Department of Industrial Engineering
Faculty of Engineering Science and Technology

Optimization Models and Methods for Sustainable Reverse Logistics Network Design

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Hao Yu

A dissertation for the degree of Philosophiae Doctor – May 2018

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Abstract

With the increased focus on sustainable development and circular economy, as never before, the value recovery and re-creation from the End-of-Use and End-of-Life products has been paid considerable attention by the whole society. Reverse logistics is believed as one of the most effective and promising means for the value recovery from End-of-Use and End-of-Life products, which is the process for value re-creation through a series of activities, i.e., reuse, repair, remanufacturing, recycling and energy recovery. An extensive effort has been spent on both theoretical development and practical applications in reverse logistics during the past three decades. Today, an increasing number of companies have adopted reverse logistics in their daily business due to the pressure from the environmental conscious consumers and more stringent environmental regulations enacted.

However, due to the stochastic reverse product flow, unstable quality, the changing costs for facility operation and transportation, as well as the price fluctuation of the recovered products and energy, the design of a reverse logistics network is much more complicated in comparison with that of a conventional forward supply chain. In addition, an improperly designed reverse logistics system may incur an increased cost on facility operation and transportation, while, at the same time, has significant environmental impacts and pose a potential risk on the local residents. Therefore, it is of paramount importance to develop advanced optimization models and methods for providing decision-makers and practitioners with better support and implications for the planning of a reverse logistics system in a more sustainable way.

The contemporary optimization models and methods in this field mainly focus on the economic benefits from the reverse logistics activities; however, the environmental and social sustainability of reverse logistics is rarely accounted. Furthermore, the majority of the models are developed under deterministic environmental without proper management of the market fluctuation as well as other uncertainties. Therefore, this PhD project aims to remedy the problems of the existing optimization models in order to improve the decision-making of reverse logistics network design and optimization

with the consideration of environmental issues, uncertainty as well as some other important impact factors.

The results have contributed to the literature of sustainable reverse logistics network design in several aspects:

1. Development of the improved optimization models for balancing the trade-off between economic benefits, environmental impact and social responsibility in sustainable reverse logistics network design.
2. Incorporating different objective functions, constraints and elements in the modelling in order to test the effectiveness of different operational strategies, network structures and policy mechanisms.
3. Incorporating system flexibility in the modelling of a multi-product sustainable reverse logistics network in order to manage the impact from uncertainties.
4. Improvement on the solution methods for the complex decision-making problems with multiple objective functions and under an uncertain environment.
5. Gaining in-depth managerial implications for the decision-makers, supply chain managers as well as practitioners through the analysis and comparative study of the results obtained from numerical experiments.

List of Included Papers

Number	Publications
Paper 1	Hao Yu and Wei Deng Solvang. "A general reverse logistics network design model for product reuse and recycling with environmental considerations", *The International Journal of Advanced Manufacturing Technology,* 2016, 87, 2693-2711.
Paper 2	Hao Yu and Wei Deng Solvang. "Incorporating flexible capacity in the planning of a multi-product multi-echelon sustainable reverse logistics network under uncertainty", *Journal of Cleaner Production,* 2018, 198, 285-303.
Paper 3	Hao Yu and Wei Deng Solvang. "A stochastic programming approach with improved multi-criteria scenario-based solution method for sustainable reverse logistics design of waste electrical and electronic equipment (WEEE)", *Sustainability*, 2016, 8, 1331.
Paper 4	Hao Yu and Wei Deng Solvang. "A carbon-constraint stochastic optimization model with augmented multi-criteria scenario-based risk-averse solution for reverse logistics network design under uncertainty", *Journal of Cleaner Production*, 2017, 164, 1248-1267.
Paper 5	Hao Yu and Wei Deng Solvang. "A multi-objective location-allocation optimization for sustainable management of municipal solid waste", *Environment, Systems and Decisions*, 2017, 37, 289-308.
Paper 6	Hao Yu and Wei Deng Solvang. "An improved multi-objective programming with augmented $\varepsilon -$ constraint method for hazardous waste

	location-routing problems", *International Journal of Environmental Research and Public Health*, 2016, 13, 548.

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I would also like to express my gratitude to Professor Gilbert Laporte for the invitation of a five-month research visit at the Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT), which is one of the most prestigious research centers in operational research and decision-making in the world. The five-month stay in Montréal is really amazing and fantastic for me. I met so many interesting people and attended several academic seminars as well as other activities, which improved my knowledge and broadened my horizon. The research visit is fully supported by the "OptiLog 4.0" project financed by the Research Council of Norway under Transport 2025 Programme. Besides, I am also very grateful for the help and supports from my supervisor in the application of this project.

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Finally, I would like to thank my parents for their unconditional love and supports throughout the years. I would like to give special thanks to my beloved wife, Xu Sun, for her love, support and encouragement. I have conducted extensive research in many complex decision-making problems, but marrying you is the most important and correct decision I have made in my life. I would like to extend this special thanks to my beloved daughter, Yihan Yu, who is the most precious gift in my life. I have been teaching the course of Project Management for several years, but you are the best and most important project in my life.

Hao Yu

Montréal, November 2018

To my beloved parents and wife, Xu Sun and daughter Yihan Yu.

To my grandma in Heaven.

To begin with the research journey:

"BE PRACTICAL AS WELL AS GENEROUS IN YOUR IDEAS KEEP YOUR EYES ON THE STARS AND KEEP YOUR FEET ON THE GROUND"

Theodore Roosevelt

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List of Abbreviations

BLLs	Blood Lead Levels
CLSC	Closed-Loop Supply Chain
EEA	European Environmental Agency
EEE	Electrical and Electronic Equipment
EOL	End-of-Life
EOU	End-of-Use
EPR	Extended Producer Responsibility
EU	European Union
ICITM	International Conference on Industrial Technology and Management
IEEE	Institute of Electrical and Electronic Engineers
IEEM	International Conference on Industrial Engineering and Engineering Management
INFORMS	The Institute for Operations Research and Management Science
IP	Integer Programming
IWAMA	International Workshop of Advanced Manufacturing and Automation
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-linear Programming
MIP	Mixed Integer Programming
MOP	Multi-Objective Programming
MOMIP	Multi-Objective Mixed Integer Programming
MOSP	Multi-Objective Stochastic Programming
MS	Management Science
MSW	Municipal Solid Waste
NLP	Non-Linear Programming
OR	Operational Research/Operations Research
RL	Reverse Logistics
RLND	Reverse Logistics Network Design
SCM	Supply Chain Management
SSCM	Sustainable Supply Chain Management
SP	Stochastic Programming

UN	United Nations
US	United States
WEEE	Waste Electrical and Electronic Equipment
WTE	Waste-to-Energy

1 Introduction

In the latest three decades, with more stringent environmental policies implemented and ever-increasing public focus on circular economy and sustainable development, the value recovery and re-creation from the end-of-life (EOL) and end-of-use (EOU) products have been given considerable attention by the government, decision-makers, companies as well as academic researchers around the world (Demirel and Gökçen, 2008, John et al., 2017, Soleimani et al., 2017). Not only from the perspective of landfill depletion and environmental pollution but also from the economic perspective, the value recovery from EOL and EOU products improves the utilization of recourses and also yields profits through some high value-added operations, i.e. remanufacturing (Guide Jr, 2000, Govindan et al., 2015a, Coelho and Mateus, 2017).

Reverse logistics is the system dealing with the whole process and material flow for value recovery and re-creation from EOL and EOU products, and the typical operations in a reverse logistics system consist of collection, transportation, inspection, disassembly, and distribution for repair, reuse, remanufacturing, recycling, energy recovery and proper disposal of the EOL and EOU products (Rogers and Tibben-Lembke, 2001). Through implementing the reverse logistics activities in an effective and efficient manner, companies can save costs through the improved use of materials (Kannan et al., 2012), while simultaneously obtain a higher customer loyalty and potential profitability in future (Kannan, 2009).

The planning of a reverse logistics system is a complex decision-making problem, which has never lost its appeal to both academic researchers and practitioners. In this PhD project, improved optimization models and methods are developed for sustainable reverse logistics network design. The optimization models and methods can better formulate the features of sustainability in reverse logistics network design and remedy the problems of the models and methods in existence while, at the same time, maintaining a high reliability and computational efficiency. In addition, some interesting findings and managerial implications are also obtained from the experimental analysis.

This PhD thesis is a collection of six research papers and consists of two parts. The first part is an introductive section including Chapters 1-4, which aims at giving the background, motivations, objective, problem statement, research gap, research design, basic knowledge and methodology, as well as a summary of contributions. The second part comprises six journal articles and forms the main methodological development and contributions of the PhD project.

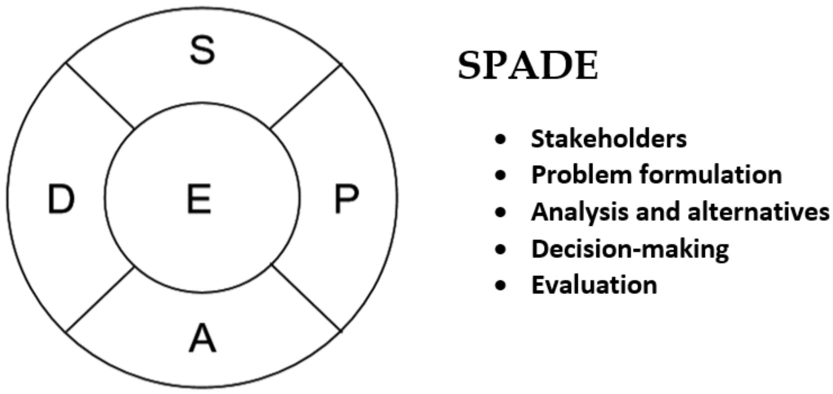


Figure 1-1 Graphical representation of SPADE methodology or framework (Haskins, 2008).

The introductive section of the PhD thesis is structured from a *System Engineering* perspective, and Figure 1-1 illustrates the graphical representation of the **SPADE** methodology/framework proposed by Haskins (2008). In Chapter 1, the background knowledge and definitions of EOL and EOU products, Extended Producer Responsibility (EPR), reverse logistics, reverse logistics network design and sustainable reverse logistics network design are first introduced, and the motivation and objective of the research are then discussed. Finally, a stakeholder analysis of the PhD project is given latter in this chapter. Chapter 2 presents the problem statement, state-of-the-art literature review and the research focus of this PhD project. In Chapter 3, the research design, analysis and selection of different modelling techniques and solution methods are introduced. Furthermore, this chapter also provides brief introductions and justifications of the selected mathematical modelling techniques and methods for sustainable reverse logistics network design. Chapter 4 summarizes the main contributions of the PhD project and proposes directions for future research. In addition, this chapter can also be considered as the starting point for the second part of the PhD thesis, which clearly presents the structure of the included papers in the development on modelling techniques, solution methods and managerial implications.

1.1 Background

With the rapid advancement on technology and productivity, boom of economy, globalization as well as increased customers' expectation, more and more innovative and well-designed consumer products have been introduced to make our life better and more convenient (Yu and Solvang, 2016a, Jabbarzadeh et al., 2018). This has resulted in a much shorter product lifecycle and a rapid increase on waste generation (Keyvanshokooh et al., 2013), and waste electrical and electronic equipment (WEEE) is one of the best examples. Since 2005, the increase on the annual WEEE generation reaches approximately three times higher than that of the other waste (Rahmani et al., 2014). The treatment of the increased waste generation has become a significant burden for any unban community.

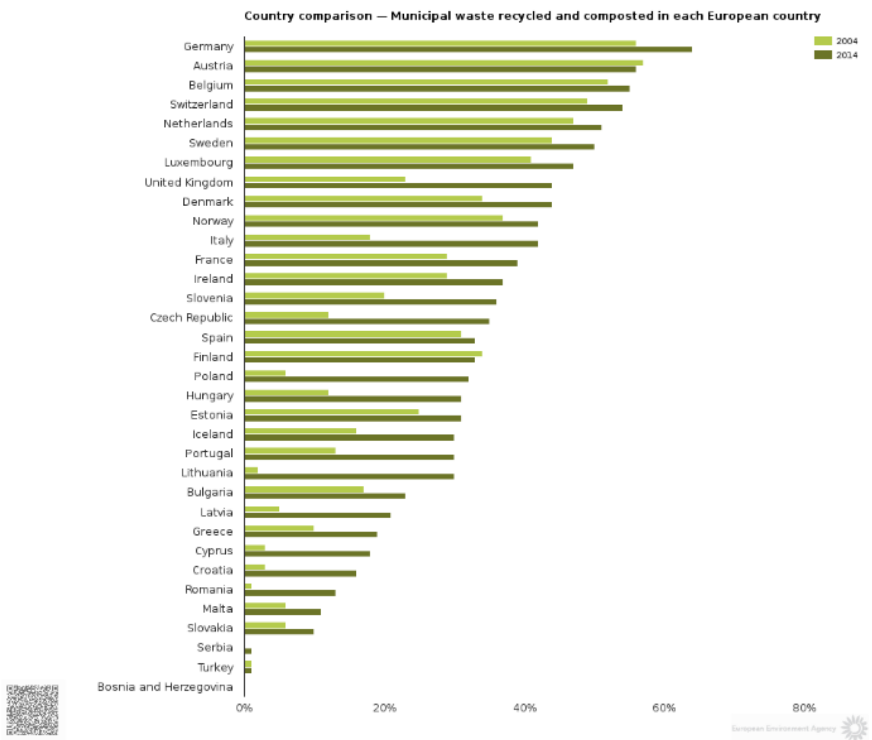


Figure 1-2 Comparison of the portion of municipal solid waste recycled and composted in each European country in 2004 and 2014 (EPA, 2016).

Over the years, businesses have only focused on the value creation through the forward supply chain activities, but have not taken into consideration of their products after the life span (Kannan, 2009). Conventionally, most EOL and EOU products are considered as "waste", and landfill is the most common destination for them (EEA, 2012). However, landfill of waste not only causes significant economic losses on waste of resources (e.g. the precious metals from WEEE) but also leads to several environmental problems, i.e., land depletion, water pollution and emissions of hazardous gases (Slack et al., 2005). In the European Union (EU), significant efforts have been made for implementing stringent environmental regulations (e.g., the WEEE Directive, Landfill Directive, Restriction of Hazardous Substances Directive and EOL vehicles Directive, etc.) and establishing formal recycling channels in order to divert the EOL and EOU products from landfill to other value recovery options.

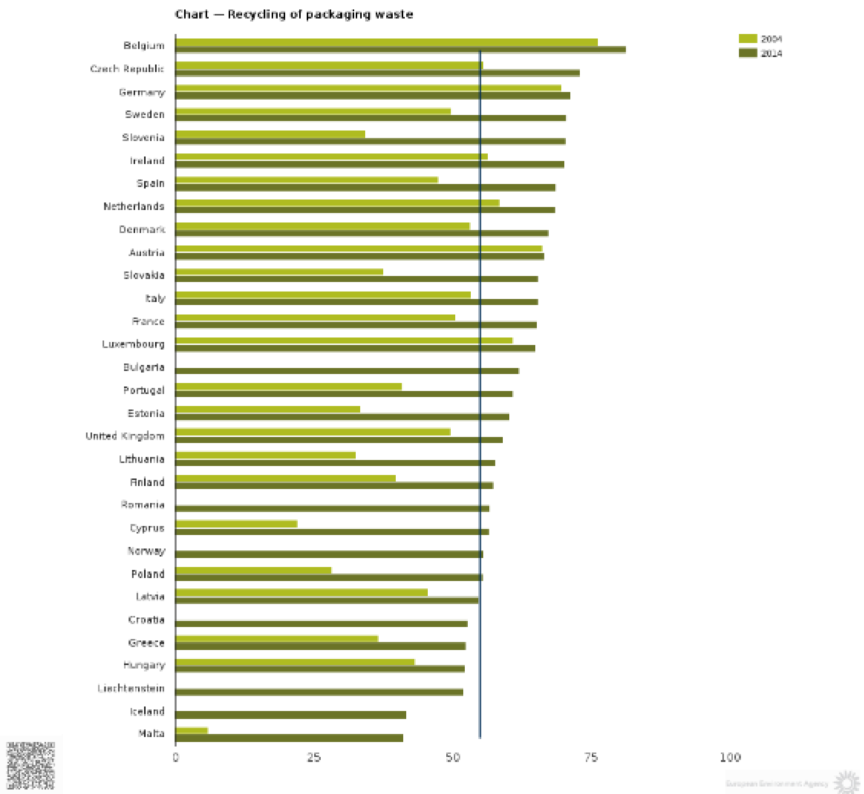


Figure 1-3 Comparison of the portion of packaging waste recycled in each European country in 2004 and 2014 (EPA, 2016).

Those efforts have significantly improved the recycling rate of the EOL and EOU products across the EU countries. Figure 1-2 and Figure 1-3 illustrate the comparison of the recycled rate of municipal solid waste and packaging waste in each European country in 2004 and 2014. On average, 43% of municipal solid waste and 65% of packaging waste have been recycled in the EU in 2014, and the recycled portion of them has increased by 13% and 10%, respectively, compared with that in 2004 (EPA, 2016). The improvement on recycling rate can be mainly explained by the EU's determination on continuously strengthened regulation as well as enacting of corresponding legislative mechanisms, i.e., Extended Producer Responsibility (EPR), etc.

Diverting EOL and EOU products from landfill to more sustainable recycling operations not only recovers the remaining value from the waste and improves the utilization of materials, but also reduces negative environmental impact from waste management, i.e., greenhouse gas emissions. Figure 1-4 illustrates the greenhouse gas emissions from municipal solid waste management in the EU plus Switzerland and Norway from 1990 to 2012. As can be seen in Figure 1-4, the direct greenhouse gas emissions from waste landfill increases gradually in 1990s due to the increase on waste generation, but it decreases significantly from 2000 due to more portion of municipal solid waste are recycled or incinerated. The increased recycling and incineration activities have led to more direct greenhouse emissions from those operations, however, this has also resulted in a significant increase on avoided greenhouse emissions mainly from landfill. Thus, the efforts on waste recycling have led to a significant reduction on the total greenhouse gas emissions from municipal solid waste management.

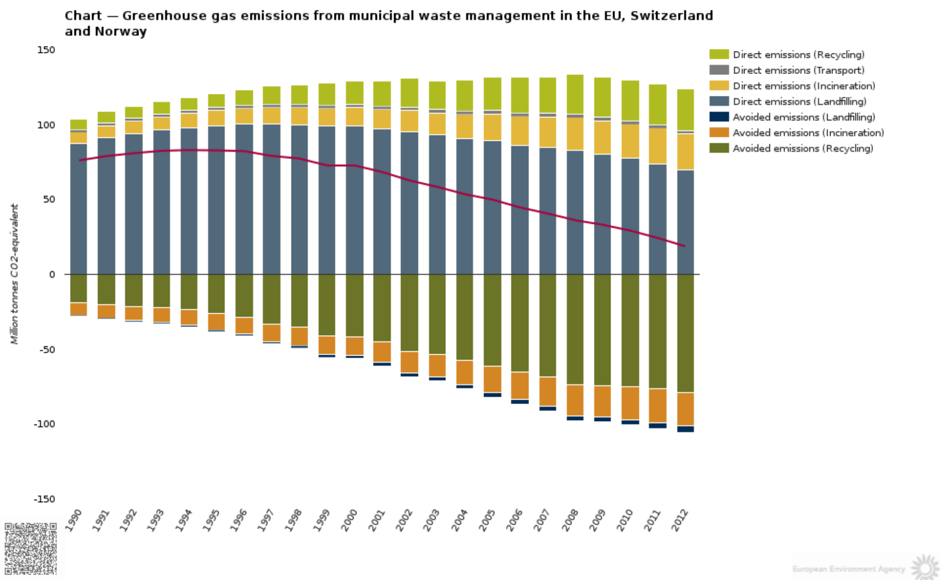


Figure 1-4 Greenhouse gas emissions from municipal solid waste management in the EU, Switzerland and Norway from 1990 to 2012. Note: the avoided emissions are plotted as negative values, and the total annual net GHG emissions are given in the red line (EPA, 2014).

Exempt from the legislative requirements, another important driving force for companies and organizations to participate in the recycling activities of their EOL and EOU products is the pressure from more environmentally conscious consumers. Investigations have revealed the change of pattern of consumption and consumer behaviors, and an increasing number of consumers are willing to pay more for the green and sustainable products and services (Namkung and Jang, 2017, Kumar and Ghodeswar, 2015). Therefore, from the business perspective, taking responsibility for the recovery of EOL and EOU products improves the utilization of materials and long-term profitability of a company while, at the same time, enhance the company's social responsible image and customer relationships (Klausner and Hendrickson, 2000).

However, managing the value recovery activities of EOL and EOU products is not an easy and isolated endeavor. It involves various operations, i.e., collection, transportation, pre-processing as well as different value recovery activities, and needs collective efforts from the government, companies, organizations, research institutions as well as the whole society. Furthermore, inappropriate value recovery activities may lead to a reduced economic benefit and significant environmental impact. Due to this reason, the concept of reverse logistics has been proposed in order to provide a holistic picture for systematically managing those activities and interactions among different stakeholders in the value recovery process of EOL and EOU products.

1.1.1 End-of-Life product and End-of-Use product

The difference between End-of-Life (EOL) and End-of-Use (EOU) products is discussed from the perspective of a product useful lifespan. As defined by Kongar et al. (2015), EOL product is "*a product has completed its service lifetime and has reached the end of its useful life*". In accordance with this definition, an EOL product has reached the end of its useful lifespan for consumers with tremendous reduction on its functionality and usefulness. Thus, the economic value or physical conditions of a EOL product has reduced to a minimum level at which point it should be "take-back" for value-added recovery or proper disposal (Östlin et al., 2009).

The definition of EOU return is given by Östlin et al. (2009) as "*those situations where the user has a return opportunity at a certain life stage of the product*". Different from an EOL product, the EOU return is not necessarily occurred at the end of a product useful lifespan, and it can happen at every stage where the usefulness of a product is finished or reduced for an individual consumer. However in this case, the EOU products may still be at good conditions and remain useful for other customers, and they can be re-introduced into market after proper treatment. For example, the return of leased cars and returnable bottles and other containers (Campos et al., 2017), the re-sell of consumer electronics in the second-hand markets (e.g., Amazon.com: Refurbished & Used: Electronics), and so forth.

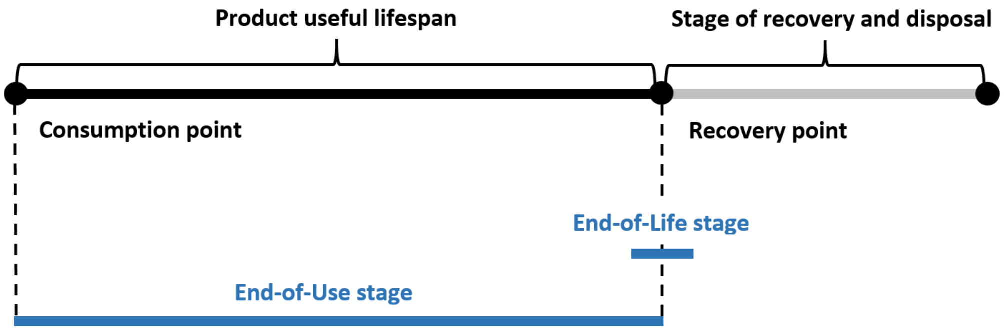


Figure 1-5 End-of-Use stage and End-of-Life stage on a product useful life span.

