	55	71	98	177	61	128	155
5	169	113	187	133	120	111	159	51	60	110
6	166	159	120	61	66	110	123	200	146	106
7	134	107	108	59	110	109	125	82	102	126
8	111	62	105	102	163	112	58	111	52	158

EMS4	Recovery	1		2		3		4		5
Collection	A	B	A	B	A	B	A	B	A	B
1	137.931	400	153.8462	545.4545	409.8361	324.6753	137.931	274.7253	310.559	588.2353
2	51.81347	169.4915	256.4103	288.4615	268.8172	847.4576	156.25	800	298.5075	422.5352
3	319.1489	204.0816	363.6364	196.0784	185.1852	318.4713	124.2236	283.0189	180.7229	294.1176
4	256.4103	165.7459	461.5385	727.2727	704.2254	510.2041	282.4859	655.7377	234.375	129.0323
5	177.5148	442.4779	267.3797	300.7519	416.6667	450.4505	314.4654	980.3922	666.6667	363.6364
6	60.24096	125.7862	166.6667	655.7377	454.5455	272.7273	243.9024	100	342.4658	283.0189
7	74.62687	373.8318	370.3704	677.9661	363.6364	183.4862	400	365.8537	196.0784	396.8254
8	270.2703	322.5806	190.4762	392.1569	122.6994	357.1429	344.8276	180.1802	576.9231	126.5823