Figure 1-5 illustrates the comparison between EOL stage and EOU stage on a product useful lifespan. Due to the difference on the product quality of EOL and EOU returns, the value recovery options are by no means identical. Usually, the EOU products, especially the ones returned at the early stage of product useful lifespan, are at good or reasonable conditions and thus can be reused, repaired and refabricated before re-entering the distribution channels (Östlin et al., 2009, Campos et al., 2017). However, on the other hand, the EOL products are usually at much worse situations with significant reduction on the quality and functionalities, so more complicated and comprehensive procedures including disassembly, inspection, remanufacturing, component reuse, and part and material recycling are used for the value recovery of EOL products.

1.1.2 Extended Producer Responsibility

Conventionally, the manufacturer's responsibility for their products is within the production, distribution as well as support and maintenance throughout the product useful lifespan, and the recovery and disposal of EOL and EOU products used to be considered a separated process as waste management. However, with the increased focus on environmental problems, public health and sustainable development (Atasu and Subramanian, 2012), the manufacturer's responsibility has been extended throughout the entire lifespan of their products with the Extended Producer Responsibility (EPR), as illustrated in Figure 1-7. The concept of EPR was first proposed in Germany and Sweden at the beginning of 1990s (Lifset et al., 2013). Defined by Lindhqvist (2000), EPR refers to "*a policy principle to promote total life cycle environmental improvements of product systems by extending the responsibilities of the manufacturer of the product to various parts of the entire life cycle of the product, and especially to the take-back, recycling and final disposal of the product*". With this regard, the manufacturers have to be actively involved in the value recovery and proper disposal of their products after the useful lifespan, i.e., WEEE, EOL vehicles, etc.

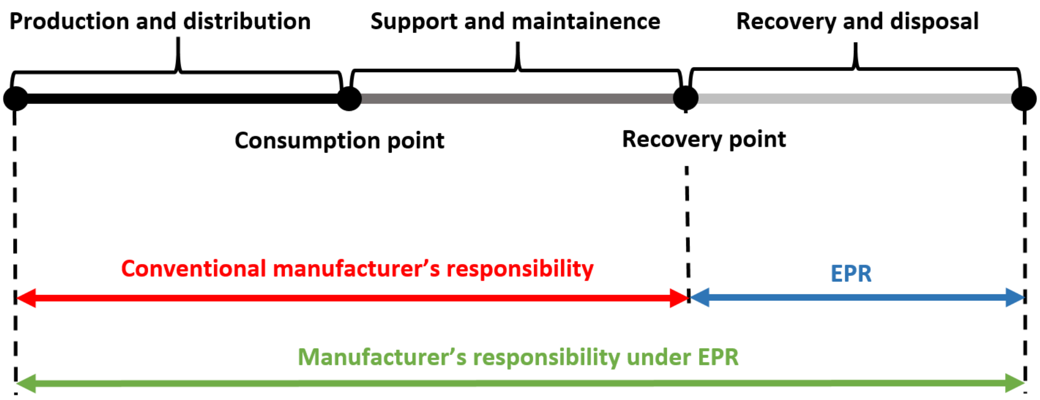


Figure 1-6 Conventional manufacturer's responsibility, EPR and the manufacturer's responsibility under EPR over the entire product lifespan.

In order to promote EPR in the management of EOL and EOU products, several legislative mechanisms have been implemented. Their practices have been investigated by researchers in many countries and regions all over the world, i.e., European Union (EU) (Mayers et al., 2005, Khetriwal et al., 2009), Canada (McKerlie et al., 2006), China (Xiang and Ming, 2011, Kojima et al., 2009), and Brazil (Milanez and Bührs, 2009), etc. Those legislative mechanisms have effectively promoted the participation of companies in EPR schemes and forced them to think about the recovery of their products at the very beginning of product design phase. For example, investigations have showed the recovery of WEEE has been improved in Nordic countries after the successful implementation of the WEEE Directive (Ylä-Mella et al., 2014b, Ylä-Mella et al., 2014a).

The legislative requirements on manufacturers' participation in the value recovery and disposal of EOL and EOU products give the opportunities for some companies to improve their profitability, recourse utilization as well as efficiency, but it is considered a challenge for many other companies (Spicer and Johnson, 2004). The complication and complex nature in managing the material, information and capital flows in EOL and EOU returns reduce the enthusiasm of companies' involvement in this business. Due to this reason, it is of importance to develop an effective system for EOL and EOU recovery system, while simultaneously maintaining the cost efficiency.

1.1.3 Reverse logistics

Reverse logistics (RL) is the term used to describe the activities for value recovery and proper disposal of EOL and EOU products. The practices of reverse logistics can be dated back for several decades. For instance, the manufacturers of bottled soda recycle the bottles and trays. However, the concept of reverse logistics has not been referred in literature until late 1980s. Lynagh et al. (1990) referred to the reverse channel as "*The movement of goods from a consumer towards a producer in a channel of distribution*". Pohlen and Theodore Farris (1992) viewed reverse logistics as "*The dislocation of goods from the customer back to the manufacturer through distribution channels*". Fleischmann et al. (1997) described reverse logistics as "*Reverse logistics encompasses the logistics activities all the way from used products no longer required by the user to products again usable in a market*". Throughout the 1980s and early 1990s, the descriptions of reverse logistics were limited to the movement of materials in an opposite way as that of the forward flow. Nevertheless, the purposes and activities of reverse logistics are not clearly identified in these earlier studies.

In order to specify the objective and activities of a reverse logistic system, the first definition of reverse logistics was given by Stock (1992) as:

"*Reverse logistics is the term often used in regard to the role of logistics in recycling, waste disposition and hazardous waste management; the broader perspective contains all actions connected with logistics in the relationship of materials reduction, recycling, substitution or reuse and also material disposition*".

Different from the other descriptions from that period, the definition presents a complete overview for answering two important questions: "what is the meaning of reverse logistics" and "what activities are included in reverse logistics". Following this definition, a more specific description of reverse logistics activities was given by Stock (1998) as:

"*The role of logistics in product returns, source reduction, recycling, materials substitution, reuse of materials, waste disposal and refurbishing, repair, and remanufacturing*".

Reverse logistics has been defined by different researchers and organizations with different focuses, among which the value recovery and re-creation from EOL and EOU products and proper disposal of unrecoverable parts are emphasized. In this regard, a highly cited definition of reverse logistics was given by Rogers and Tibben - Lembke (2001) as:

"*Reverse logistics is the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished products and related information from the consuming point back to the original point for the purpose of recapturing value or proper disposal*".

The definition focuses on the economic benefits from the value recovery of EOL and EOU products and specifies the activities performed in the reverse flow. While, some extended the definition of reverse logistics to a broader perspective in order to include more objectives and options.

The definition given by Reverse Logistics Association (RLA) is:

"*We refer to the term reverse logistics as all activity associated with a product/service after the point of sale, the ultimate goal to optimize or make more efficient aftermarket activity, thus saving money and environmental resources*".

This definition extended the objective of reverse logistics from a solo economic consideration to taking into account both economic and environmental performances. In addition, the definition focuses not only on the treatment of EOL and EOU products but also include more activities in the reverse channels, i.e., customer return of defective products, etc. This provides a broader view of reverse logistics activities and has been taken into further discussion in several research works. Among which, the one conducted by Buxbaum (1998) argues that retailers consider reverse logistics as a way to transport the products returned by customers back to the distributors or producers, while the producer or manufacturer tend to see the reverse logistics as the process of receiving defective products and used products from the distributors, retailers and customers.

With the broader view, de Brito and Dekker (2003) identify five types of material flows in reverse logistics activities:

1. ***Manufacturing returns*** of defective products, components and defects related to the manufacturing process.
2. ***Commercial returns*** under certain or pre-defined conditions.

3. ***Product recalls*** for those products with serious quality defects or safety problems.
4. ***Warranty returns and service returns*** for product repair, replacement and maintenance.
5. ***EOU returns and EOL returns*** for value recovery and waste disposal.

Compared with other returned flows in reverse logistics, the recovery of EOU and EOL products has been predominately focused in literature due to two reasons. First, the generation of EOL and EOU return is much more than the other types of product return, and the associated economic values and environmental impact are therefore more significant. Second, compared with other types of product return, the recovery and disposal of EOL and EOU products are through a much more complex network structure with more stakeholders. Due to this reason, the decision-making problems of EOL and EOU returns are more complicated, so significant research efforts have been spent in this field.

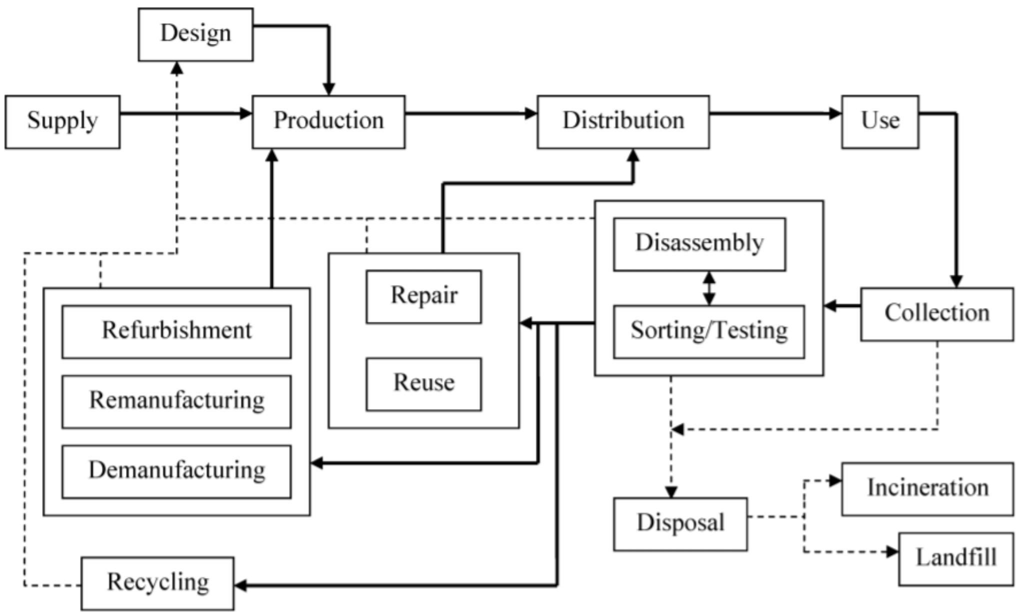


Figure 1-7 A conceptual framework of reverse logistics system (Sasikumar and Kannan, 2008).

Therefore, in this PhD project, the focus is given to the management of the reverse flows of EOL and EOU products. Figure 1-7 illustrates the structure of a generic reverse logistics system. As shown, the reverse logistics system has an opposite material flow compared with that of a forward one. The system starts from the end-customers and moves upstream towards different destinations for the value recovery operations. Finally, the non-recoverable parts and components will be sent to disposal.

1.1.4 Reverse logistics network design

The research on the topics and problems related to reverse logistics has been extensively focused due to its effectiveness and usefulness on value recovery and re-creation from the EOL and EOU products. Figure 1-8 summarizes some of the current research focuses on reverse logistics. A large variety of tools, methodologies, and techniques are investigated and applied in this field in order to provide the government, policy makers as well as practitioners with better supports for decision-making from either an overall holistic system perspective (e.g., facility location and network problem) or an individual company's perspective (e.g., route planning, inventory management and supplier selection).

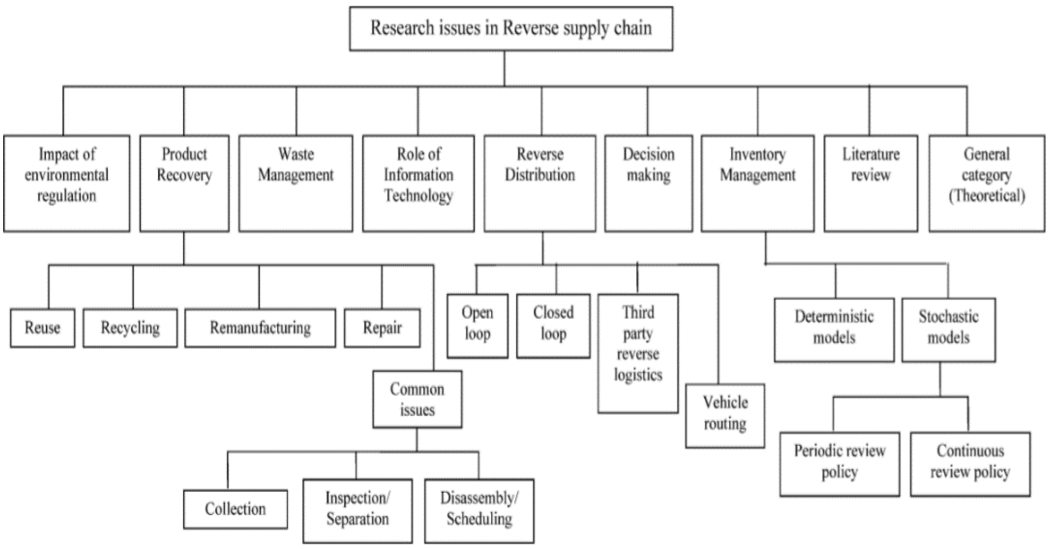


Figure 1-8 Research problems on reverse logistics (Sasikumar and Kannan, 2009).

The network planning of a reverse logistics system is one of the most important strategic decisions (Melo et al., 2009). It involves the determination of the number and locations of the new facilities to be opened, identification of the mode for transportation, determination of the facility operational plan and transportation strategy, and establishment of distribution channels for the treatment of EOL and EOU products (Melo et al., 2014, John et al., 2018).

1.1.5 Sustainable reverse logistics network design

In order to define sustainable reverse logistics network design, an extensively adopted definition of sustainability or sustainable development is first introduced in this section. Sustainable development, as defined by the Brundtland Commission of the United Nations, is "*development that meets the present without compromising the ability of future generation to meet their own needs*" (UN, 1987). As shown in Figure 1-9, the World Summit 2005 introduces three pillars to support a sustainable development society, namely, economic sustainability, environmental sustainability and social sustainability (Chopra and Meindl, 2007).

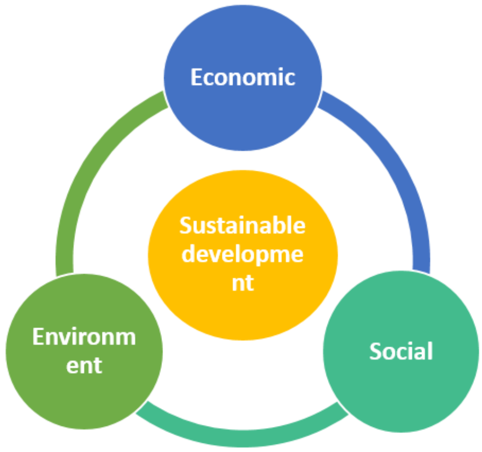


Figure 1-9 The three dimensions for sustainable development.

With the adaptation of the sustainability in supply chain management, several researchers have tried to define and investigate the concept of sustainable supply chain management (SSCM). It refers to "*a firm's plans and activities that integrate environmental and social issues into supply chain management in order to improve the company's environmental and social performance and that of its suppliers and customers without compromising its economic performance*" (Seuring and Müller, 2008, Gimenez et al., 2012). The concept of sustainable supply chain management only focuses on the environmental and social performance of the forward supply chain. However, the environmental and social sustainability related to the reverse logistics for recovering EOL and EOU products has not been adequately focused and investigated, and the definition of sustainable reverse logistics has not been given in literature. Due to this reason, the concepts of sustainable reverse logistics and sustainable reverse logistics network design are defined in this PhD thesis.

In order to capture the characteristics of a generic sustainable reverse logistics system for EOL and EOU returns, based upon the definition of reverse logistics given by Rogers and Tibben - Lembke (2001), an extended definition is given as follows for sustainable reverse logistics:

"Sustainable reverse logistics is the process of designing, implementing and maintaining the efficient, cost effective, environmentally friendly and socially responsible flow of the returned EOL and EOU products together with raw materials, in- and/or post-process inventory, finished products as well as the related information and capital from the consuming point back to the original point for the purpose of recapturing value and/or proper disposal".

This definition specifies the focus of a sustainable reverse logistics system, which emphasizes not only the economic benefits but also the environmental and social performance. For example, the treatment of EOL returns containing hazardous materials in a sustainable reverse logistics system should not only considering the cost or economic performance, but also taking into account of the environmental impact and risks imposed to people (social sustainability). In addition, from the perspective of supply chain management (Chopra and Meindl, 2007), the capital follow of the reverse logistics system is also given in the definition.

Based on the definitions of sustainable reverse logistics and reverse logistics network design, the term of sustainable reverse logistics network design can be defined as follows:

"Sustainable reverse logistic network design is to balance the trade-off among economic, environmental and social performance of the reverse logistics system in an optimal fashion through a serious important design-makings at both strategic and tactical levels including facility locations, capacity installation, and the planning of demand allocation, facility operation as well as transportation strategy".

1.2 Motivation and objectives of the PhD project

1.2.1 Motivations of the PhD research

In literature, reverse logistics has been extensively and predominately focused from the perspective of the economic dimension of sustainable development through the recovery of resources and re-creation of value from

EOL and EOU products. Nevertheless, holding in mind, one should never overestimate the economic benefits from the recovery of EOL and EOU products while underestimate the possibility of negative influences on the environment and threats to people's health from the improper reverse logistics activities.

Figure 1-10 WEEE recycling in Guiyu, China (Huo et al., 2007).

Previous investigations have revealed many of such instances among which the recycling of WEEE in Asia is one of the most extensively focused cases (Huo et al., 2007, Deng et al., 2006, Leung et al., 2006, Tang et al., 2010, Zheng et al., 2015, Labunska et al., 2015, Wu et al., 2016, Damrongsiri et al., 2016). Figure 1-10 illustrates the informal recycling of WEEE in Guiyu, China. Guiyu is a region comprising of several small villages in Guizhou Province, Southern China, and most people in this region used to work in agriculture. Since 1995, the import and recycling of WEEE from other countries, especially the United States (US), via Hong Kong, has become one of the most important industries for the local economic development. WEEE contains both precious metals and toxic materials, so the recycling of them should be conducted with a high technological level in order to minimize the impacts and risks on the environment and people.

However, as shown in Figure 1-10, the recycling of WEEE in Guiyu was done in a primitive way for recovering copper through burning wires and recovering gold as well as other precious metals through using acid chemical strippers (Leung et al., 2006). Moreover, the non-recoverable parts and components from WEEE were burned and dumped arbitrarily. Even if the import of WEEE has improved the local economy, those primitive recycling operations have also resulted in serious environmental pollutions, i.e., heavy metal contamination of soil and water (Leung et al., 2006, Adeola, 2018), and has posed significant risks and impacts on the health and lifestyles of the workers as well as local residents. Furthermore, studies have also revealed a causal relationship between the environmental contamination from the improper reverse logistics activities for WEEE recycling and elevated Blood Lead Levels (BLLs) of children in Guiyu (Huo et al., 2007).

Figure 1-11 Guodingshan incineration plant in Wuhan, China (Hu et al., 2015).

As discussed in previous section, a sustainable reverse logistics system should not only focus on the economic performance but also be able to balance the environment and social dimensions of sustainable development through a series of decision-makings among which the network design is the most important strategic one. An improperly planned reverse logistics network may hinder the viability of the economic benefits from the recovery of EOL and EOU products while simultaneously and dramatically increases the environmental impact and risk to people. Hu et al. (2015) discussed the environmental and social problems related to the improper location selection of Guodingshan incineration plant in Wuhan, China.

Waste incineration is a Waste-to-Energy (WTE) process converting MSW into energy that can be used for electricity generation and space heating. The combustion of MSW results in air pollution and emission of other pollutants, i.e., flying ash, so it is usually required that a buffer zone should be set up between the incineration plant and residential areas. However, as can be seen in Figure 1-11, the Guodingshan incineration plant is surrounded by several residential buildings and has a large amount of emissions when it operates. Guodingshan incineration plant is established in 2006. Since then, it has been continuously complained by the local residents for the air pollution due to the lack of pollution controls and the short proximity to the residential areas.

Figure 1-12 Location analysis of the impact of Guodingshan incineration plant on nearby residential areas (Hu et al., 2015).

In China, it is regulated that a minimum 1000 meters' buffer zone should be established from the waste incineration plant. However, as can be seen in Figure 1-12, six residential arears are located within 1000 meters from Guodingshan incineration plant and more than 30,000 residents living within a proximity less than 800 meters (Hu et al., 2015). That poses significant risk on the health of nearby residents, i.e., cardiovascular diseases (Fiordelisi et al., 2017), respiratory diseases (Ancona et al., 2015, Hu et al., 2015), etc., due to the exposure to air pollution from waste incineration.

The problem related to Guodingshan incineration plant is mainly caused by the improper locations and network planning of the reverse logistics system.

Not only in Wuhan but also in other cities and municipalities in China, the inappropriate design and planning of reverse logistics systems have increasingly resulted in many environmental and social problems. In recent years, because of the perceptions of potential risk and environmental pollution, several protests have been reported in China for resisting the establishment of facilities and projects in reverse logistics (Huang, 2015, Hornby and Lin, 2016, Huang et al., 2015, Johnson et al., 2018).

Based upon the discussions above, the motivation of this PhD project is to first include the environmental and social dimensions of sustainable development in sustainable reverse logistics network design, and then to provide advanced supporting tools for a better decision-making in order to balance economic, environmental and social sustainability.

1.2.2 Challenges to sustainable reverse logistics network design

Sustainable reverse logistics network design is a complex decision-making problem that has to take into account of several objectives simultaneously and involves many different stakeholders. Compared with the network design problem of a traditional forward supply chain, the planning of a reverse logistics system is more complicated due to the following reasons.

1. First, reverse logistics involves more types of different activities and operations, i.e., collection, inspection, sorting and disassembly, transportation and distribution, repair, reuse, remanufacturing, recycling, energy recovery and disposal. This results in a much more complicated network structure.
2. Reverse logistics involves more uncertainties in the returned flow of EOL and EOU products in terms of both quantity and quality (John et al., 2018, Alshamsi and Diabat, 2015, Talaei et al., 2016). And also, in the long period of the lifecycle of a reverse logistics system, some other parameters, i.e., generation of EOL and EOU products, price of the recovered products and cost for facility operation and transportation, etc., may be heavily influenced by the market fluctuation and thus can hardly be predicted accurately (Soleimani et al., 2016, Yu and Solvang, 2017a).
3. Reverse logistics is considered one of the most important steps for sustainable development and circular economy, the inappropriate recovery of EOL and EOU products may generate significant environment impacts and pose potential risks for the local residents,

i.e., the intercontinental transshipment of waste electrical and electronic equipment (WEEE) as well as the low-tech recovery activities undertaken at southeast Asia. Thus, this should be taken into account in the reverse logistics network design.

4. Finally, due to the heterogeneous nature, the processing operations performed at remanufacturing and recycling centers of different EOL and EOU products are by no means identical (Guide Jr, 2000), and this further complicates the reverse logistics network design problem with the considerations of the trade-off between productivity and flexibility of those operations (Yu and Solvang, 2017a).

1.2.3 Objectives and research questions of the PhD project

A great number of mathematical models and methods have been developed in literature for the decision-support of reverse logistics network design with predominate focus on economic performance. However, the modelling efforts in existence are not fully capable to resolve all the challenges regarding the balance of the other dimensions in sustainable reverse logistics network design, control of uncertainty existed in the input information, determination of system flexibility, and so forth.

Therefore, in this PhD project, the primary objective is to develop improved optimization models and methods in order to tackle those challenges and provide decision-makers and practitioners with supports and implications in sustainable reverse logistics network design. From the theoretical and methodological perspective, the PhD project aims at contributing in the literature through the development and improvement of the mathematical model and solution methods for better modelling and reflecting the problem. While, from the practical perspective, the PhD project aims to provide some generic managerial implications through extensive numerical experiments under complex environment and properly designed analytical process. With which, a better decision-making of sustainable reverse logistics network design can be done.

Another objective of the PhD project is to develop and test the optimization models and methods under complex environments so that they can be used for decision-making under a large variety of different environments, i.e., different EOL and EOU streams, different levels of uncertainty, different network structure, and so forth. In such a way, the optimization models and methods should be able to capture the generic features of a sustainable reverse logistics system. While at the same time, they should also be flexible enough for modification in order to reflect the characteristics of a specific system or case.

Besides, in this PhD project, three types of EOL and EOU streams with different features are focused, and thus the model development should provide decision-support tools and implications regarding those three types of EOL and EOU products.

- ***Reverse flow of ordinary EOL and EOU products*:** This type of return contains a large amount of recyclables for value recovery, i.e., WEEE, EOL vehicles, etc., and is suitable for some value-added operations, i.e., remanufacturing, etc.
- ***Reverse flow of MSW:*** This stream contains of a large amount of organic and biodegradable substances for energy recovery through biological, biochemical, and thermal treatments. It is noteworthy that, due to the separation rate of MSW is by no means identical in different countries, the design of a sustainable reverse logistics system for MSW may be of great difference.
- ***Reverse flow of the EOL and EOU products containing hazardous materials and substances:*** This stream contains hazardous substances that may pose significant threat and risk on the environment and people. Thus, special focus needs to be given in the risk control in this stream.

Finally, through the development and improvement on the modelling, solution methods as well as the analysis of managerial implications, the PhD project aims at answering the following research questions.

1. What is the trade-offs between the economic performance and environmental impact in sustainable reverse logistics network design?
2. How to improve the quality of the optimal trade-offs (Pareto optimal solutions) calculated?
3. How to deal with the uncertainties in sustainable reverse logistics network design?
4. How to improve the quality of decision-making under uncertainty and environmental regulations for sustainable reverse logistics network design?

5. How to test the effectiveness of the environmental regulations as well as some other legislative mechanisms for sustainable reverse logistics network design?
6. How to plan a sustainable reverse logistics system with different types of EOL and EOU streams?
7. What are the managerial implications can be obtained from the modelling and numerical experimentations for sustainable reverse logistics network design?

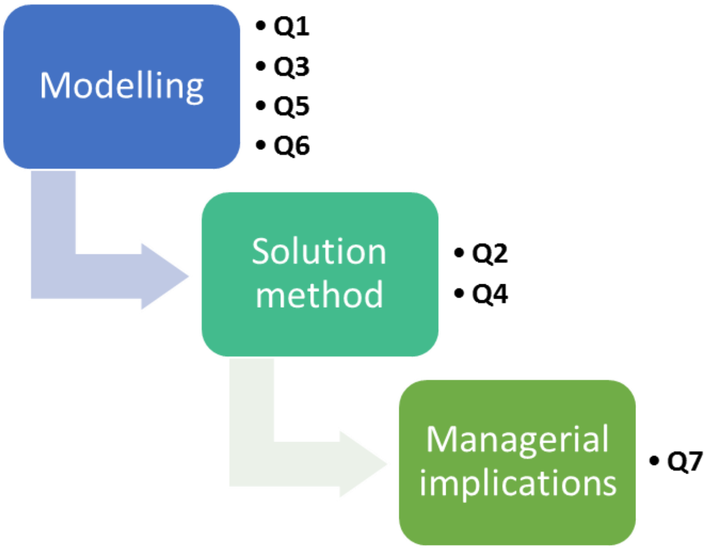


Figure 1-13 Research questions with respect to modelling, solution method and managerial implications reverse logistics network design.

Figure 1-13 illustrates the domain of the research questions with respect to the development on modelling, solution methods and managerial implications in this PhD project. As shown, questions 1, 3, 5 and 6 focus on the modelling efforts in order to formulate new objectives, constraints and elements, and to improve the treatment of uncertain parameters. Questions 2 and 4 emphasize the development of solution methods and algorithm for the proposed optimization problems. Finally, question 7 aims to provide decision-makers and practitioners with some managerial implications in sustainable reverse logistics network design.

1.3 Stakeholders of the PhD project

Stakeholders of the PhD project are those individuals or groups whose interests will be affected by the development of the project, and they can also affect the progress of the project in many different ways (Pinto, 2015). In general, there are two types of stakeholder groups: internal stakeholders and external stakeholders. For the external stakeholders, they can be further divided into two layers with either direct impact or indirect influence on the project development.

As can be seen in Figure 1-14, the internal stakeholders of this PhD project include the PhD candidate, the supervisor, Department of Industrial Engineering, as well as the PhD Programme of Applied Mathematics and Computational Engineering at Faculty of Engineering Science and Technology. The internal stakeholders are an important element in stakeholder analysis, and the impact from them is usually felt in a positive way (Pinto, 2015), say, they wish to have a successful project.

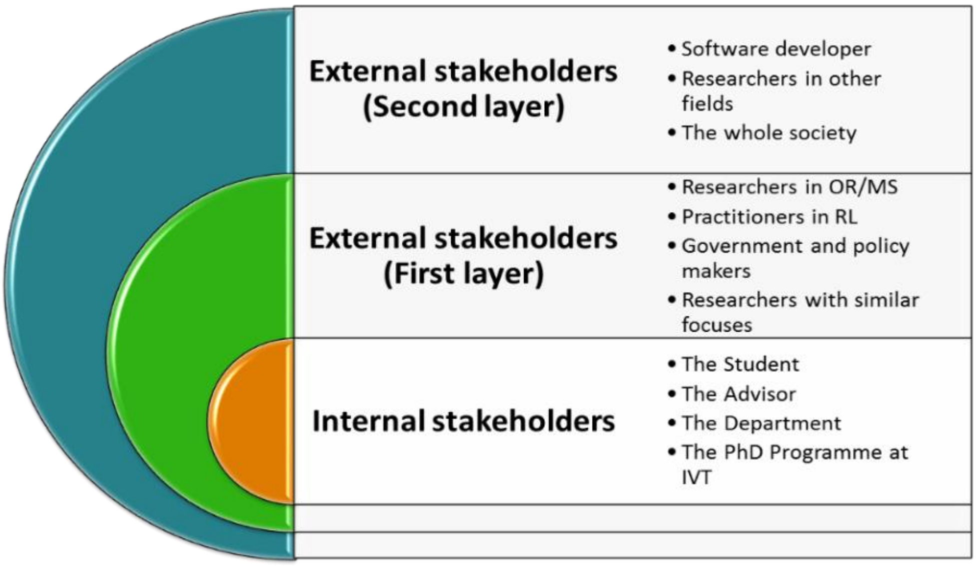


Figure 1-14 Stakeholder analysis of the PhD project.

Two layers of external stakeholders are involved in this PhD project. The first layer external stakeholders are the individuals and groups whose stakes may be directly affected by the development of the project.

- *Academic researchers in relevant fields including operational research (OR) and management science (MS)*: The results of this PhD project contribute to the development of knowledge in the application of operational research and mathematical modelling methods to resolve practical complex decision-making problems.

- ***Practitioners in reverse logistics***: The results of the PhD project provide advanced tools and knowledge for a better decision-making of the planning and operation of a reverse logistics system.
- ***Government and policy makers***: The results of the PhD project provide advanced decision-support systems for testing and validating the effectiveness of different policy mechanisms, i.e., carbon policy, incentives, etc. In addition, the results of the PhD project provide valuable managerial implications.
- ***The other research groups with similar focus***: The influence of the development of this PhD project may affect the other research groups with similar focus from two opposite perspectives. On the one hand, the result may provide them with new methods, tools, insights and inspirations that will contribute to the development of their own projects and knowledge. While, on the other hand, this group of the stakeholders may also be considered as the competitors. Reverse logistics network design is an extensively focused topic, and the publication of any new ideas is about timing and competition with other researchers.

The second layer of external stakeholders are indirectly affected from the development of the PhD project, and the following groups are considered as the second layer of stakeholders.

- ***Researchers in other fields***: The results may be used cross-disciplinarily in other research fields for resolving complex optimization problems with focus on mathematical modelling and operational research.
- ***Software developer***: The results of the PhD project contribute to the development of new solution method for complex decision-making problems, which may be used for the design and improvement of the commercial optimization solvers.
- ***The whole society***: The results of the PhD project contribute to a better future for the whole society by providing tools and implications for the planning of a more sustainable reverse logistics system.

2 Problem Statement

2.1 Problem description

Reverse logistics network design is a complicated decision-making problem in Operational Research (OR) and Management Science (MS). With the difference on the system focus and the heterogeneous characteristics of the EOL and EOU products received, a variety of operations and activities are performed for the value recovery and proper disposal. Figure 2-1 illustrates the network structure of a generic multi-echelon reverse logistics system.

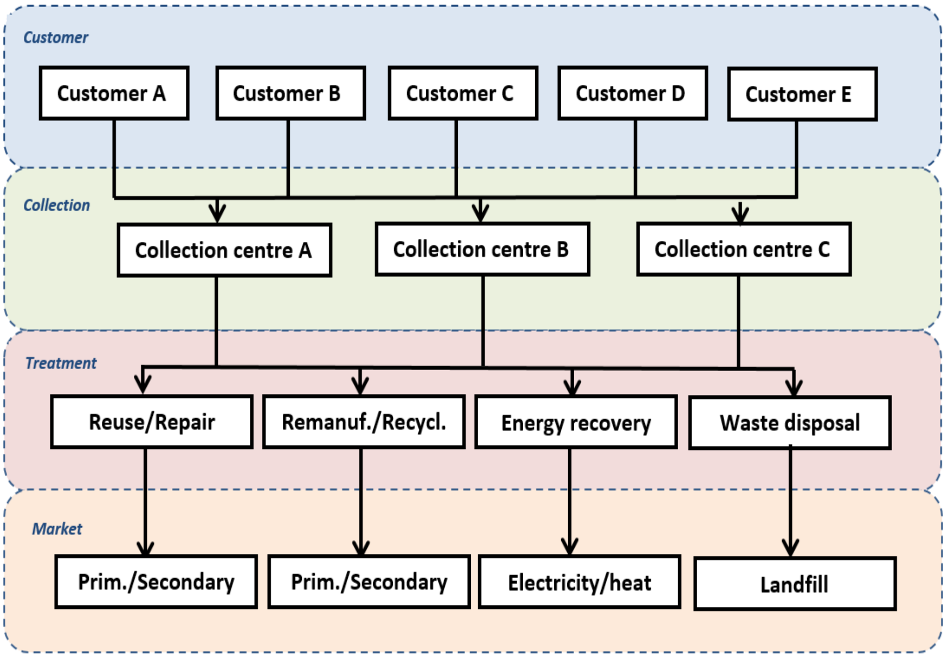


Figure 2-1 The network structure of a generic multi-echelon reverse logistics system (Yu and Solvang, 2016b).

As shown in Figure 2-1, the main operations in a generic reverse logistics system include customer return and local collection, central collection for quality inspection, sorting and disassembly, value recovery operations for EOL and EOU products including reuse, repair, remanufacturing, recycling and energy recovery, and disposal for non-recoverable products. The material flow of the reverse logistics starts from the customer return to the retailers or local collection centers for EOL and EOU products, and then those products are collected and processed at the central collection centers where quality inspection, sorting and disassembly are conducted. In accordance with the type of product and quality level, different value recovery operations are performed. Finally, the recovered products and energy will be sold in the market. Herein, it is noteworthy that the market includes both primary market for remanufactured products and recovered energy as well as secondary market for reused and repaired products, and recycled parts, components and materials.

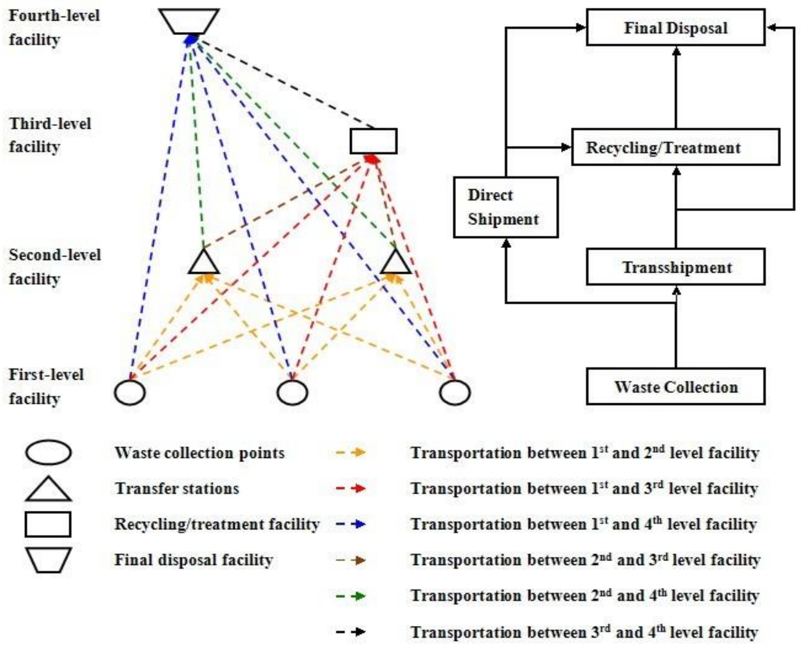


Figure 2-2 Reverse logistics system for waste management (Yu and Solvang, 2017d).

With the different purposes and characteristics of a reverse logistics system, different operations, facilities and modes of transportation are implemented for the value recovery from EOL and EOU products. In this PhD project, different network structures and configurations are formulated and tested for providing managerial insights into the implementation of different network options. For instance, Figure 2-2 shows a reverse logistics system for the management of municipal solid waste (MSW). In this network structure, the MSW can be either transported directly from the local collection centers to the treatment facilities or transshipped via a central collection and distribution center.

Sustainable reverse logistics network design aims at balancing the trade-off among economic, environmental and social sustainability in an optimal fashion through a series of decision-makings. In order to capture the features of different reverse logistics systems, improved optimization models and methods are developed in this PhD project, which aim at dealing with the different issues in the design of a multi-product multi-echelon sustainable reverse logistics network. For obtaining this goal, several modelling and optimization techniques are used, i.e., stochastic programming, multi-objective programming and mixed integer programming in order to formulate and tackle the complex decision-making problems, i.e., the impact from uncertainty, trade-off between economic performance and environmental impacts in the value recovery, policy mechanisms and system flexibility.

Considering the timing of decision-making, the planning of a sustainable reverse logistics system includes two stages of decisions at both strategic and operational levels, and the decisions have to be made under a certain level of uncertainty. From the modeling perspective, this feature can be well captured by formulating a two-stage stochastic programming. As many argues (King and Wallace, 2012, Birge and Louveaux, 2011), formulating an uncertain decision-making problem with a two-stage stochastic programming provides decisions at two levels with different characteristics: robust or flexible. The first stage decisions are made before the realization of uncertain parameters and should be robust to withstand random events (e.g. a bus schedule). While on the other hand, the second stage decisions can be made after the realization of the scenarios with more certain information of the problem and should be flexible to cope with the change of external environment in order to maximize the benefits.

In the planning of a sustainable reverse logistics network, the optimization models and methods developed in this PhD project aim at supporting decisions at both levels:

1. First level decisions include:
    - Number and locations of different facilities
    - Capacity installation at different facilities
    - Determination of the level of flexibility at different facilities
2. Second level decisions:
    - Operational plan of different facilities
    - Demand allocations of EOL and EOU products
    - Transportation strategy among different facilities

It is obviously that the first stage decisions determines the physical configurations of the network structure and thus have long-term impact on the performance of a sustainable reverse logistics network system. Therefore, those decisions should be featured with robustness. While, on the other hand, even if the models can also determine optimal values for the second stage decisions, they can be easily altered and continuously optimized after the realization of uncertainty due to their flexible nature.

Based on the discussion above, it is noteworthy that the focus of sustainable reverse logistics network design problem should be predominately given to the determination of the robust and optimal decisions at the first stage with respect to the defined objectives of system design.

2.2 State-of-the-art research on reverse logistics network design

Quantitative modelling efforts for a logistics system aim at providing decision-makers and stakeholders with strategic analysis for an effective and efficient decision-making of logistics network design (Fahimnia et al., 2015). Due to the complex nature of a sustainable reverse logistics system, the network design problem has been focused by both academic researchers and practitioners (Govindan et al., 2015b, Yu and Solvang, 2016b), and numerous mathematical models have been developed for a large variety of industries and businesses (Alshamsi and Diabat, 2015). Comprehensive reviews of literatures related to reverse logistics problems have been given with different focuses, i.e., conceptual development and perspectives (Wang et al., 2017, Agrawal et al., 2015), industry focused studies (Campos et al., 2017), quantitative models and techniques (Govindan et al., 2015b, Govindan and Soleimani, 2017, Bazan et al., 2016, Fleischmann et al., 1997), and modelling methods incorporating with sustainability (Ilgin and Gupta, 2010, Eskandarpour et al., 2015).

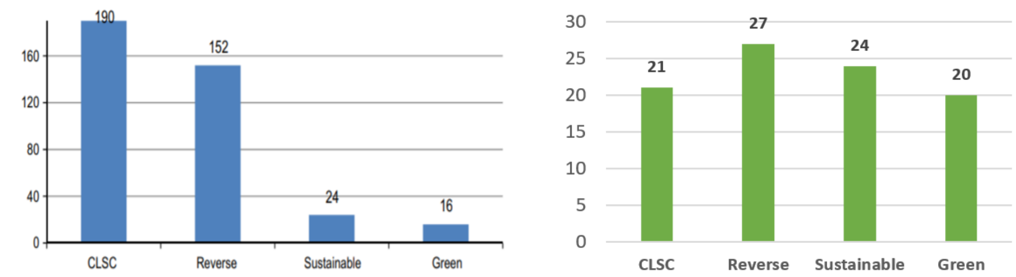
Due to the quantitative nature, the literature review given in the PhD research presents an overview of the recent development and advancement of the optimization models and methods for reverse logistics network design. Detailed literature review and comparison are provided in the included papers in this PhD thesis. **Paper 1** (Yu and Solvang, 2016b) includes a comprehensive literature survey on the optimization models and methods published before 2016. **Paper 2** (Yu and Solvang, 2018) and **Paper 4** (Yu and

Solvang, 2017a) present the latest development on modelling techniques and solution methods with focus on uncertainty as well as other characteristics. **Paper 3** (Yu and Solvang, 2016c), **Paper 5** (Yu and Solvang, 2017d) and **Paper 6** (Yu and Solvang, 2016c) give the literature review on the optimization models and methods for planning a sustainable reverse logistics system with the focus on different types of returned streams: WEEE management, MSW management and hazardous waste management, respectively.

In this section, based on the papers reviewed in **Paper 2**, a vis-à-vis comparison between the latest development and earlier research works on optimization models and methods for reverse logistics network design is presented in Figure 2-3, Figure 2-4 and Figure 2-5. In those figures, 48 latest research papers published in academic journals with focus on the optimization models and methods for reverse logistics network design are reviewed, and the result is compared with that from Govindan et al., (2015c). For the selection of the relevant papers, the databases: *Web of Science* and *Scopus* were used with different combinations of the keywords, i.e., "reverse logistics", "model", "facility location", "operational research", "optimization", "network planning" and "network design", and only journal articles are included in the literature search. The selected papers were then undergone a manual check for the relevance of the topic of interest in order to eliminate the non-relevant papers.

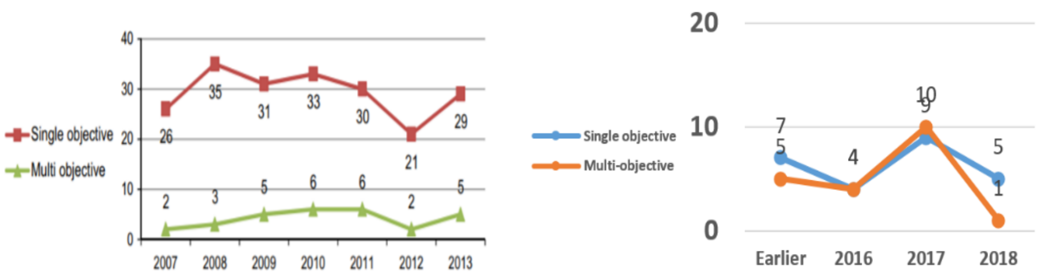
Figure 2-3 illustrates the comparison of the network structure and environmental consideration for reverse logistics network design. Figure 2-4 and Figure 2-5 compare the objectives and material flows of the optimization models and methods for reverse logistic network design. As can be seen in the figures, the earlier optimization models are formulated with single objective function focusing only on the economic performance of the reverse logistics system (Govindan et al., 2015c). The objective is either to maximize profits or minimize costs (Govindan et al., 2015c, John et al., 2018)., but the other aspects for sustainable development has not been focused and formulated until the recent three years. Moreover, some earlier research works consider the environmental problems of an integrated forward/reverse logistics network, but only the environmental impact from the forward logistics activities is emphasized.

With more emphasis on the environmental and social aspects of sustainability, the trade-off between economic performance and sustainability-related measures of reverse logistics network design has been increasingly focused in recent research works (Yu and Solvang, 2016b, Govindan et al., 2015b, Govindan et al., 2016a, Govindan et al., 2016b, Kannan et al., 2012, Soleimani et al., 2017, Soleimani et al., 2016, Yu and Solvang, 2017, Feitó-Cespón et al., 2017, John et al., 2017, Keshavarz Ghorabaee et al., 2017, Talaei et al., 2016, Rahimi and Ghezavati, 2018). Furthermore, due to the pressure from the whole society and stakeholder interests (Fahimnia et al., 2015b), practice-based studies have also revealed that the top management of companies has paid much more attention for the green practices and management of the supply chain (Vlachos et al., 2007, Lacy et al., 2010). Therefore, it is of paramount importance to incorporate the sustainability-related measures in the reverse logistics network design in order to provide decision-makers and practitioners with a more appropriate trade-off analysis, insights and better suggestions.



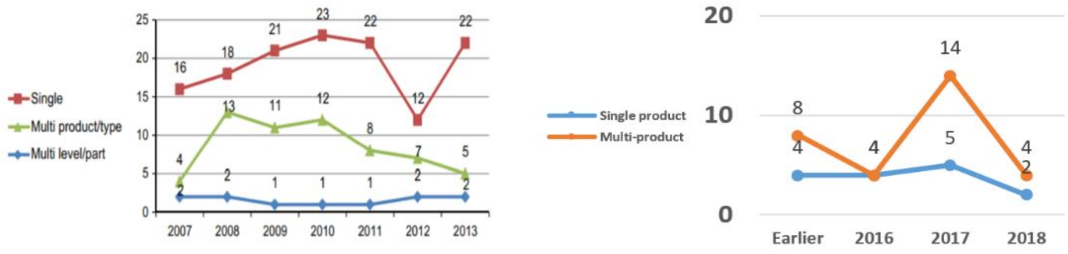
(A) (B)

Figure 2-3 The focused fields of the papers in (A) Earlier research works (Govindan et al., 2015b); (B) The latest literature.



(A) (B)

Figure 2-4 Single objective models vs. multi-objective models in (A) Earlier research works (Govindan et al., 2015b); (B) The latest literature.



(A) (B)

Figure 2-5 Single product system vs. multi-product system in (A) Earlier research works (Govindan et al., 2015b); (B) The latest literature.

Table 2-1 gives a vis-à-vis comparison of the optimization models for reverse logistics network design regarding four aspects: Network structure (Reverse logistics (RL) vs. integrated forward/reverse logistics or closed-loop supply chain (CLSC)), material flows of EOL and EOU products, design objectives, and control of uncertainty. The selection of literature focuses on the latest development and most of the literature used are recently published. In addition, some of the highly impacted earlier research works are also included in the table.

Table 2-1 A vis-à-vis comparison of the literature on reverse logistics network design

Year	Paper	Network	Flow	Objective	Uncertainty
Before 2016	Demirel and Gökçen (2008)	CLSC	Multiple	Single	Deterministic
	Pishvaee et al. (2009)	CLSC	Single	Single	Stochastic
	El-Sayed et al. (2010)	CLSC	Single	Single	Stochastic
	Pishvaee et al. (2011)	RL	Single	Single	Robust
	Kannan et al. (2012)	RL	Single	Multiple	Deterministic
	Amin and Zhang (2012)	CLSC	Multiple	Single	Deterministic
	Diabat et al. (2013)	CLSC	Multiple	Single	Deterministic
	Özkır and Başlıgil (2013)	CLSC	Multiple	Multiple	Fuzzy
	Ramos et al. (2014)	RL	Multiple	Multiple	Deterministic
	Garg et al. (2015)	CLSC	Multiple	Multiple	Deterministic
	Ghayebloo et al. (2015)	CLSC	Multiple	Multiple	Deterministic
	Capraz et al. (2015)	RL	Multiple	Single	Deterministic
	Alshamsi and Diabat (2015)	RL	Single	Single	Deterministic
2016	Demirel et al. (2016)	RL	Single	Single	Deterministic
	Ghezavati and Beigi (2016)	RL	Single	Multiple	Deterministic
	Yu and Solvang (2016b) **Paper 1**	RL	Single	Multiple	Deterministic
	Govindan et al. (2016b)	RL	Single	Multiple	Fuzzy

Table continued

	Zandieh and Chensebli (2016)	RL	Single	Single	Deterministic
	Govindan et al. (2016a)	CLSC	Multiple	Multiple	Deterministic
	Yu and Solvang (2016a) **Paper 3**	RL	Multiple	Multiple	Stochastic
	Kheirkhah and Rezaei (2016)	RL	Multiple	Single	Deterministic
	Talaei et al. (2016)	CLSC	Multiple	Multiple	Robust fuzzy
2017	Li et al. (2017)	RL	Single	Single	Deterministic
	Guo et al. (2017a)	RL	Single	Single	Deterministic
	Silva et al. (2017)	RL	Single	Multiple	Deterministic
	Guo et al. (2017b)	CLSC	Single	Multiple	Deterministic
	Budak and Ustundag (2017)	RL	Single	Single	Deterministic
	Entezaminia et al. (2017)	CLSC	Multiple	Multiple	Robust
	Keshavarz Ghorabaee et al. (2017)	CLSC	Multiple	Multiple	Fuzzy
	Jindal and Sangwan (2017)	CLSC	Multiple	Multiple	Fuzzy
	John et al. (2017)	RL	Multiple	Multiple	Deterministic
	Yilmaz et al. (2017)	RL	Multiple	Multiple	Deterministic
	Kannan et al. (2017)	RL	Multiple	Single	Deterministic
	Temur and Bolat (2017)	RL	Multiple	Multiple	Deterministic
	Fattahi and Govindan (2017)	CLSC	Multiple	Single	Stochastic
	Feitó-Cespón et al. (2017)	RL	Multiple	Multiple	Stochastic
	Babaveisi et al. (2017)	CLSC	Multiple	Multiple	Deterministic
	Soleimani et al. (2017)	CLSC	Multiple	Multiple	Fuzzy
	Alshamsi and Diabat (2017)	RL	Multiple	Single	Deterministic
	Yu and Solvang (2017a) **Paper 4**	RL	Multiple	Multiple	Stochastic
2018	Fard and Hajaghaei-Keshteli (2018)	CLSC	Single	Single	Deterministic
	Rahimi and Ghezavati (2018)	RL	Single	Multiple	Stochastic
	John et al. (2018)	RL	Multiple	Single	Deterministic
	Trochu et al. (2018)	RL	Multiple	Single	Stochastic
	Jabbarzadeh et al. (2018)	CLSC	Multiple	Single	Robust
	Haddadsisakht and Ryan (2018)	CLSC	Multiple	Single	Stochastic robust
	Yu and Solvang (2018) **Paper 2**	RL	Multiple	Multiple	Stochastic

As can be seen, the recent trend of the research on reverse logistics network design has shown that an increasing focus has been given to the balance of economic benefits and other aspects of sustainable development. Besides, it is also observed that the recent models place more emphasis on the design of a multi-product system, and the decision-making with inexact parameters is also focused compared with the models developed earlier.

2.3 The literature gap and research focus of this PhD project

This research project was started in 2016 and the motivation of this research is mainly from the survey of literature before 2016, so the similar result is obtained as that given in Govindan et al., (2015c). This section presents the literature gaps and discusses the research focus of the PhD project.

1. The focus of previous research works has predominately given to the "economically sustainable design of a reverse logistics system" but not sustainable reverse logistics network design as defined in Section 1.1.5. The earlier optimization models and methods for reverse logistics design only focus on the economic performance, so the formulation and development of multi-criteria decision support models for taking into account of the other measures of sustainability, e.g., environmental impact, in sustainable reverse logistics network design is of importance. Due to this reason, the primary objective of this PhD study is to fill the literature gap and develop improved optimization models and methods for resolving the trade-off problem between economic performance and other environmental and social performance in sustainable reverses logistics network design.
2. The planning of a reverse logistics system involves many uncertainties that are difficult to be predicted accurately, i.e., quantity and quality of EOL and EOU products, costs for facility operation and transportation, price for recovered products, and so forth. However, the majority of the earlier mathematical models are developed based upon deterministic inputs and are therefore incapable to deal with the influence from the uncertainties. Further, some stochastic optimization models are formulated and investigated for the design and development of an integrated forward/reverse logistics system, but the uncertainty issue is mainly focused on the forward channels (e.g., customer demands) not on the reverse flows that also involves

uncertainty issues. Due to this reason, the control of uncertainty in the decision-making problem of sustainable reverse logistics network design is of importance. In addition, the improvement of the solution method for an optimization model with inexact parameters is also of interest in order to guarantee the reliability and robustness of the optimal solution obtained.

3. Another problem related to reverse logistics network design is the product flow. Most of the earlier modelling efforts consider single product flow, and only some of the studies consider the recovery of multiple products, as shown in Table 2-1. Furthermore, most of the multi-product models in literature formulate a non-flexible capacity constraint with respect each type of product, while the other models are formulated through a "generic capacitated location problem" neglecting the difference between the processing procedures and resources required. However, the impact of system flexibility on sustainable reverse logistics network design has not been investigated. Modelling a reverse logistics design problem under uncertainty based upon a generic "capacitated location problem" may neither be able to find out the optimal solution in strategic decision-making nor provide valuable suggestions for the plant planning decisions, i.e., layout planning, internal route planning. Thus, this PhD research project aims also at resolving this problem.
4. Some important policy mechanisms, regulations as well as other considerations, i.e., the effectiveness of carbon policies, the effectiveness of economic incentives for promoting the reuse and recycling of EOL and EOU products, and so forth., have not been thoroughly considered and formulated in earlier optimization models. However, those may greatly affect the decision-making of the design of a sustainable reverse logistics system. Therefore, the formulation and investigation of those policy mechanisms and regulations are of interests.
5. Except the focus on improving the modelling techniques and solution methods, the experimental analysis and managerial implications are of significant importance especially for the government, policy makers as well as practitioners to have a better insight of sustainable reverse logistics network design. Therefore, in this PhD project, through the use of numerical experiments, comparative study and sensitivity

analysis, the research focus is also given to provide managerial implications related to some key problems and trade-offs in sustainable reverse logistics network design.

The PhD project aims at filling the literature gap of pervious research and resolving the aforementioned challenges through developing and testing the improved optimization models and methods for sustainable reverse logistics network design.

3 Research Design, Methods and Analysis

3.1 Research design and methods

Research design is the most important and fundamental step for any type of research. With a focus on the research development in social science disciplines, de Vaus (2001) argues that the objective of a research design "*is to ensure that the evidence obtained enables us to answer the initial question as unambiguously as possible*". No matter what is focused on a research project, i.e., test of a new theory, or development of a new model, or design a survey for obtaining implications, etc., research design aims at dealing with the logical problems. It establishes solid steps for a research project, through which the initial research questions can be answered in a scientifically and logically rigorous and practically convincing way.

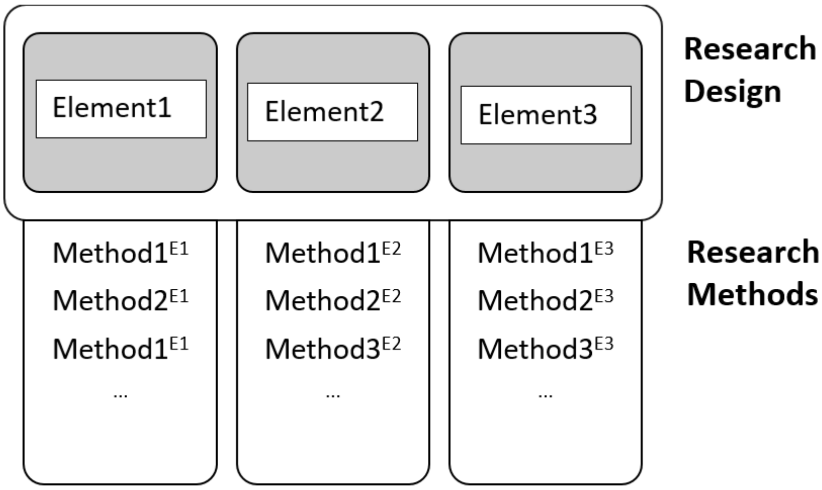


Figure 3-1 Research design and research methods for a research project.

Research design focuses on the fundamental elements of a research project, under which the methodologies and methods developed and/or employed are determined by the research methods. Figure 3-1 illustrates the difference between research design and research methods. Research methods come in two general categories: quantitative method or qualitative method (Neuman, 2013, Babbie, 2015). The quantitative method emphasizes, by using numerical, statistical, mathematical and analytical approaches, to understand, generalize and explain a particular phenomenon and/or to predict a future event in the nature or human society (Babbie, 2015). In social science disciplines, a quantitative model aims to use numbers as input for analysing a phenomenon, optimizing a system or making a decision. It is noteworthy that the inputs of a quantitative model may be both subjective or objective values (Pinto, 2015). The qualitative method, on the other hand, employs and relies on non-numerical information for observation, analysis and decision-making.

3.2 Research design of the model development for sustainable reverse logistics network design

Sustainable reverse logistics network design is a complex decision-making and optimization problem. The research conducted in this PhD project is featured with quantitative nature and aims to develop and improve the optimization models and methods for sustainable reverse logistics network design. In order to achieve goal, the fundamental elements of the research design of this PhD project are given as follows.

- System and environment
- Purpose of the model
- Assumptions
- Modelling and solution method
- Software selection and integration
- Numerical experiments

In the following sections, the connections and influences of those elements and factors for the model development are discussed in the context of sustainable reverse logistics network design.

3.2.1 System and environment

When an optimization model is built, it is of essential importance to take into account of the system and environment under which the model is developed and is used for decision-making. Reverse logistics is a complex system that involves different activities and stakeholders, and many influencing factors should be taken into consideration in the development of the decision-support models for sustainable reverse logistics network design. In this PhD research project, the influencing factors used to describe the system and environment for model development are identified in Table 3-1.

Table 3-1 System and environment of the model development for sustainable reverse logistics network design

Types of influencing factors	Influencing factors	Alternatives
Nature of the system and environment	Types of the reverse flow	• Return of ordinary EOL and EOU product • Return of MSW • Return of hazardous materials and waste
	Uncertainty and fluctuations	• Low level of uncertainty • Medium level of uncertainty • High level of uncertainty
Technological factors	Recovery options	• Reuse and repair • Remanufacturing • Recycling • Energy recovery • Disposal
Logistical factors	Products in the reverse flow	• Single type of product • Multiple types of product
	Network structure	• Single echelon • Multiple echelons
	Transportation mode	• Direct transport • Indirect transport via intermediate nodes • Mixed direct and indirect transport
	Capacity options	• Rigid capacity • Flexible capacity
Regulation factors	Legislative requirements	• Carbon tax • Carbon cap • Recoverable amount requirement • Restrictions on the entry of landfill
Evaluation factors	Performance objectives	• Economic performance • Environmental friendliness • Social responsibility

In accordance with their characteristics, the influencing factors can be categorized into five classes and are described by several alternatives. With the combination of the alternatives with respect to each influencing factor, the system and environment of a specific reverse logistics system, under which the decision-making model is developed, can then be depicted accordingly. Taking the model development in **Paper III** as an example, the characteristics of the system and environment can be described in Table 3-2.

Table 3-2 System and environment of the model development for sustainable reverse logistics network design for WEEE recovery in **Paper III**

Types of influencing factors	Influencing factors	Alternatives
Nature of the system and environment	Types of the reverse flow	• Return of ordinary EOL and EOU product • Return of hazardous materials and waste
	Uncertainty and fluctuations	• High level of uncertainty
Technological factors	Recovery options	• Reuse and repair • Recycling • Disposal
Logistical factors	Products in the reverse flow	• Multiple types of product
	Network structure	• Multiple echelons
	Transportation mode	• Indirect transport via intermediate node
	Capacity options	• Rigid capacity
Regulation factors	Legislative requirements	• Carbon tax
Evaluation factors	Performance objectives	• Economic performance • Environmental friendliness

The formulation of an optimization model for a decision-making problem is contextual, which means it is heavily influenced by the system and environment. Even if for the same decision-making problem, i.e., sustainable reverse logistics network design, under different system and environment, different modelling techniques, parameters and decision variables may be selected, and different objectives and constraints may be formulated, and different implications may be obtained. For the given problem in **Paper III**, the reverse flow includes multiple types of WEEE containing both precious metals and hazardous substances, and the network structure is a multi-echelon system with several value recovery operations and indirect transport mode via intermediate collection center. The reverse logistics system is operated under high level of uncertainty, so the control of uncertainty should be taken into account in the model development. Further, for reducing the carbon footprint from the reverse logistics activities, a carbon tax policy is formulated and is then integrated into the objective function as a soft constraint in the model development.

Nevertheless, when the system and environment change, the model may be developed in an entirely different way. In sustainable reverse logistics network design, even if the decision-making on each project is considered an ad-hoc endeavor, the optimization models, on the other hand, should share some common elements based on which the decision-support model for a specific problem under a different system and environment can be effectively and efficiently re-formulated.

In the PhD project, through the modelling efforts in six research papers, the generic features of sustainable reverse logistics network design is focused by covering a large variety of complex system and environment, i.e., from a single product flow, simplified logistical configuration under deterministic environment to a multi-product flow, complex logistical configuration under stochastic environment. In this PhD Project, the improved optimization models and methods are formulated and tested under some comprehensive environments. Thus, they can form the fundamental elements for modelling a variety of complicated decision-making problems on sustainable reverse logistics network design.

3.2.2 The purpose of model development

The objective of the improved optimization models and methods is, through mathematical modelling, optimization and numerical analysis, to provide decision-makers, supply chain managers as well as the other practitioners with an effective and efficient quantitative tool for supporting the decision-making of sustainable reverse logistics network design under a large variety of complex system and environment. Figure 3-2 illustrates the decision-making process of sustainable reverse logistics network design. As shown, there are three main elements of the planning: input information, decision-support system, and output information, respectively.

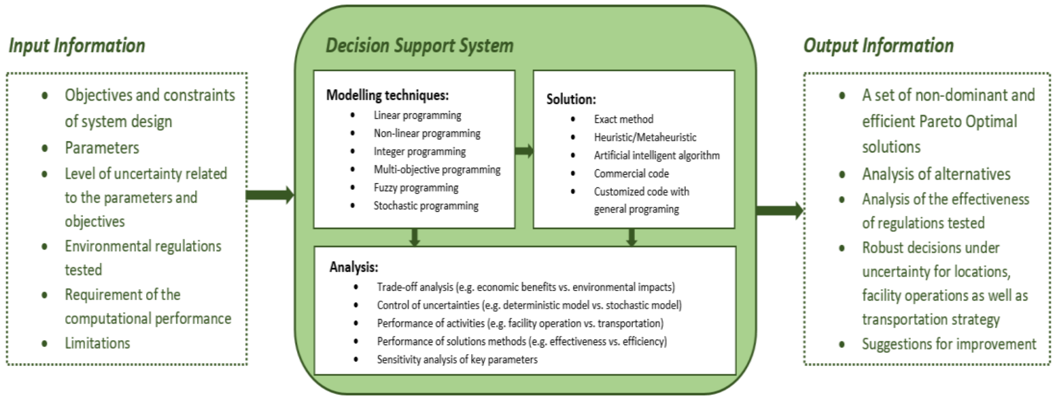


Figure 3-2 Decision-making for sustainable reverse logistics network design.

The elements in input information, decision-support system and output information are presented as follows.

Input information:

- Objectives and constraints
- Parameters
- Level of uncertainty of some key parameters
- Legislative mechanism
- Requirement on computational efficiency

Decision support system:

- Selection of appropriate modelling techniques
- Selection of appropriate solution methods
- Modelling the system and programming the solution code
- Analysis of the result, i.e., trade-off analysis, control of uncertainties, performance of activities, performance of solution methods and algorithm, as well as sensitivity analysis of some key parameters

Output information:

- A set of optimal trade-offs (high quality non-dominant and efficient Pareto optimal solutions)

- Robust decisions under a deterministic or uncertain environment, i.e., the number and locations of facilities opened, facility operation plans as well as the transportation strategy
- Analysis of the alternative plans
- Analysis of the impact from market fluctuation
- Analysis of the effectiveness of the environmental regulations and other policies tested.
- Suggestions for the improvement

The input information depicts the system and environment under which the reverse logistics system is operated, and thus decision-support is in need. In addition, the input information also specifies the requirement on performance, i.e., computational time, and provides knowledge on parameters. Through the "magic box" of decision-support system including optimization and analysis of numerical results, some important managerial implications can be obtained for a better decision-making of sustainable reverse logistics network design.

Therefore, the purpose of model development is to properly convert and correctly interpreted the problem identified, system and environment as well as other relevant information into the objective of the "magic box", based upon which the assumptions can be made, the models and solution method can be formulated, and numerical experiments can be designed. Taking **Paper III** as an example, the purpose of model development can be described as the development of a mathematical model for supporting the design of a reverse logistics system dealing with multiple products of WEEE, considering both economic and environmental sustainability, and operating under a high level of uncertainty.

3.2.3 Assumptions

In the model development, several assumptions are made in order to simplify the modelling and computation. Although different assumptions may be given for sustainable reverse logistics network design under different system and environment, six general assumptions shared by all the papers in this PhD project are given as follows.

1. The locations of different nodes as well as other relevant network information are known.
2. The candidate locations for new facilities have been determined.
3. The relevant parameters for economic and environmental analysis are known or can be estimated by statistical analysis, experience as well as other methods.
4. For facility selection, the cost and environmental impact are associated with the operations conducted for value recovery or disposal.
5. The linearly proportional relationship is used to formulate the change of variable costs and carbon emissions related to facility operation and transportation with respect to the quantity received.
6. Demand satisfaction, flow balance and capacity requirements are fulfilled in all situations.

The first three assumptions require adequate input information is available for decision-making. The fourth and fifth assumptions simplify the modelling of economic and environmental performance with respect to facility selection, operation and transportation. The last assumption gives the logistical requirement. Besides, new assumptions may be given for a specific reverse logistics system under different environments. For example, in **Paper V,** a new assumption is made to allow the mixed transport mode for MSW management, while this assumption is not given and implemented in other models developed under different system and environment.

It is noteworthy that, in the design of a supply chain network or a logistics system, some assumptions above are under critics by some practitioners for the unrealistic or imprecise representation of the system modelled. For example, for calculating the transportation costs, researchers usually implement a linear relationship between unit cost and quantity transported, but practitioners may prefer to calculate it with the use of trucks. Even if the calculation based on the use of trucks is more realistic, but from a modelling perspective, this will convert a linear constraint to a non-linear integer constraint that requires significant efforts to deal with the re-formulation and the computational challenges. Further, for a decision-making at strategic level, the benefits yielded from the re-formulation may be very limited. Thus, holding in mind, even if the most sophisticated model is just a partial reflection of the real system (Pinto, 2015). With those assumptions, the model development aims to mathematically capture the most important characteristics of the decision-making problem on sustainable reverse logistics network design, but it is not with an objective to re-create every tiny and insignificant details of the problem.

3.2.4 Modelling and solution methods

In order to achieve the objective and purpose of the decision-support model, several modelling techniques and solution methods in operational research are investigated. Operational research/operations research (OR), as defined by The Institute for Operations Research and Management Science (INFORMS), is "*a scientific approach to analysis problems and make decisions. It uses mathematics and mathematical modeling on computers to forecast the implications of various choices and zero in on the best alternatives*"(INFORMS, 2018). Even if sustainable reverse logistics network design is a new problem, it can be formulated based upon some established and well-understood problems in operational research.

Figure 3-3 illustrates the evolutionary process from a location problem to a complex sustainable reverse logistics network design problem. Nevertheless, from the modelling perspective, all the problems listed belong to the same class. In essence, the modelling of the sustainable reverse logistics network design problem is not a creation process but rather an improvement process based upon some established and well-studied models. In accordance with the purpose of model development, new parameters are selected, new objectives and constraints are formulated, and a more complex environment is mathematically simulated.

Figure 3-3 Evolutionary process of the model development for sustainable reverse logistics network design.

The most important decisions in modelling is, based on the purpose of model development, to determine which modelling techniques should be used, and then developing an effective and efficient solution method. In sustainable reverse logistics network design, the mathematical modelling, design of solution method, and analysis of the result from computational experiments are the most essential parts for the decision-making. Due to the complexity of sustainable reverse logistics network design, the formulation of the problem may involve several modelling techniques, i.e., linear programming, non-linear programming, integer programming, mixed integer programming, multi-objective programming, goal programming, fuzzy programming, stochastic programming and robust programming, etc. The combination of several mathematical modelling techniques in a decision-support model will greatly increase the computational complexity of the problem, so different solution methods and algorithms are developed in order to resolve the optimization problem.

In order to choose the proper methods for modelling and resolving the optimization problem of sustainable reverse logistics network design, Figure 3-4 shows the selection process among different alternatives. As shown, the initial step is, based on the purpose of model development, to identify the design requirements of a sustainable reverse logistics system including the objectives and constraints. The second step is to identify the alternative methods. In this step, there are two layers of alternatives. The first layer is to determine the modelling techniques to be used, and for each of them, there are different alternatives for the solution methods, which is given in the second layer. It is noteworthy that different methods may be applied to solve the same problem, but their performance in quality and computational efficiency may be with great difference. Usually, it is another trade-off to be balanced in the model development. For example, as discussed in **Paper II**, compared with the weighting method, the augmented ε-constraint method can generate better solutions with a compromise on computational efficiency.

The third step is the analysis of alternatives and decision-making. In this step, the criteria for the selection of alternative methods are first defined in accordance with the goal of analysis. Then, each criterion will be allocated to a weight in order to represent its relative importance, and the performance is also evaluated. Finally, the risk management of each alternative is performed and the recommended alternative is suggested. The fourth step is to select alternative and consider the feasibility of the implementation. When considering the feasibility of the selected alternative methods, the limitation on time, budget as well as performance of the project should be taken into account.

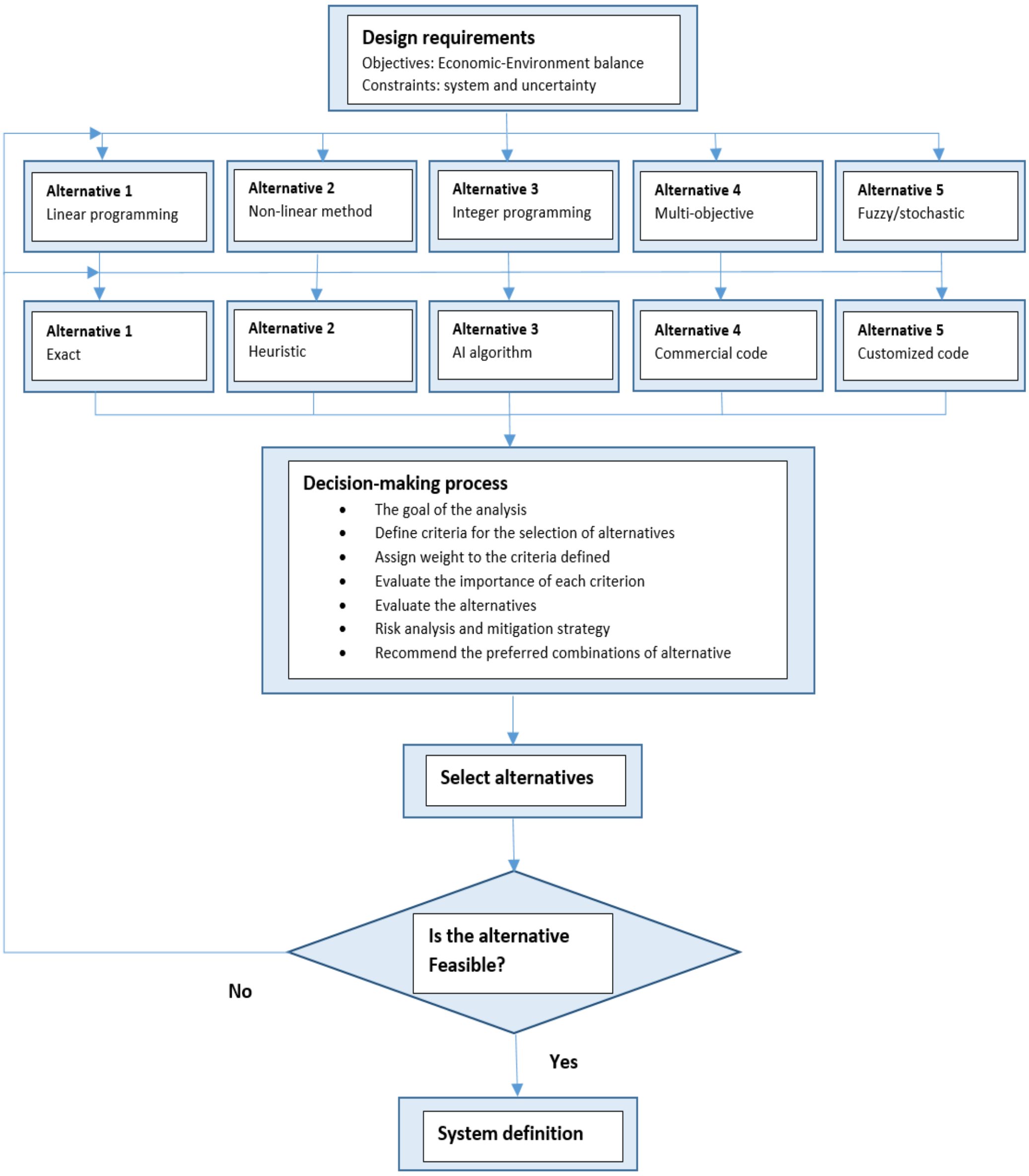


Figure 3-4 Selection method for the alternatives of modelling techniques and solution methods.

3.2.5 Software selection and integration

After a mathematical model has been formulated and a solution method has been designed, the natural next step is to generate the computer code for testing them. In this phase, one has to decide which programs or optimization packages should be used, i.e., a commercial one, or an open source one, or designing a new dedicated program. Investigations have been conducted for benchmarking and comparing different optimization solvers and packages (Dolan and Moré, 2002). In this PhD project, five influencing factors are mainly considered in the software selection.

- ***Availability:*** means whether the product license is available for using the solver.
- ***Reliability:*** means if the solver has been extensively tested and is reliable on its performance.
- ***Capability:*** means if the solver is capable with solving a large variety of optimization problems.
- ***Effectiveness and efficiency:*** measures how good the optimal solution can be achieved and how fast the problem can be solved with the solver.
- ***Integration:*** measures how the different elements are connected and integrated.

Compared with the open source ones, most commercial solvers have been well tested in practices and reported in literature. Therefore, considering the reliability, only widely used commercial optimization packages are taken into consideration in this project.

Today, a large amount of high-performance commercial solvers is available and free for use in academia, i.e., Lingo, CPLEX, Gurobi, Xpress, Julia, etc. Each of which is with different focuses on performance. For example, CPLEX aims at providing a powerful solver for large-scale integer and mixed integer programming, while on the other hand, Xpress puts predominate focus on the convex optimization problems. Meanwhile, some optimization solvers can be applied to solve a large amount of different types of problems, i.e., Lingo, while the others focus on one or some specific types of problems. Thus, the selection is done considering the balance among different factors.

In this PhD thesis, Lingo is selected and used for coding the optimization models and methods developed. The reason for that is, compared with other solvers, Lingo is a powerful solver and has a good capability to solve a large variety of different types of optimization problems including linear programming, integer/mixed integer programming quadratic programming, and non-linear programming. Further, the latest version is also capable with converting a deterministic problem to a stochastic problem with a given type of probability distribution on the stochastic parameters and then solving it. Meanwhile, Lingo's performance on the effectiveness and efficiency also fulfills the requirement of this project.

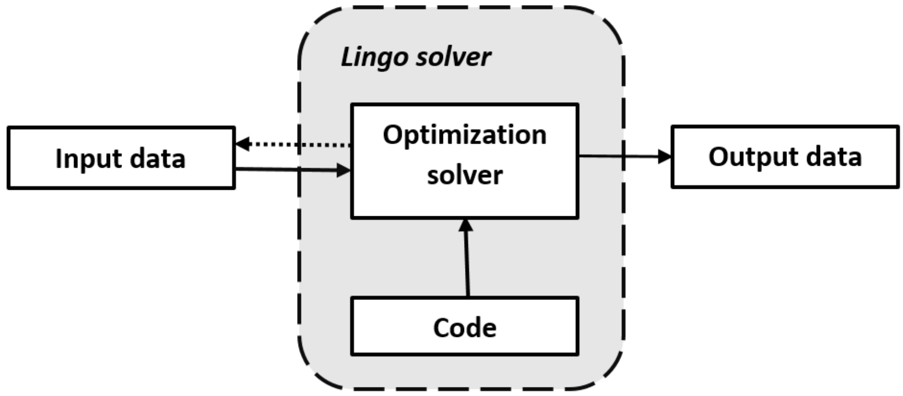


Figure 3-5 Integration of code, data and optimization solver in Lingo.

Another important consideration is integration. The optimization performed on a computer requires three basic elements: code, data and solver. Usually, code and data are generated on different files. Code is generated from the model and solution method and can be used for different problems with the same structure. However, on the other hand, data is collected or generated, and used only for a specific problem. As shown in Figure 3-5, the files of code and data are generated individually. The code is first inputted to the solver, with which the required data file will be recalled and inputted to the solver, and finally the optimization results will be outputted.

Compared with many other optimization solvers, all the Lingo solvers are directly connected with the coding environment, through which the problem can be seamlessly and quickly directed to the proper solver in memory without passing through many layers of intermediate files (LINDO, 2018). The advantage of the integration between the solver and coding environment is that it eliminates the compatibility problem between the programming language and solver components (LINDO, 2018). Nevertheless, on the other hand, this integration limits only one dedicated language can be used for modelling and coding under the lingo environment, which reduces its flexibility to integrate with some common programming languages, i.e., Python, C++, etc.

3.2.6 Numerical experiments

In comparison with classical laboratory experiment, the term of numerical experiment or numerical experimentation refers to "*calculation with numerical models*" (Bowman et al., 1993). With the properly designed numerical experiments, some deep insights into the model's behavior as well as the nature and behavior of the problem or system it formulates can be obtained in an effective and efficient manner. In sustainable reverse logistics network design, there are three purposes for the design of numerical experiments: verification of the model, validation of the model, as well as performing analysis and obtaining managerial implications. It is extremely important to understand the difference between verification and validation in the context of model development for sustainable reverse logistics network design. Verification of a model focuses on the model itself and aims to answer the question "Do we model the problem correctly?" While, on the other hand, validation of a model focuses on the modelling process and aims to answer the question "Do we model the correct problem?"

Figure 3-6 illustrates the model development and decision-making for sustainable reverse logistics network design, which include four fundamental elements. The first one is the identification of the problem and the system and environment for model development, which can be described using Figure 3-1. The second step is to translate the problem into the purpose of the model and assumptions, based upon which the mathematical model, solution method as well as computer code are developed. The third step is the verification and validation of the model through numerical experiments. After which, the managerial implications can be obtained for decision-making. In this section, the design of numerical experiments for verification, validation and analytical process in sustainable reverse logistics network design is introduced.

3.2.6.1 Numerical experiments for model verification

With properly designed numerical experiments, the model verification is first conducted. For sustainable reverse logistics network design problem, as well as many other decision-support models developed with operational research methods, the model verification through numerical experiments is relatively straightforward. First, the indicators for performance evaluation are defined, and then a set of small-sized problems is solved to test whether the developed model, solution method and computer code can fulfill the initial design requirements.

In the PhD project, two indicators are used for the model verification: quality of the solution and computational efficiency. Herein, the quality of solution indicates whether the best solution can be calculated with the optimization model. For example, if the purpose of model development is to find out a transport mode under which the economic efficiency is maximized, then the model should be able to determine the one with lowest transportation costs. Usually, in this phase, the computational efficiency is very high for small sized problems. Otherwise, it could be a huge problem for the model and thus needs to be handled immediately.

Two methods are used for data generation in the numerical experiment for model verification. The first one is to adopt data and parameters from the other literature having similar data structure in the numerical experiment or case study, and in this way, the result can be compared directly with that in the literature and its quality can then be quickly evaluated. The other method is to create a small sized fictional problem with the assumption of parameters. The optimal solution of the problem created should be easily obtained with analytical methods and can therefore be used as the reference value for performance evaluation of the optimization model.

It is noteworthy that the model verification with a single round numerical test is highly risky. One instance is from Soleimani et al. (2016) in which a new solution method for stochastic optimization problem is proposed and tested with a numerical experiment for model verification. The solution method performs well under the data structure in their paper, but it may generate very bad solutions under some other types of data structure, as detailed in **Paper IV**. Thus, in the verification phase, testing the model with several sets of parameters with different data structure is an effective way to ensure the reliability of the model verification.

When problems happen in model verification, as shown in Figure 3-6, it is necessary to thoroughly revisit the model development with respect to the purpose in order to check if the purpose and assumptions are correctly formulated in the mathematical model, and whether the solution methods and computer code are properly developed.

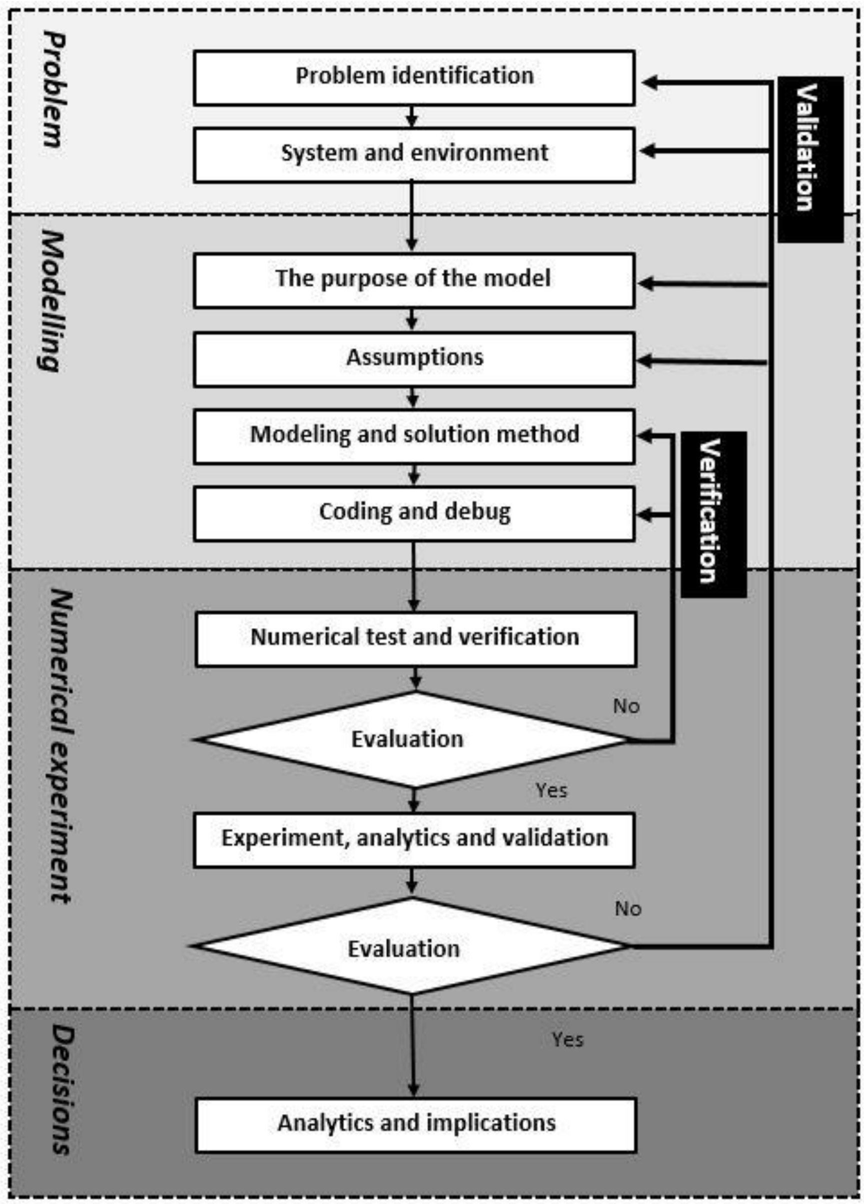


Figure 3-6 The model development for sustainable reverse logistics network design.

3.2.6.2 Numerical experiments for model validation

The second step is the validation of the model. Through numerically re-creating the complex system and environment under which the problem is modelled and the model is developed for decision-support, the numerical experiments aim at testing and validating if the proposed model is capable with an accurate reflection of the problem it formulates. Compared with model verification, the model validation is not that straightforward and analytical analysis should be conducted based upon the numerical results calculated.

In this PhD project, the optimization models and methods developed aim at, instead of resolving a single case study, dealing with a large variety of decision-making problems for sustainable reverse logistics network design under different complex system and environment, so the design of numerical experiments for model validation should be of generality in the data structure. Due to this reason, instead of generating a set of parameters for a specific problem, a parameter space is first generated based on literature study, expert interview and assumptions in order to numerically re-create or simulate the system and environment where the model is applied for decision-making. Then, a set of problems with different sizes are randomly generated from the parameter space.

Those problems are first resolved with the model and computer code that have already been verified. In this phase, the computational performance can be tested with different sized problems. If the computational time exceeds the requirement, it is necessary to go back to the model development steps in order to check if the model can be reformulated or whether the solution method can be optimized for improving the computational efficiency. For example, performing linearization on some non-linear objectives or constraints, or converting a hard constraint into a soft one, or replacing an inequality constraint with an equality one if possible, and so forth. When some of those are performed, holding in mind, it is extremely important to consider whether this will has a significant influence on the model's reflection of the problem. If the answer is yes, the model may probably be calculated much quickly, but for a wrong problem.

The model validation aims at answering the question if the optimal solution of the model is the optimal solution to the problem modelled. Nevertheless, the numerical results from the experiments cannot directly answer this question, and further analysis, i.e., trade-off analysis, comparative study, etc., have to be done in order to derive a reasonable and reliable answer to it. When problems are found in model validation, usually much more efforts will be spent to go back to the very beginning of the model development and check if the problem and system have been appropriately interpreted and whether the purpose and assumptions are properly given. After that, the mathematical model, solution method as well as computer code will be modified accordingly.

In this PhD project, when the model for sustainable reverse logistics network design for MSW management was formulated in **Paper V**, the environmental impacts was quantified and evaluated by carbon emission as that in **Paper I**, which focuses on an ordinary reverse stream. With that, the optimal plan is to open several landfills and diverts most organic MSW from energy recovery through incineration to landfill. Clearly, in this case, the optimal solution of the model is not the best choice to the problem. The reason for that is the misinterpretation of the system and misuse of the environmental indicator, which results in the mismatch between the model and the problem modelled.

In MSW management system, a large portion is organic waste. From an environmental perspective, incineration is a better choice than landfill, because it is an energy recovery option. However, if the environmental influence is only evaluated by carbon emission, then landfill becomes a more environmentally friendly choice in such a system. In order to solve this problem in **Paper V**, the system and environment, purpose and assumptions were revisited and modified for better capturing the features of the sustainable reverse logistics network design for MSW management. Then, the mathematical model was re-formulated in order to incorporate with a more sophisticated indicator for evaluating environmental performance.

Based on the discussion above, not only the numerical results but also the analytical competence, experience and familiarity with the system or problem modelled, are all form the fundamental elements for the model validation for sustainable reverse logistics network design.

3.2.6.3 Analysis and managerial implications

After verification and validation of the model, managerial implications can be obtained from the analysis of the results of numerical experiments in order to get a better understanding of the system behavior and sensitivity of some key parameters, and then supporting the decision-making of sustainable reverse logistics network design.

In this PhD project, the model is not tested with a real world case study, so the analytical process aims not at providing definitive implications to a specific problem or case. Instead, it aims, through testing the optimization models and methods under a large variety of complex numerical environments, to generalize some implications that may be shared by most sustainable reverse logistics systems.

Further, the parameter generation, design of numerical experiments, analytical process for managerial implications are detailed in each paper of the thesis. Those examples present the system and environment under which the optimization models and methods can be applied for sustainable reverse logistics network design (applicability) and illustrate the way in which they are used (application).

3.3 Modelling methods for sustainable reverse logistics network design

In this section, the modelling methods used for formulating the sustainable reverse logistics network design problem is introduced. Taking into account of the project scope, focus as well as the main objectives, several modelling techniques and solution methods are used to mathematically formulate and resolve the sustainable reverse logistics network design problem with focus on the balance between economic benefits and environmental impact under an uncertain environment.

Table 3-3 Selection of the modelling techniques for formulating the sustainable reverse logistics network design problem

Modelling technique	Function
Linear/Non-linear programming	Describing the connections between parameters and decision variables in the objective functions and constraints
Mixed integer programming	Determining two different types of decisions regarding the selection of facilities (binary integer variables) and other decisions related to facility operation and transportation
Multi-objective programming	Performing the trade-off analysis of different conflicting objectives in reverse logistics network design
Stochastic programming	Controlling and revealing the impact from the uncertainties

Table 3-3 illustrates the modelling techniques used in this PhD project, and the following sections give brief introductions of those modelling techniques.

3.3.1 Linear programming and non-linear programming

Linear programming and non-linear programming are fundamental techniques for modelling a complex decision-making problem. Since the development of the simplex method by Dantzig G.B. in 1947, linear programming has become the most extensively used optimization technique in operational research, optimization, management science, industrial engineering as well as other disciplines for resolving a maximization or minimization problem consisting of linearly related objective function and constraints (Sakawa et al., 2013).

$$\text{Minimize} \sum_{i \in I} \sum_{j \in j} a_i x_i + b_j y_j$$

Subject to:

$$\sum_{i \in I} c_{ik} x_i + \sum_{j \in J} d_{jk} y_j = p_k, \forall k \in K$$

$$\sum_{i \in I} e_{im} x_i + \sum_{j \in J} f_{jm} y_j \leq q_m, \forall m \in M \tag{1}$$

$$x_i, y_j \geq 0, \forall i \in I, j \in J$$

Equation (2) presents an example of a linear programming problem with minimization objective. This problem includes two groups of decision variables x_i and y_j, and I is the set of decision variable x indexed by i and J is the set of decision variable y indexed by j. a_i and b_j are coefficients of the two groups of decision variables. The model includes three groups of constraints for giving requirements on different relationships between parameters and decision variables: equality, inequality and non-negative. Herein, c_{ik}, d_{jk}, e_{im}, f_{jm} are coefficients of decision variable in the constraints, and p_k and q_m are right-hand-side restrictions. The numbers of formulas in each group of constraint is given by sets K and M, respectively.

Equation (2) includes only linear relationships, so it can be re-written as a simplified formula by introducing the coefficient vectors $\boldsymbol{a}$, $\boldsymbol{p}$ and $\boldsymbol{q}$ and matrix $\boldsymbol{C}$ and $\boldsymbol{E}$, as shown in Equation (2).

$$
\begin{aligned}
&\text{Minimize } \boldsymbol{ax} \\
&\text{Subject to:} \\
&\boldsymbol{Cx} = \boldsymbol{p} \\
&\boldsymbol{Ex} \leq \boldsymbol{q} \\
&\boldsymbol{x} \geq \boldsymbol{0}
\end{aligned}
\tag{2}
$$

Equation (3) and Equation (4) show the procedures for transformation from the original problem to the simplified formula. As can be seen, the coefficient vector $\boldsymbol{a}$ represents the set of $(a_1, \dots, a_{i+j})$ where the elements $a_{i+1}, \dots, a_{i+j}$ actually equal to $b_1, \dots, b_j$ in the original problem. With the same idea, c_{ik} and d_{jk} form the $(i+j) \times k$ coefficient matrix $\boldsymbol{C}$, and e_{im} and f_{jm} form the $(i+j) \times m$ coefficient matrix $\boldsymbol{E}$, and $\boldsymbol{0}$ is a $i+j$ dimensional column vector. The solution domain of a linear programming is a convex, and the fundamental approach to solve a linear programming problem is simplex method.

$$
\begin{aligned}
&\boldsymbol{a} = (a_1, \dots, a_i, b_1, \dots, b_j) \\
&\boldsymbol{x} = (x_1, \dots, x_i, y_1, \dots, y_j)
\end{aligned}
\tag{3}
$$

$$
\begin{aligned}
&\boldsymbol{C} = \begin{bmatrix} c_{11} & \cdots & c_{i1}, d_{11} & \cdots & d_{j1} \\ \vdots & \ddots & \vdots \ \vdots & \ddots & \vdots \\ a_{1k} & \cdots & c_{ik}, d_{1k} & \cdots & d_{ik} \end{bmatrix} \\
&\boldsymbol{E} = \begin{bmatrix} e_{11} & \cdots & e_{i1}, f_{11} & \cdots & f_{j1} \\ \vdots & \ddots & \vdots \ \vdots & \ddots & \vdots \\ e_{1m} & \cdots & e_{im}, f_{1m} & \cdots & f_{im} \end{bmatrix} \\
&\boldsymbol{p} = (p_1, \dots, p_k), \boldsymbol{q} = (q_1, \dots, q_m)
\end{aligned}
\tag{4}
$$

The problem becomes a non-linear programming when a non-linear relationship is imposed in the objective function and/or constraints. Equation (5) modifies the original linear programing to a non-linear programming by changing the inequality constraint with a non-linear relationship. Compared with a linear programming, a non-linear optimization problem is much more difficult to solve due to its computational complexity.

$$\text{Minimize} \sum_{i \in I} \sum_{j \in j} a_i x_i + b_j y_j$$

Subject to:

$$\sum_{i \in I} c_{ik} x_i + \sum_{j \in J} d_{jk} y_j = p_k, \forall k \in K$$
$$\sum_{i \in I} e_{im} x_i + \sum_{j \in J} \frac{f_{jm}}{y_j} \leq q_m, \forall m \in M \quad (5)$$
$$x_i, y_j \geq 0, \forall i \in I, j \in J$$

In sustainable reverse logistics network design, both linear programming and non-linear programming are used as the fundamental elements to describe the relationships between parameters and decision variables in the objective function and constraints. Due to the computational complexity of a non-linear problem, most of the optimization models are formulated as a linear programming or eventually converted to a linear programming through different linearization approaches.

In this PhD project, combining with other modelling techniques, linear programming is used in **Paper 2**, **Paper 3**, **Paper 4** and **Paper 6**.

Paper 1 and **Paper 5** investigate the modelling with either a non-linear constraint of environmental requirement or a non-linear disutility objective function for measuring environmental impact. In both papers, the computational efficiency is tested with the increase on the size of problem.

3.3.2 Mixed integer programming

In some cases, the relationship between parameters and decision variables in an optimization problem cannot be properly formulated only by using a linear programming or a non-linear programming. For example, in order to deal with the seasonal demand on ski equipment, a manufacturing company may hire some temporary workers in winter to increase the production capacity, and the manager want to make a decision on how many temporary workers should be recruited. With a linear programming model, an optimal solution may be obtained at 21.7 person, which is not realistic. The reason for this unrealistic solution is due to the continuous feasible domain of a linear programming. In order to resolve this problem and get a proper solution, another constraint should be imposed to restrict the feasible solution domain of this decision-making problem belongs to the set of integers.

$$\text{Minimize} \sum_{i \in I} \sum_{j \in j} a_i x_i + b_j y_j$$

Subject to:

$$\begin{aligned}
&\sum_{i \in I} c_{ik} x_i + \sum_{j \in J} d_{jk} y_j = p_k, \forall k \in K \\
&\sum_{i \in I} e_{im} x_i + \sum_{j \in J} f_{jm} y_j \leq q_m, \forall m \in M \\
&x_i, y_j \geq 0, \forall i \in I, j \in J \\
&x_i, y_j \in \mathbb{Z}, \forall i \in I, j \in J
\end{aligned} \tag{6}$$

Equation (6) converts the original linear programming given in Equation (1) into an integer programming by introducing an integer constraint for decision variables x_i and y_j. It is easy to see that, compared with the continuous solution domain of the original linear programming, the feasible solution domain of an integer programming becomes much narrow including only discrete integer points within the original feasible space. The basic idea to solve an integer linear programming is to convert the original problem into a set of linear programming by introducing new constraints. The well-developed solution approaches are branch and bound method and cutting plane method, both of which are exact methods. In recent years, several heuristic and approximation methods are developed, through the calculation of a "near optimal solution" instead of finding out the exact optimal solution, in order to improve the computational efficiency of large integer programming problems.

Some optimization problems include both integer variables and continuous variables, and this is called a mixed integer programming. Derived from the original linear optimization problem in Equation (1), Equation (7) presents an example of a mixed integer programming. In this optimization problem, x_i is a group of binary decision variables for answering "yes" or "no" questions (if x_i equals to 1, the answer is yes, and if x_i is 0, otherwise), and y_j is a group of linearly related continuous decision variables.

$$
\begin{aligned}
&\text{Minimize} \sum_{i\in I}\sum_{j\in j} a_i x_i + b_j y_j \\
&\text{Subject to:} \\
&\sum_{i\in I} c_{ik} x_i + \sum_{j\in J} d_{jk} y_j = p_k, \forall k \in K \\
&\sum_{i\in I} e_{im} x_i + \sum_{j\in J} f_{jm} y_j \leq q_m, \forall m \in M \\
&x_i, y_j \geq 0, \forall i \in I, j \in J \\
&x_i \in \{0,1\}, \forall i \in I, j \in J
\end{aligned}
\tag{7}
$$

Due to its flexibility, the mixed integer programming with binary decision variables has been extensively applied for modelling and resolving many complex decision-making problems, among which the planning of a reverse logistics network is one of the most focused problems. In reverse logistics network design, the binary decision variables determine whether a new facility is open at a candidate location, while the continuous variables determine the facility operation plan and transportation strategy of EOU and EOL products. In literature, significant efforts have been spent to model the reverse logistics network design problem with this type of mixed integer programming (e.g., Kannan et al. (2017), Diabat et al. (2013), Kannan et al. (2017), Zandieh and Chensebli (2016), Alshamsi and Diabat (2015), Alshamsi and Diabat (2017), etc.).

In this PhD project, as a basic modelling foundation, the mixed integer programming with binary decision variables has been used in all the papers. Combined with linear programming, **Paper 2**, **Paper 3**, **Paper 4** and **Paper 6** are formulated as mixed integer linear programming, while **Paper 1** and **Paper 5** are modelled as mixed integer non-linear programming.

3.3.3 Multi-objective programming

In many cases, decision-making involves several objectives that are usually in conflict with one another. For example, when you book a hotel room in a popular destination for your next vacation, you may have in mind for several objectives: central location with easy access to public transport, low price, fantastic amenities, and so forth. However, it is impossible to optimize all the objectives at the same time without a compromise, and in this case, you may make a decision with the balance between convenience and the money in your pocket. In order to model such a decision-making problem, the multi-objective programming technique is introduced to optimally balance the trade-off among several conflicting objectives.

$$
\begin{aligned}
&\text{Minimize} \sum_{i\in I}\sum_{j\in j} a_{i1}x_i + b_{j1}y_j \\
&\qquad\vdots \\
&\text{Minimize} \sum_{i\in I}\sum_{j\in j} a_{in}x_i + b_{jn}y_j \\
&\text{Subject to:} \\
&\sum_{i\in I} c_{ik}x_i + \sum_{j\in J} d_{jk}y_j = p_k, \forall k \in K \\
&\sum_{i\in I} e_{im}x_i + \sum_{j\in J} f_{jm}y_j \leq q_m, \forall m \in M \\
&x_i, y_j \geq 0, \forall i \in I, j \in J \\
&x_i \in \{0,1\}, \forall i \in I, j \in J
\end{aligned}
\tag{8}
$$

Equation (8) converts the mixed integer linear programming given in Equation (7) into a multi-objective mixed integer linear programming with n objective functions. Equation (8) can be re-written into a simplified general form as shown in Equation (9), where $z(\boldsymbol{x}) = \left(z_1(\boldsymbol{x}), z_2(\boldsymbol{x}), \dots, z_n(\boldsymbol{x})\right)^T$ is a n-dimensional vector and X is the set of feasible solutions in decision space, where $X \subseteq \mathbb{R}^n$. In a multi-objective optimization problem, the optimal trade-off among different objective functions is called a Pareto optimal solution. The definition of Pareto optimal solution or efficient solution is given by Sakawa et al. (2013) as:

"A point $\boldsymbol{x}^*$ is said to be a Pareto optimal solution *if and only if there does not exist another* $\boldsymbol{x} \in X$ *such that* $z_u(\boldsymbol{x}) \leq z_u(\boldsymbol{x}^*)$ *for all* u *and* $z_v(\boldsymbol{x}) \neq z_v(\boldsymbol{x}^*)$ *for at least one* v*"*

It is obvious from the definition that, at a Pareto optimal point, the target objective value cannot be improved without a compromise on the performance of other objective functions. In addition, there exists an infinite number of Pareto optimal solutions for a multi-objective optimization problem.

$$\begin{aligned} &\text{Minimize } z(\boldsymbol{x}) = \left(z_1(\boldsymbol{x}), z_2(\boldsymbol{x}), \dots, z_\mathrm{n}(\boldsymbol{x})\right)^T \\ &\text{Subject to:} \\ &\boldsymbol{x} \in X \end{aligned} \tag{9}$$

The basic idea to solve a multi-objective programming is to convert it into a set of single objective optimization problems through different approaches, among which the weighting method and ε-constraint method are the most extensively focused ones. This section provides a brief introduction of those methods, and a detailed introduction and comparison is given in **Paper 2** and **Paper 6**.

$$\begin{aligned} &\text{Minimize } \boldsymbol{w}z(\boldsymbol{x}) = \sum_{u=1}^{n} w_u z_u(\boldsymbol{x}) \\ &\text{Subject to:} \\ &\boldsymbol{x} \in X \end{aligned} \tag{10}$$

Zadeh (1963) first introduced weighting method to resolve the multi-objective optimization problems. Equation (10) presents a general form of the weighting method, where $\boldsymbol{w} = (w_1, w_2, \dots, w_k)$ is the weight vectors of each objective function. The weight represents the relative importance of the objective functions in decision-making, and the multi-objective programming then becomes the optimization problem of a single objective weighted sum function and can be resolved. Due to its simplicity and computational efficiency, weighting method has been extensively used to resolve multi-objective programming problems. However, as argued by many (Das and Dennis, 1997, Mavrotas, 2009), the weighting method suffers from the low effectiveness in determining high quality and evenly distributed non-dominant Pareto optimal solutions.

$$\begin{aligned}
&\text{Minimize } z_v(\boldsymbol{x}) \\
&\text{Subject to:} \\
&z_u(\boldsymbol{x}) \leq \varepsilon_u, u = 1, 2, \dots, k, u \neq v \qquad (11) \\
&\boldsymbol{x} \in X
\end{aligned}$$

The ε-constraint method is another well-known scalarization approach. The basic idea of ε–constraint method is to choose one objective function from the original multi-objective programming and transform the other objective functions into inequality constraints, and the Pareto optimal solution is then calculated by resolving the derived single objective constrained optimization problem (Haimes, 1971). Equation (11) shows a general form of ε-constraint method, where the right-hand-side value ε_u is determined by the trade-off matrix (Mavrotas, 2009). Compared with weighting methods, ε-constraint method has a better performance in the quality of Pareto optimal solutions obtained, but, at the time, the conversation to a constrained problem increases the computational complexity.

Modelling the reverse logistics network design problem with multi-objective programming are focused in recent research works in order to balance the system performance in several dimensions other than economic focus (e.g., Govindan et al. (2016b), Soleimani et al. (2017), Yu and Solvang (2016b), Yu et al. (2016), Entezaminia et al. (2017), Yilmaz et al. (2017), etc.).

In this PhD project, multi-objective programming approach is used in **Paper 1**, **Paper 2**, **Paper 5** and **Paper 6** in order to balance the economic performance and environmental impact of reverse logistics network design.

Paper 1 and **Paper 5** are formulated as multi-objective mixed integer non-linear programming and resolved with normalized weighting method.

Paper 2 and **Paper 6** are formulated as multi-objective mixed integer linear programming and resolved with modified ε-constraint method in order to improve the quality of the Pareto optimal solutions obtained.

3.3.4 Stochastic programming

Decision-making in the real world is rarely done with all the information exactly known in advance, but some important decisions must be made before the information becomes available (King and Wallace, 2012). For example, when you book a flight ticket from Oslo to New York City for your vacation with a connecting flight via Copenhagen, you may have two different options with the same price range. The first option gives the shortest travel time, but you only have 50 minutes to catch up the next flight. However, if you miss your connecting flight, you may have to wait for one or two days for getting a seat in the flight to New York City during the holiday season. While, with the second option, you have one night to stop at the Copenhagen airport, but the total travel time becomes much longer and you have an extra cost for booking a hotel room for the stay. In this case, you face a challenging question due to the uncertainty of the future. If everything goes well, the first option is the definitely best choice, but if something happens (e.g., delay of the first flight due to weather conditions or airport traffic), there will be a much higher cost on time and money. In order to model such problems with uncertainty and provide implications for decision-making, stochastic programming is a powerful technique in operational research.

$$\text{Minimize} \sum_{i \in I} a_i x_i + \sum_{s \in S} \sum_{j \in J} P_s b_{j,s} y_{j,s}$$

Subject to:

$$\begin{aligned}
&\sum_{i \in I} c_{ik} x_i + \sum_{j \in J} d_{jk,s} y_{j,s} = p_k, \forall k \in K, s \in S \\
&\sum_{i \in I} e_{im} x_i + \sum_{j \in J} f_{jm,s} y_{j,s} \leq q_m, \forall m \in M, s \in S \\
&x_i, y_{j,s} \geq 0, \forall i \in I, j \in J, s \in S \\
&x_i \in \{0,1\}, \forall i \in I, j \in J
\end{aligned} \tag{12}$$

Equation (12) presents an example of a stochastic mixed integer linear programming with a minimization objective function, reformulated from Equation (7). The given example is a two stage-stochastic programming, where S and s are set and index of scenarios and P_s is the probability of the realization of scenario *s*. In a two-stage stochastic optimization problem, the first stage decisions have to be made before the realization of uncertain parameters and is thus featured with "robustness", while the second stage decision is made after the realization of scenarios and should be "flexible".

Figure 3-7 illustrates the comparison of decision-making with a deterministic model and a two-stage stochastic model. As many argues (Birge and Louveaux, 2011, King and Wallace, 2012), with a deterministic model, even if the impacts from the change of some key parameters may be found with sensitivity analysis, but it is likely to neglect some important features and cannot tell you how to react to the variation. However, with a stochastic model, the robust decisions and valuable managerial insights can be obtained for a better decision-making under uncertainty.

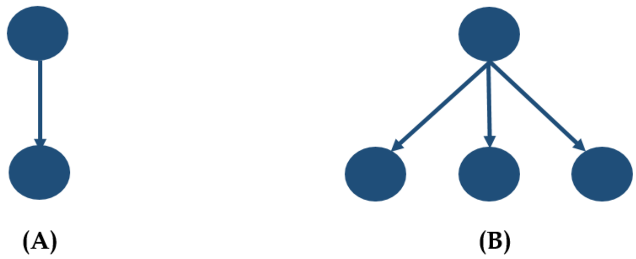


Figure 3-7 Illustration of the scenario tree for a small sized (A) Deterministic problem; (B) Two stage stochastic problem.

In sustainable reverse logistics network design, as discussed in Chapter 2, the decisions are inherently at two stages. The first stage is at strategic level determining the number and locations of facilities to be opened, and those decisions should be robust and remain unchanged in a long period. The second stage decisions are at tactical and operational levels including the processing plan at the facilities and transportation strategy. In the latest decade, stochastic optimization models have been developed for modelling the reverse logistics network design problem, and early modelling efforts with two-stage stochastic programming are given by Pishvaee et al. (2009) and El-Sayed et al. (2010) for optimizing the economic performance.

The basic principle of a stochastic programming is to model the uncertainty and randomness with a set of scenarios. In order to formulate the uncertainties in the future, several possible value of the stochastic parameters are first generated, and each of them represents a prediction of the uncertain parameters in the planning horizon. With the combinations of different stochastic parameters, a set of scenarios (s) with the probability of occurrence (P_s) is then generated for representing the future conditions of an optimization problem. Thus, the optimal solution of a stochastic model is not to seek the best solution for a single scenario (sub-optimal solution), but it is to find out the most robust decision throughout all the possible scenarios.

Due to the consideration of the influence from the uncertain issues, implementing stochastic programming to model a decision-making problem usually leads to a weaker solution compared with that obtained from a deterministic model, but it is more realistic. In reverse logistics network design problem, a stochastic model may lead to a lower profits or a higher costs due to more facility opened in order to satisfy the constraints for all the scenarios. The recent research works on stochastic modelling efforts for sustainable reverse logistics network design take into account of not only economic performance but also other measures of sustainable development (Rahimi and Ghezavati, 2018, Yu and Solvang, 2016a, Feitó-Cespón et al., 2017, Yu and Solvang, 2017a, Yu and Solvang, 2017b, Yu and Solvang, 2017c). Reformulated from Equation (12), Equation (13) presents an instance of a multi-objective stochastic decision-making model.

$$\begin{aligned}
&\text{Minimize } \sum_{i\in I} a_{i1}x_i + \sum_{s\in S}\sum_{j\in J} P_s b_{j1,s} y_{j,s} \\
&\qquad\qquad\vdots \\
&\text{Minimize } \sum_{i\in I}\sum_{j\in j} a_{in}x_i + \sum_{s\in S}\sum_{j\in J} P_s b_{jn,s} y_{j,s} \\
&\text{Subject to:} \\
&\sum_{i\in I} c_{ik}x_i + \sum_{j\in J} d_{jk,s} y_{j,s} = p_k, \forall k \in K, s \in S \\
&\sum_{i\in I} e_{im}x_i + \sum_{j\in J} f_{jm,s} y_{j,s} \le q_m, \forall m \in M, s \in S \\
&x_i, y_{j,s} \ge 0, \forall i \in I, j \in J, s \in S \\
&x_i \in \{0,1\}, \forall i \in I, j \in J
\end{aligned} \tag{13}$$

The inclusion of those factors may lead to infeasible solutions to the stochastic optimization problem due to the more tightened environmental requirements imposed on a reverse logistics system. In this case, the stochastic model may be reformulated through relaxing some constraints in order to generate meaningful solution. From a practical perspective of reverse logistics network design, the relaxation on the model constraints indicates a further compromise on the economic performance or a reduction on the service level of a reverse logistics system to allow, for example, not all the EOL and EOU products have to be treated in some scenarios (Ashfari et al., 2014, Yu and Solvang, 2017a).

From the mathematical modelling perspective, the reformulation can be done with a chance-constrained stochastic model, as shown in Equation (14). Herein, β_k and ε_m are the required probability to be satisfied by the constraints. Compared with the original stochastic programming given Equation (12), the chance-constrained stochastic model becomes a relaxed version and requires the model constraints to be fulfilled only at a given probability.

$$\begin{aligned}
&\text{Minimize } \sum_{i \in I} a_i x_i + \sum_{s \in S} \sum_{j \in J} P_s b_{j,s} y_{j,s} \\
&\text{Subject to:} \\
&Prob\left(\sum_{i \in I} c_{ik} x_i + \sum_{j \in J} d_{jk,s} y_{j,s} = p_k \right) \geq \beta_k, \forall k \in K, s \in S \\
&Prob\left(\sum_{i \in I} e_{im} x_i + \sum_{j \in J} f_{jm,s} y_{j,s} \leq q_m \right) \geq \varepsilon_m, \forall m \in M, s \in S \\
&x_i, y_{j,s} \geq 0, \forall i \in I, j \in J, s \in S \\
&x_i \in \{0,1\}, \forall i \in I, j \in J
\end{aligned} \tag{14}$$

Even though the infeasibility problem of the original stochastic programming may be mathematically resolved with a reformulated chance-constrained stochastic model, the practical implications in reverse logistics network design is to permit a reduced service level in some scenarios, which, in other words, means it is OK to leave the garbage on the streets if there is not enough capacity. This will significantly and negatively influence the satisfaction of the local residents for the public service, so it is neither a good nor an easy decision for the decision-make to take. Further, it is also argued by some researchers that a chance-constrained stochastic model without proper account to the impacts from the excluded cases may result in very bad decisions in terms of the overall performance (King and Wallace, 2012).

Due to the reasons discussed above, in this PhD project, the infeasibility problem of the stochastic model for reverse logistics network design is resolved through the compromise on economic benefits or the improvement on flexibility when multiple products are recovered.

In this PhD project, combined with other modelling techniques, stochastic programming is used to formulate the reverse logistics network design problem in **Paper 2**, **Paper 3** and **Paper 4** in order to effectively control the uncertainty in decision-making.

Paper 2 formulates a multi-objective two-stage stochastic mixed integer linear programming model for sustainable reverse logistics network design under uncertainty.

Paper 3 and **Paper 4** investigate reverse logistics network design problem with two different carbon policies: carbon tax and carbon cap, namely. Two-stage stochastic mixed integer linear programming incorporating with either a soft constraint (carbon tax) or a hard constraint (mandatory carbon cap) is modelled and resolved with an augmented multi-criteria scenario-based risk-averse method.

3.3.5 Summary of the modelling techniques

Table 3-4 gives a summary of the modelling techniques used with respect to each included paper in this PhD project.

Table 3-4 Summary of the modelling techniques used with respect to each paper of the PhD project

Modelling technique	Paper1	Paper2	Paper3	Paper4	Paper5	Paper6
Linear programming	√	√	√	√	√	√
Non-linear programming	√				√	
Mixed integer programming	√	√	√	√	√	√

Table continued

Multi-objective programming	∨	∨			∨	∨
Stochastic programming		∨	∨	∨		

3.4 Analysis and evaluation of the model development in the PhD project

3.4.1 Evaluation criteria

In this section, the criteria for evaluating the model development are first introduced in Table 3-5, and the first five criteria are adopted from Souder (1984) and Souder and Sherman (1994).

Table 3-5 Criteria for evaluating the model development in this PhD project

Criteria	Explanation
Realism	The model should be able to establish a realistic and complete reflection of the system modelled
Capability	The model should be able to support decision-making under a large variety of different situations
Flexibility	The model should be capable with modification and updates as required
Ease of use	The model should be simply enough to be used by the ones without technical background
cost	The model should be cost efficient
Robust	It supposed to be difficult to obtain useless answers from the model implementation
Consistency of the result	The model should be able to obtain consistent result following logically from the assumptions of the model

3.4.2 Discussions

Using the evaluation criteria listed in Table 3-5, both strengths and some limitations of the model development in this PhD project are discussed with respect to each criterion.

- ***Realism***: Compared with the models in literature, the optimization models can better formulate the features of sustainable reverse logistics network design through improving the objectives and constraints to include environmental and social sustainability, establishing a more complex system under uncertain environment, enabling flexibility on both transportation and facility operations, and so forth. Nevertheless, holding in mind, even if the most sophisticated model is still only a partial reflection of the real problem or system (Pinto, 2015). For this project, the developed models can be further improved in many ways, i.e., incinerating with a mixed capacity installation at remanufacturing plant, etc., in order to better reflect the features of a sustainable reverse logistics system.

- ***Capability:*** The models are developed under complex system and environment and can thus be used for resolving a large variety of sustainable reverse logistics network design problems with different network structures, different product streams, different requirements, and so forth.
- ***Flexibility:*** In essence, the modelling of sustainable reverse logistics network design problem is not a creation process but rather an improvement process based upon some established and well-studied models. In accordance with the purpose of model development, new parameters are selected, new objectives and constraints are formulated, and a more complex environment is mathematically simulated. All of which can be considered in a way that, through adding or removing some "building blocks" in a model, creating a proper reflection of the problem. Thus, when new requirements are given, the model is flexible enough to be updated by modifying, adding or removing some elements. In the PhD project, one limitation is associated with the compatibility of Lingo solver, which does not support some common programming languages.
- ***Ease of use:*** Because the data and code files are created independently, the users just need to input data on an Excel file with pre-defined structure and run the code, and the optimal result as well as the values of decision variables can then be outputted to another Excel file for analysis and decision-making. Thus, the models can be used by people even without any background in optimization and computer programming.
- ***Cost:*** Some powerful commercial optimization solvers provide free license for the use in academia, so the cost issue is not considered in the research. Nevertheless, when the model is used for solving a real problem, an industrial or commercial license is needed. That is usually

expensive, for example, an extended industrial license for Lingo with several solver options costs more than 10,000 US dollars. Thus, the cost efficiency should be considered when the model is used in industry.

- ***Robustness:*** The models developed in this PhD project have been tested, verified and validated with extensive numerical experiments. The quality of solution and computational efficiency are at satisfactory level, so the result calculated by the models is robust. That means, the models are able to calculate the optimal solutions within reasonable time as required, and with a high level of confidence, the optimal solution of model is also the optimal one to the problem.
- ***Consistency of the result:*** As discussed early in this chapter, the purpose of the PhD project is to generalize some implications that may be shared by most sustainable reverse logistics design problems through extensive numerical experiments. In this regard, the generic features and managerial implications are obtained in a consistent way throughout the papers in the PhD project. Nevertheless, in order to show the numerical-based analytical process for sustainable reverse logistics network design, some case-based implications are also given and discussed.

4 Conclusion and Future Works

In this chapter, the summary, conclusions and contributions of the PhD project are first given in Section 4.1 and Section 4.2, and the directions for future research are then suggested in Section 4.3.

4.1 Summary and structure of the included papers

The PhD thesis consists of six articles published at peer reviewed international journals. **Paper 3** and **Paper 6** are published in gold open access journals, while the others are published in traditional journals with green open access through self-archive at the institutional repository: Munin. In addition, some of the results are presented at international conferences including IEEE International Conference on Industrial Engineering and Engineering Management (IEEM 2017), International Workshop of Advanced Manufacturing and Automation (IWAMA 2017), and IEEE International Conference on Industrial Technology and Management (ICITM 2018). Table 4-1 illustrates the contribution of the PhD candidate to the papers in this PhD project. The topics are viewed from two perspectives including intellectual input and implementation. Then, eight sub-topics are identified as research idea, literature review, modelling, solution method, computer coding and programming, experiment and paper writing.

Table 4-1 Contribution of the PhD candidate to the papers in the PhD thesis

Topic	Paper1	Paper2	Paper3	Paper4	Paper5	Paper6
Research idea	1	1	1	1	1	1
Literature review	1	1	1	1	1	1
Modelling	1	1	1	1	1	1
Solution method	1	1	1	1	1	1
Computer coding	1	1	1	1	1	1
Experiment	1	1	1	1	1	1
Analysis	1	1	1	1	1	1
Paper writing	1	1	1	1	1	1

Note: The level of the PhD candidate's contribution is ranked from 1 to 3, where 1 is the highest and 3 is the lowest.

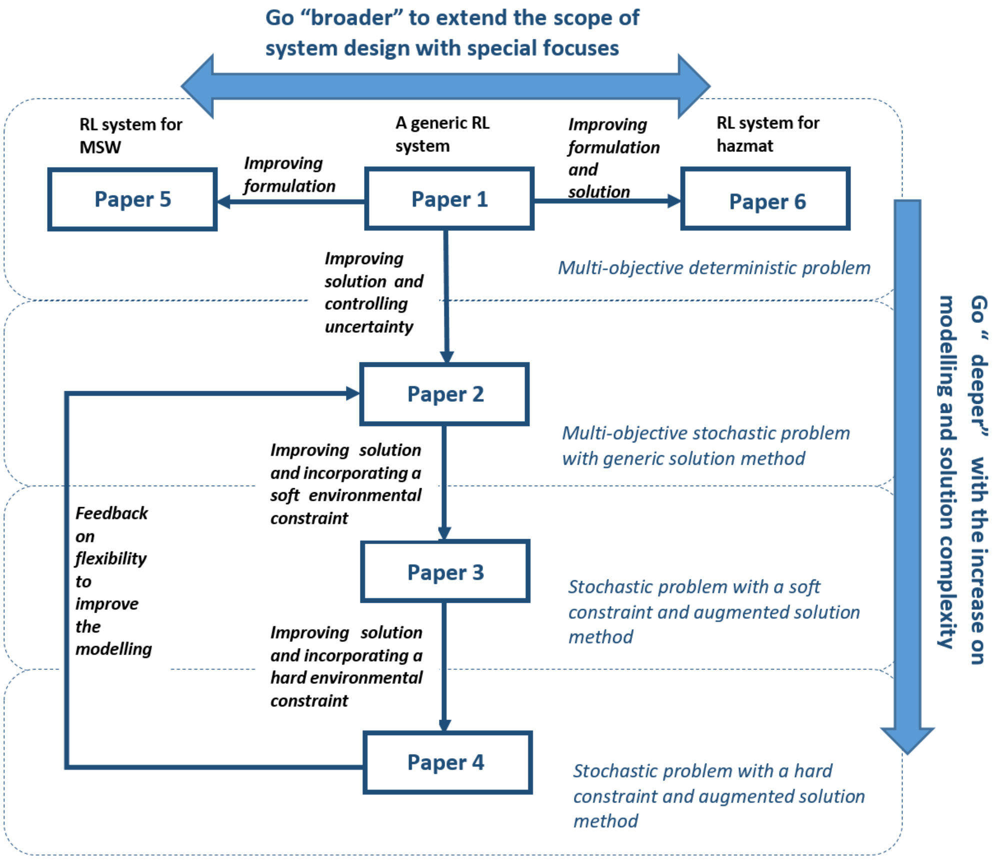


Figure 4-1 Graphical representation of the structure of the papers included in this PhD project.

The structure of the included papers in this PhD project is shown in Figure 4-1. As can be seen, the papers can be categorized into two groups with different focuses. The first group of papers consists of **Paper 1**, **Paper 5** and **Paper 6**. This group of papers are developed under deterministic environment and, in general, at the same level of complexity in mathematical modelling. The objective of this group of papers is mainly go "broader" through extending the scope of the system design with different focuses in order to account different types of EOL and EOU products.

Paper 1 is among the first modelling efforts in the literature to implement a bi-objective mixed integer non-linear programming to balance the economic performance and environmental impact in the planning of a generic reverse logistics network. The problem is modelled as a single product system under deterministic environment, and a non-linear environmental constraint is formulated to regulate the landfill waste. The model is resolved by a normalized weighting method, and managerial implications are obtained with respect to the trade-off between the overall system operating costs and carbon emissions. The impact from facility operations and transportation are also thoroughly analysed and discussed. In addition, due to the non-linear nature, computational performance of different sized problems is also compared in this paper.

Paper 5 improves the mathematical model from **Paper 1** in order to accommodate the characteristics of a sustainable reverse logistics system for MSW management. In this paper, more comprehensive environmental evaluation method (non-linear disutility function) is formulated and the carbon emissions from the transportation of MSW are mainly focused. Besides, the paper also extends the structure of the reverse logistics system in order to include both direct transport and indirect shipment via transfer stations. The paper provides managerial implications among three objectives and comparison of computational efficiency of the optimization problem. Finally, a comparative study is given in order to show the applicability of the model developed.

Paper 6 formulates a bi-objective mixed integer linear programming model for resolving the location-routing problem of a reverse logistics system for hazardous waste management. In this paper, the objective function for evaluating the environmental impact of a reverse logistics system is replaced by a risk management objective (social responsibility). Compared with the optimization models in literature, the formulation of the risk management objective has been greatly improved in this paper, and also for the first time, a lexicographic ε–constraint method is implemented for generating high quality Pareto optimal solutions for the multi-objective optimization problem.

The second group of papers also starts from **Paper 1** and consists of **Paper 2**, **Paper 3** and **Paper 4**. In this group, the last three papers are developed under stochastic environment in order to better control the uncertainty in decision-making. With this group of papers, the objective is to "go deeper" for improving the modelling and quality of the result obtained and exploring managerial implications with the implementation and development of some advanced modelling techniques and solution methods. The complexity of modelling and solution methods increases gradually throughout those papers.

Paper 2 improves the mathematical model from **Paper 1** and transforms it into a bi-objective two-stage stochastic mixed integer linear programming with consideration of heterogamous product flow and control of uncertainty. The model is resolved under a stochastic environment and compares two solution methods for multi-objective programming (normalized weighting method and augmented ε–constraint method). The experimental result shows the impact from uncertainty in reverse logistics network design. Moreover, combining with the conclusion obtained from **Paper 4**, the paper also presents a modified model incorporating with flexible capacity for managing the uncertainty in a multi-product flow. The experimental result gives managerial insights into the impact from system flexibility in the planning of a multi-product sustainable reverse logistics system under uncertainty.

Paper 3 and **Paper 4** formulate the sustainable reverse logistics network design problem under stochastic environment with two different policies on carbon emissions. **Paper 3** incorporates a soft constraint (penalty) in a two-stage stochastic programming for analysing the impact from carbon tax policy, while **Paper 4** implements a hard constraint for evaluating the carbon cap policy. In order to resolve the stochastic optimization problem, an augmented multi-criteria scenario-based risk-averse solution method is developed in order to account both economic performance and reliability of the optimal solutions. In both papers, from the numerical experiments and analysis, managerial implications are obtained regarding with the impact from different carbon policies and government subsidy. Moreover, **Paper 4** presents valuable insights into the impact from system flexibility for a multi-product reverse logistics system, which serves as the most important intellectual input to **Paper 2**.

4.2 Conclusion and the contributions

In this PhD project, six optimization models and methods are developed for sustainable reverse logistics network design. Compared with the modelling efforts in literature, the models developed in this project focus primarily on sustainability in reverse logistics network design and aim at balancing the trade-off among economic performance, environmental friendliness and social responsibility through a series of decision-makings on facility location, operations, capacity installation, and transportation.

The optimization models are developed, tested, verified and validated under complex environments incorporating with different network structures, different product flow, different environmental requirements, and different objectives, etc. Based on which, a large variety of situations can be re-created with reformulation through adding or removing some "building blocks" in the models. In order to solve the proposed mathematical models, improved solution methods are also developed in this PhD project. From a methodological development perspective, the modelling techniques from operational research are first used to formulate and solve a decision-making problem: sustainable reverse logistics network design. While, on the other hand, the knowledge built from the problem-based modelling and investigation also contributes the advancement of the modelling techniques and solution methods in operational research.

Except from the contribution on modelling and solution methods, through extensive numerical experiments under different environments, some generic managerial implications are obtained for providing insights into the behavior of the model and the problem. In this PhD project, the numerical experiments are not designed for resolving a single problem and deriving a definitive conclusion for that problem, but instead, they are designed to generalize some implications that may be shared by most sustainable reverse logistics systems through testing the optimization models and methods under a large variety of complex numerical environments.

Based upon the development on modelling, solution methods as well as managerial implications, the research questions proposed in this PhD project are answered in Table 4-2.

Table 4-2 The answers to the research questions of the PhD project

Research questions	Papers and methods	Methodological development
Q1: What is the trade-offs between economic performance and environmental impact in reverse logistics network design?	**Paper 1**: Multi-objective programing with the weighting method **Paper 2**: Multi-objective programming with an augmented ε-constraint method	Developing models for sustainable design of a single product reverse logistics system and providing Pareto optimal solutions.
Q2: How to improve the quality of the optimal trade-offs (Pareto optimal solutions) calculated?	**Paper 2**: Multi-objective programming with an augmented ε-constraint method **Paper 6:** Multi-objective programming with a	Improving the effectiveness for resolving a multi-objective optimization problem with the implementation of advanced solution methods.

Table continued

	lexicographical ε-constraint method	
Q3: How to deal with the uncertainties in sustainable reverse logistics network design?	**Papers 2**: Stochastic multi-objective programming **Papers 3**: Stochastic programming **Papers 4**: Stochastic constrained programming	Incorporating the uncertainties in the design and planning of a sustainable reverse logistics network.
Q4: How to improve the quality of decision-making under uncertainty and environmental regulations for reverse logistics network design?	**Papers 3**: Stochastic programming with an augmented multi-criteria scenario-based solution method **Papers 4**: Stochastic constrained programming with an augmented multi-criteria scenario-based solution method	Improving the reliability and quality of the solutions for a stochastic optimization problem with the development of a robust and reliable solution method.
Q5: How to test the effectiveness of the environmental regulations as well as some other legislative mechanisms for reverse logistics network design?	**Paper 1**: Incorporating and testing environmental regulations for landfill waste **Paper 2**: Incorporating and testing environmental regulations for landfill waste **Paper 3**: Incorporating and testing the carbon tax regulation with a soft constraint **Paper 4**: Incorporating and testing the carbon cap regulation with a hard constraint	Providing decision-support tools for accommodating, testing and validating different regulations and policy mechanisms in sustainable reverse logistics network design under both deterministic and uncertain environment.
Q6: How to plan a sustainable reverse logistics system with a special focus?	**Paper 5**: Multi-objective programming incorporating carbon reduction as well as other environmental impacts in the design of a reverse logistics system for	Providing decision-supports models for the planning of a sustainable reverse logistics system with a special focus, i.e. risk.

Table continued

	municipal solid waste management **Paper 6**: Multi-objective programming incorporating an improved risk minimization formula for the planning of a hazardous waste management system	
Q7: What are the managerial implications can be obtained from the modelling and numerical experimentations for sustainable reverse logistics network design?	**Paper 1**: Trade-off analysis, performance of activities and sensitivity analysis **Paper 2**: Trade-off analysis, performance of activities, control of uncertainty and sensitivity analysis **Paper 3**: Performance of activities, control of uncertainty and sensitivity analysis **Paper 4**: Performance of activities, control of uncertainty and sensitivity analysis **Paper 5**: Trade-off analysis, performance of activities, sensitivity analysis and comparative study **Paper 6**: Trade-off analysis, performance of activities and sensitivity analysis	Providing in-depth managerial implications for sustainable reverse logistics network design in several aspects including: 1, Trade-offs between economic and environment performance 2, Impacts from uncertainties 3, Effectiveness of different environmental regulations 4, Impacts of flexibility in designing a multi-product reverse logistics system 5, Trade-offs between costs and other sustainability-related objectives 6, Insight of the impact from facility operations and transportation

The contributions to the research community is given in Section 4.2.1, and Section 4.2.2 discusses the contributions to the industry.

4.2.1 Contributions to the research community

This PhD project has developed improved optimization models and methods for sustainable supply reverse logistics network design, which remedy the deficiencies of the mathematical models in the literature. The contributions to the research community are mainly addressed from the advancement of the mathematical modelling and solution methods.

1. Development on the mathematical modelling:
    - Developing improved optimization models for the design problem of a single/multi-product multi-echelon sustainable reverse logistics under a deterministic/uncertain environment.
    - Modelling different network structures in order to accommodate the characteristics of different reverse logistics systems. For example, the network structure with both direct transport and indirect transport via central collection centers.
    - Formulating a more flexible material flow in sustainable reverse logistics network design so as to permit multiple recovery options for the same type of product and to perform the optimal decision-making accordingly.
    - Incorporating environmental considerations and regulations (e.g. carbon emission objectives, different carbon policies and/or requirement on landfill waste) in sustainable reverse logistics network design.
    - Incorporating the flexibility consideration on facility capacity in the planning of a sustainable multi-product reverse logistics system with uncertain parameters, and the impact of flexibility is thoroughly discussed.
    - Improving the formulation and modelling of some specific reverse logistics systems, e.g. hazardous waste management system with improved formula for risk management.
2. Development on the solution methods:
    - Developing customized solution methods for resolving a multi-objective optimization problem of sustainable reverse logistics network design and comparing the effectiveness of different solution methods, i.e., normalized weighting method, lexicographic ε-constraint method, and augmented ε-constraint method.
    - Testing and comparing the computational efficiency of different solution methods for resolving different sized multi-objective mixed integer optimization problems for sustainable reverse logistics network design.

- Based on a recently developed solution method for resolving a stochastic optimization problem given by Soleimani et al. (2016), this PhD project develops an augmented multi-criteria scenario-based risk-averse solution method for improving the effectiveness and reliability of the optimal solution to a stochastic optimization problem for sustainable reverse logistics network design. The augmented solution method can effectively resolve the deficiencies of the original method and can greatly improve the flexibility of the method and quality of the optimal solution to a risk-averse stochastic optimization problem.

4.2.2 Contributions to the industry

The contributions to the industry is discussed from two perspectives. First, the optimization models, solution methods and computer codes developed in this research project form the most essential parts of an improved decision-support system that can be widely used by government, supply chain managers and practitioners for making a better decision on the planning of a single/multi-product multi-echelon sustainable reverse logistics system with/without the consideration of uncertainty.

Second, this PhD project presents valuable discussions and findings on the managerial implications of sustainable reverse logistics network design. Even if the optimization results are heavily influenced by the data generated, some generic managerial implications can still be obtained for a better understanding of the interactions in sustainable reverse logistics network design.

- In general, environmental consideration may result in a weaker performance on the profitability or cost management of a reverse logistics system. In this case, government subsidy may be used as an important leverage for compensating the economic loss and promoting the sustainable recovery of EOL and EOU products (Yu and Solvang, 2017a).
- The effectiveness for the reduction of environmental impacts with increased investment may be significantly different at the different stages. In addition, the contribution from facility operations and transportation to economic benefits and environmental impacts of a

reverse logistics system may be of great difference (Yu and Solvang, 2016b).

- The uncertainty in the reverse logistics network design may lead to a reduced performance on both economic benefits and environment impacts (Yu and Solvang, 2018).
- Under an uncertain environment, when the generation of waste products is very high, the capacity of the planned reverse logistics system may be exceeded. In this case, the decision-maker has to determine either to implement a reduction on the service level or to have more investments on capacity expansion. Nevertheless, it is wise to think about the future capacity expansion at the initial planning stage of a reverse logistics system (Yu and Solvang, 2017a).
- In a multi-product reverse logistics system, the insufficient capacity may only be caused by one or some of the products, but a low utilization of capacity may be observed for the other products. Therefore, another effective alternative to resolve this problem is to improve the flexibility of the facilities in order to enable the conversion of capacity between different products (Yu and Solvang, 2017a).
- When the reverse logistics system is operated under an uncertain environment and affected heavily by the market fluctuation, a highly flexible configuration may provide a better chance to generate higher profits while simultaneously has lower carbon emissions (Yu and Solvang, 2018).
- The implementation of a flexible configuration in the planning of a sustainable reverse logistics system for dealing with multiple heterogamous products may improve both economic and environmental performances only when the efficiency loss is maintained in a proper level. In another words, if the companies in the reverse logistics system have to spend significant efforts in order to achieve a high flexibility, the benefits gained may be negligible or even negative (Yu and Solvang, 2018)..

4.3 Suggestions for future works

The PhD project has developed improved optimization models and methods and provided some important managerial implications for sustainable reverse logistics network design. Nevertheless, the research result of the PhD project is not without limitations and some ideas and suggestions for future improvement are discussed as follows.

1. First, the uncertainty associated with the planning of a reverse logistics system may include more aspects. For example, the consumer's attitude towards the recovered products may change over time, and this will affect the profitability of the reverse logistics system. Therefore, future research works may be performed to formulate more uncertain parameters in the decision-making.
2. Second, in this PhD project, the economic performance and environmental impact are mainly taken into consideration in the decision-making of sustainable reverse logistics network design. For future research, the modelling and formulation of the social aspect of sustainable development are of interest.
3. Third, the inclusion of social sustainability formula and more uncertain parameters will eventually result in an increased computational complexity of the optimization problem. Due to this reason, the development of high performance algorithm, i.e., heuristics, meta-heuristics, hyper-heuristics as well as other approximation methods, is important in order to deliver high quality solutions within acceptable computational time.
4. Fourth, in this PhD project, the sustainable reverse logistics network design problem is considered from the holistic view of an overall system. However, the companies and organizations in the reverse logistics are individual elements of the system and thus may implement different strategies in the operations and transportation, and in some cases, those strategies may be conflicting with one another. Therefore, the modelling with game theoretic method and multi-level programming of the decision-making problems from the perspectives of individual companies could be an interesting topic for future research in sustainable reverse logistics design.

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Paper I

A general reverse logistics network design model for product reuse and recycling with environmental considerations

Hao Yu and Wei Deng Solvang

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Incorporating flexible capacity in the planning of a multi-product multi-echelon sustainable reverse logistics network under uncertainty

Hao Yu*, Wei Deng Solvang

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

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ABSTRACT

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

1. Introduction

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

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

* Corresponding author.
E-mail addresses: hao.yu@uit.no (H. Yu), wei.d.solvang@uit.no (W.D. Solvang).

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the business (Govindan et al., 2016a).

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

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

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

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

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

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

The main contributions of this research are summarized as follows:

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

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

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

Articles	Product flow		Capacity			Network		Objectives				Parameter	Modelling approach	Solution		Solver	Validation
	Single	Multiple	Non-flexible	Flexible	Unspecified	Forward	Reverse	Economic	Environmental	Social	Others			Exact	Approximation		
Pishvaee et al. (2009)	✓				✓	✓	✓	✓				Non-deterministic	Stochastic MIP	✓		LINGO	Experiment
El-Sayed et al. (2010)	✓				✓	✓	✓	✓				Non-deterministic	Stochastic MIP	✓		XpressSP	Experiment
Pishvaee et al. (2011)	✓				✓	✓	✓	✓				Non-deterministic	Robust MIP	✓		CPLEX	Experiment
Kannan et al. (2012)	✓				✓		✓	✓	✓			Deterministic	MIP	✓		LINGO	Experiment
Demirel et al. (2016)	✓				✓		✓	✓				Deterministic	MIP	✓		GAMS CPLEX	Case
Alshamsi and Diabat (2015)	✓				✓		✓	✓				Deterministic	MIP	✓		GAMS CPLEX	Case
Ghezavati and Beigi (2016)	✓				✓		✓	✓		✓		Deterministic	MOMIP		✓	MATLAB GAMS	Experiment
Yu and Solvang (2016b)	✓				✓		✓	✓	✓			Deterministic	MOMIP	✓		LINGO	Experiment
Govindan et al. (2016b)	✓				✓		✓	✓	✓	✓		Non-deterministic	Fuzzy MOMIP	✓	✓	MATLAB MINITAB	Experiment
Zandieh and Chensebli (2016)	✓				✓		✓	✓				Deterministic	MIP		✓	MATLAB	Experiment
Li et al. (2017)	✓				✓		✓	✓				Deterministic	MIP		✓	C++	Experiment
Silva et al. (2017)	✓				✓		✓	✓		✓		Deterministic	MOMIP	✓		CPLEX	Case
Guo et al. (2017a)	✓				✓		✓	✓				Deterministic	MIP		✓		Case
Guo et al. (2017b)	✓				✓	✓	✓	✓	✓			Deterministic	Two-stage MIP		✓		Case
Budak and Ustundag (2017)	✓				✓		✓	✓				Deterministic	MIP	✓		Xpress IVE	Case
Fard and Hajaghaei-Keshteli (2018)	✓				✓	✓	✓	✓				Deterministic	Game theoretic tri-level MIP		✓		Experiment
Rahimi and Ghezavati (2018)	✓				✓		✓	✓	✓	✓		Non-deterministic	Stochastic MOMIP	✓		GAMS	Experiment
Demirel and Gökçen (2008)		✓	✓			✓	✓	✓				Deterministic	MIP	✓		GAMS CPLEX	Experiment
Amin and Zhang (2012)		✓			✓	✓	✓	✓				Deterministic	MIP	✓		GAMS	Experiment
Diabat et al. (2013)		✓			✓	✓	✓	✓	✓			Deterministic	MIP	✓		GAMS CPLEX	Experiment
Özkır and Başlıgil (2013)		✓			✓	✓	✓	✓			✓	Non-deterministic	Fuzzy MOMIP	✓		GAMS	Experiment
Ramos et al. (2014)		✓			✓		✓	✓	✓	✓		Deterministic	MOMIP	✓		CPLEX	Case
Garg et al. (2015)		✓			✓	✓	✓	✓	✓			Deterministic	MOMIP	✓		LINGO	Experiment
Ghayebloo et al. (2015)		✓			✓	✓	✓	✓	✓			Deterministic	MOMIP	✓		GLPK	Experiment
Capraz et al. (2015)		✓			✓		✓	✓				Deterministic	MIP	✓		CPLEX	Case
Govindan et al. (2016a)		✓			✓	✓	✓	✓	✓	✓		Deterministic	MOMIP	✓		LINGO	Experiment
Yu and Solvang (2016a)		✓	✓				✓	✓	✓			Non-deterministic	Stochastic MIP	✓		LINGO	Experiment
Kheirkhah and Rezaei (2016)		✓	✓				✓	✓				Deterministic	MIP	✓		GAMS	Experiment
Talaei et al. (2016)		✓	✓			✓	✓	✓	✓			Non-deterministic	Robust fuzzy MIP	✓			Experiment
Entezaminia et al. (2017)		✓	✓			✓	✓	✓				Non-deterministic	Robust MIP	✓		CPLEX	Case
Keshavarz Ghorabaee et al. (2017)		✓	✓			✓	✓	✓	✓			Non-deterministic	Fuzzy MOMIP	✓			Experiment
Jindal and Sangwan (2017)		✓	✓			✓	✓	✓	✓			Non-deterministic	Fuzzy MOMIP	✓		LINGO	Experiment
John et al. (2017)		✓	✓				✓	✓	✓			Deterministic	MIP	✓		LINGO	Experiment

(*continued on next page*)

Table 1 (*continued*)

Articles	Product flow		Capacity			Network		Objectives				Parameter	Modelling approach	Solution		Solver	Validation
	Single	Multiple	Non-flexible	Flexible	Unspecified	Forward	Reverse	Economic	Environmental	Social	Others			Exact	Approximation		
Yilmaz et al. (2017)		˅			˅		˅	˅		˅		Deterministic	MOMIP	˅		OPL	Case
Kannan et al. (2017)		˅	˅				˅	˅				Deterministic	MIP	˅		LINGO	Experiment
Temur and Bolat (2017)		˅			˅		˅	˅	˅			Deterministic	MOMIP	˅		GAMS CPLEX	Case
Fattahi and Govindan (2017)		˅	˅			˅	˅	˅				Non-deterministic	Stochastic MIP		˅	GAMS CPLEX	Experiment
Feitó-Cespón et al. (2017)		˅	˅				˅	˅	˅	˅		Non-deterministic	Stochastic MOMIP	˅		MATLAB	Experiment
Babaveisi et al. (2017)		˅	˅			˅	˅	˅		˅	˅	Deterministic	MOMIP		˅		Experiment
Soleimani et al. (2017)		˅			˅	˅	˅	˅	˅	˅	˅	Non-deterministic	Fuzzy constrained MOMIP		˅	LINGO	Experiment
Alshamsi and Diabat (2017)		˅			˅		˅	˅				Deterministic	MIP		˅	CPLEX	Case
Yu and Solvang (2017)		˅	˅				˅	˅	˅			Non-deterministic	Stochastic constrained MIP	˅		LINGO	Experiment
Coelho and Mateus (2017)		˅			˅		˅	˅				Deterministic	MIP		˅	CPLEX	Experiment
John et al. (2018)		˅	˅				˅	˅				Deterministic	MIP	˅		LINGO	Case
Trochu et al. (2018)		˅			˅		˅	˅				Non-deterministic	Stochastic MIP	˅			Case
Jabbarzadeh et al. (2018)		˅	˅			˅	˅	˅				Non-deterministic	Robust MIP		˅	GAMS	Case
Haddadsisakht and Ryan (2018)		˅			˅	˅	˅	˅				Non-deterministic	Stochastic robust MIP		˅	CPLEX	Experiment
This research		˅	˅	˅			˅	˅	˅			Non-deterministic	Stochastic MOMIP	˅		LINGO	Experiment

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

implications. Finally, section 7 concludes the paper and suggests directions for future study.

2. Literature review

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

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

2.1. Economic performance focused reverse logistics network design

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

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

2.2. Multi-criteria sustainable reverse logistics network design

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

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

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

2.3. Reverse logistics network design under uncertainty

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

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

2.4. Development of highly efficient computational algorithms

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

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

2.5. Summary and literature gap

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

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

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

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

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

3. Model development

3.1. Problem description

As illustrated in Fig. 1, the main operations in a generic reverse

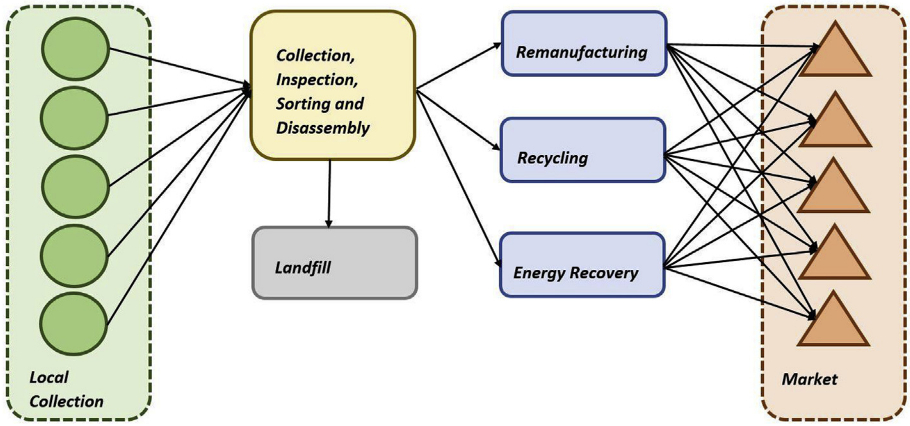

Fig. 1. Structure of a generic reverse logistics system.

Table 2
Modelling methods in sustainable reverse logistics network design.

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

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

3.2. Modelling methods

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

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

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

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

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

3.3. Notations

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

The model is formulated as follows:

Sets and indices	
W	Set of customers, indexed by w
I	Set of candidate locations for central collection centers, indexed by i
M	Set of candidate locations for remanufacturing centers, indexed by m
C	Set of recycling centers, indexed by c
R	Set of energy recovery centers, indexed by r
D	Set of landfills, indexed by d
Q	Set of products, indexed by q
S	Set of scenarios, indexed by s
V	Set of candidate locations for remanufacturing centers, recycling centers and energy recovery centers $V=\{M, C, R\}$, indexed by v
X	Set of all candidate locations $X=\{I, V\}$, indexed by x
$U(yz)$	Set of all routes between different facilities $U(y,z)=\{(w, i), (i,m), (i,c), (i,r), (i,d) \mid \forall w\in W, i\in I, m\in M, c\in C, r\in R, d\in D\}$, indexed by yz
Parameters	
Pt^s_{vq}	Price of the products or energy generated from recovering one unit of product q at facility v in scenario s
Su_{vq}	Government subsidy for recovering one unit of product q at facility v
F_x	Fixed operating costs for opening a facility at candidate location x
Oc_{xq}	Processing costs for treating one unit of product q at facility x
Gf_{dq}	Gate fee for sending one unit of product q to landfill d
Tc_{qyz}	Transportation cost for shipping one unit of product q between different facilities within the reverse logistics system
Car_{xq}	CO_2 emissions for treating one unit of product q at facility x
Car_{dq}	CO_2 emissions for landfilling one unit of product q at facility d
$CarT_{qyz}$	CO_2 emissions of the transportation of one unit of product q between different facilities within the reverse logistics system
P_s	Probability of the realization of scenario s
Pd^s_{wq}	Amount of product q collected at customer w in scenario s
Cap_{xq}	Capacity for dealing with product q at facility x
Rep_{xq}	Required rate of utilization for treating product q at facility x
γ^{rm}_q	Fraction of product q suitable for remanufacturing
γ^{ry}_q	Fraction of product q suitable for recycling
γ^{rc}_q	Fraction of product q suitable for energy recovery
π^s_q	Quality level of product q in scenario s
En_q	Environmental policy requirement presenting the minimum recovered percentage from the recoverable fraction of product p
A_q	Percentage of the recoverable fraction if product q is at good quality, $A_q = Percentage\ of\ set\ \{\gamma^{rm}_q\cup\gamma^{ry}_q\cup\gamma^{rc}_q\}\le 100\%$, It is noted that $\sum(\gamma^{rm}_q, \gamma^{ry}_q, \gamma^{rc}_q), \forall q\in Q$ may be more than 100% due to the overlap fraction suitable for multiple treatments.
A^C_q	Percentage of the non-recoverable fraction if product q is at good quality, $A^C_q = Percentage\ of\ the\ complement\ set\ of\{\gamma^{rm}_q\cup\gamma^{ry}_q\cup\gamma^{rc}_q\}$, and $A^C_q + A_q = 100\%$
Cap^{Flex}_x	Flexible capacity of facility x
ϑ^{Flex}_{xq}	Conversion rate of the usage of flexible capacity for processing product q at facility x
Ef^{Loss}_i	Rate of the efficiency loss for implementing flexible capacity at facility x
Rep^{Flex}_i	Required rate of utilization of facility x with flexible capacity
Decision variables	
Loc_x	Binary decision variables determining if a new facility is open at candidate location x
Qn^s_{xq}	Quantity of product q treated at facility x in scenario s
Qtn^s_{qyz}	Quantity of product q transported via route yz in scenario s

$$
\begin{aligned}
\text{Min Obj1} = &\sum_{s\in S} P_s\Bigg(\sum_{q\in Q}\sum_{m\in M}\Big(Pt^s_{mq}+Su_{mq}\Big)+Qn^s_{mq}\\
&+\sum_{q\in Q}\sum_{c\in C}\Big(Pt^s_{cq}+Su_{cq}\Big)Qn^s_{cq}+\sum_{q\in Q}\sum_{r\in R}\Big(Pt^s_{rq}+Su_{rq}\Big)Qn^s_{rq}\\
&-\Bigg(\Bigg(\sum_{i\in I}F_iLoc_i+\sum_{m\in M}F_mLoc_m+\sum_{c\in C}F_cLoc_c+\sum_{r\in R}F_rLoc_r\Bigg)\\
&+\sum_{s\in S}P_s(\sum_{q\in Q}\sum_{i\in I}Oc_{iq}Qn^s_{iq}+\sum_{q\in Q}\sum_{m\in M}Oc_{mq}Qn^s_{mq}\\
&+\sum_{q\in Q}\sum_{c\in C}Oc_{cq}Qn^s_{cq}+\sum_{q\in Q}\sum_{r\in R}Oc_{rq}Qn^s_{rq}+\sum_{q\in Q}\sum_{d\in D}Gf_{dq}Qn^s_{dq}\\
&+\sum_{q\in Q}\sum_{w\in W}\sum_{i\in I}Tc_{qwi}Qtn^s_{qwi}+\sum_{q\in Q}\sum_{i\in I}\sum_{m\in M}Tc_{qim}Qtn^s_{qim}\\
&+\sum_{q\in Q}\sum_{i\in I}\sum_{c\in C}Tc_{qic}Qtn^s_{qic}+\sum_{q\in Q}\sum_{i\in I}\sum_{r\in R}Tc_{qir}Qtn^s_{qir}\\
&+\sum_{q\in Q}\sum_{i\in I}\sum_{d\in D}Tc_{qid}Qtn^s_{qid}\Bigg)\Bigg)
\end{aligned}
\tag{1}
$$

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

Subject to:

(1) Demand satisfaction

$$Pd^s_{wq}=\sum_{i\in I}Qtn^s_{qwi},\ \forall s\in S,\ w\varepsilon W,\ q\in Q \tag{3}$$

(2) Flow balance

$$\sum_{w\in W} Qtn^s_{qwi} = Qn^s_{iq},\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{4}$$

$$\sum_{i\in I} Qtn^s_{qim} = Qn^s_{mq},\ \forall s\in S,\ m\varepsilon M,\ q\in Q \tag{5}$$

$$\sum_{i\in I} Qtn^s_{qic} = Qn^s_{cq},\ \forall s\in S,\ c\varepsilon C,\ q\in Q \tag{6}$$

$$\sum_{i\in I} Qtn^s_{qir} = Qn^s_{rq},\ \forall s\in S,\ r\varepsilon R,\ q\in Q \tag{7}$$

$$\sum_{i\in I} Qtn^s_{qid} = Qn^s_{dq},\ \forall s\in S,\ d\varepsilon D,\ q\in Q \tag{8}$$

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

(3) Capacity constraints

$$Qn^s_{iq} \le Cap_{iq}Loc_i,\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{10}$$

$$Qn^s_{mq} \le Cap_{mq}Loc_m,\ \forall s\in S,\ m\varepsilon M,\ q\in Q \tag{11}$$

$$Qn^s_{cq} \le Cap_{cq}Loc_c,\ \forall s\in S,\ c\varepsilon C,\ q\in Q \tag{12}$$

$$Qn^s_{rq} \le Cap_{rq}Loc_r,\ \forall s\in S,\ r\varepsilon R,\ q\in Q \tag{13}$$

(4) Utilization requirements

$$Qn^s_{iq} \ge Rep_{iq}Cap_{iq}Loc_i,\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{14}$$

$$Qn^s_{mq} \ge Rep_{mq}Cap_{mq}Loc_m,\ \forall s\in S,\ m\varepsilon M,\ q\in Q \tag{15}$$

$$Qn^s_{cq} \ge Rep_{cq}Cap_{cq}Loc_c,\ \forall s\in S,\ c\varepsilon C,\ q\in Q \tag{16}$$

$$Qn^s_{rq} \ge Rep_{rq}Cap_{rq}Loc_r,\ \forall s\in S,\ r\varepsilon R,\ q\in Q \tag{17}$$

(5) Conversion constraints

$$\pi^s_q \gamma_{qm} Qn^s_{iq} \ge \sum_{m\in M} Qtn^s_{qim},\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{18}$$

$$\pi^s_q \gamma_{qc} Qn^s_{iq} \ge \sum_{c\in C} Qtn^s_{qic},\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{19}$$

$$\pi^s_q \gamma_{qr} Qn^s_{iq} \ge \sum_{r\in R} Qtn^s_{qir},\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{20}$$

$$\sum_{d\in D} Qtn^s_{qid} \ge \left(A^C_q + \left(1-\pi^s_q A_q\right)\right) Qn^s_{iq},\ \forall s\in S,\ i\varepsilon I,\ q\in Q \tag{21}$$

(6) Environmental policy

$$\sum_{m\in M} Qtn^s_{qim} + \sum_{c\in C} Qtn^s_{qic} + \sum_{r\in R} Qtn^s_{qir} \ge \pi^s_q A_q En_q Qn^s_{iq},\ \forall s\in S,\ i\varepsilon I, q\in Q \tag{22}$$

(7) Requirements for decision variables

$$Loc_i,\ Loc_m,\ Loc_c,\ Loc_r \in \{0,\ 1\},\ \forall i\varepsilon I,\ m\in M,\ c\in C,\ r\in R \tag{23}$$

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

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

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

3.5. Model extension incorporating flexible capacity

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

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

(8) Conversion to flexible capacity

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

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

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

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

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

(9) Capacity constraints under flexible capacity

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

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

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

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

(10) Utilization constraints under flexible capacity

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

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

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

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

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

4. Solution method

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

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

$$\begin{array}{ll} Min & z(\boldsymbol{x}) = (z_1(\boldsymbol{x}),\ z_2(\boldsymbol{x}),\ \ldots,\ z_k(\boldsymbol{x}))^T \\ S.t. & \boldsymbol{x}\in X \end{array} \tag{37}$$

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

4.1. Weighting method

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

$$\begin{aligned} & Min \;\; \boldsymbol{w}z(\boldsymbol{x}) = \sum_{i=1}^{k} w_i z_i(\boldsymbol{x}) \\ & S.t. \quad \boldsymbol{x} \in X \end{aligned} \tag{38}$$

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

1. Calculating the Maximum and Minimum values of each individual objective function with both capacity settings.

Non-flexible Capacity: $Obj1_{nonf}^{Max}$, $Obj2_{nonf}^{Max}$, $Obj1_{nonf}^{Min}$, $Obj2_{nonf}^{Min}$
Solve : Max $Obj1$, $Max\ Obj2$, $Min\ Obj1$ $Min\ Obj2$, s.t. (3)–(24)

Flexible Capacity: $Obj1_{flex}^{Max}$, $Obj2_{flex}^{Max}$, $Obj1_{flex}^{Min}$, $Obj2_{flex}^{Min}$
Solve : Max $Obj1$, $Max\ Obj2$, $Min\ Obj1$ $Min\ Obj2$, s.t. (3)–(9), (18)–(24), (25)–(36)

2. Determining the weight combinations between the two objective functions (wt), where $wt_{Obj1} + wt_{obj2} = 1$.
3. Determining the set of Pareto optimal solutions through calculating the weighted sum with different weight combinations (wt).

Non-flexible Capacity: $Pareto_{nonf}^{wt}$ Solve : $Min\ Pareto_{nonf}^{w} = w_{Obj1}\frac{Obj1_{nonf}^{Max} - Obj1_{nonf}}{Obj1_{nonf}^{Max} - Obj1_{nonf}^{Min}} + w_{obj2}\frac{Obj1_{nonf} - Obj2_{nonf}^{Min}}{Obj2_{nonf}^{Max} - Obj2_{nonf}^{Min}}$, s.t. (3)–(24)

Flexible Capacity: $Pareto_{flex}^{wt}$ Solve : $Min\ Pareto_{nonf}^{w} = w_{Obj1}\frac{Obj1_{flex}^{Max} - Obj1_{flex}}{Obj1_{flex}^{Max} - Obj1_{flex}^{Min}} + w_{obj2}\frac{Obj1_{flex} - Obj2_{flex}^{Min}}{Obj2_{flex}^{Max} - Obj2_{flex}^{Min}}$, s.t. (3)–(9), (18)–(24), (25)–(36)

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

4.2. Augmented ε−constraint method

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

$$\begin{aligned} & Min \;\; z_j(\boldsymbol{x}) \\ & S.t. \quad z_i(\boldsymbol{x}) \le \varepsilon_i,\ i = 1,\ 2, \ldots, k,\ i \ne j \\ & \boldsymbol{x} \in X \end{aligned} \tag{39}$$

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

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

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

1. Calculating the payoff matrix through a lexicographic approach with both capacity settings. It is noted, compared with conventional method, the lexicographic method eliminates the dominant solutions related to the worst-case point.

   Non-flexible capacity: $Obj1_{nonf}^{Max}$, $Obj2_{nonf}^{Max-lex}$, $Obj1_{nonf}^{Min-lex}$, $Obj2_{nonf}^{Min}$
   Solve:
   a) $Obj1_{nonf}^{Max}$ = Max $Obj1$, s.t. (3)–(24)
   b) Min $Obj2$, s.t. $Obj1 = Obj1_{nonf}^{Max}$, (3)–(24)
   c) Repeating the same procedures for $Obj2$

   Flexible capacity: $Obj1_{flex}^{Max}$, $Obj2_{flex}^{Max-lex}$, $Obj1_{flex}^{Min-lex}$, $Obj2_{flex}^{Min}$
   Solve:
   a) $Obj1_{flex}^{Max}$ = Max $Obj1$, s.t. (3)–(9), (18)–(24), (25)–(36)
   b) Min $Obj2$, s.t. $Obj1 = Obj1_{flex}^{Max}$, (3)–(9), (18)–(24), (25)–(36)
   c) Repeating the same procedures for $Obj2$

2. Calculating the range for $Obj2$ with both capacity settings, because the $Obj1$ is considered at higher priority.
   Non-flexible capacity: $Range_{nonf}^{Obj2} = Obj2_{nonf}^{Max-lex} - Obj2_{nonf}^{Min}$
   Flexible capacity: $Range_{flex}^{Obj2} = Obj2_{flex}^{Max-lex} - Obj2_{flex}^{Min}$

3. Setting the values of ε_{Obj2}. In this step, the number of grids (ng) is first determined, and the variation of ε_{Obj2} is the calculated: $\Delta\varepsilon_{Obj2} = \frac{Range^{Obj2}}{ng}$.
4. Determining the set of Pareto optimal solutions through resolving the derived constrained optimization problem.

Non-flexible capacity: $Pareto^{\varepsilon}_{nonf}$

Solve: $Max\ Obj1 + \vartheta \times s_2$

s.t. $Obj2 + s_2 = \varepsilon_{Obj2}$, (3)–(24)

Flexible capacity: $Pareto^{\varepsilon}_{flex}$

Solve: $Max\ Obj1 + \vartheta \times s_2$

s.t. $Obj2 + s_2 = \varepsilon_{Obj2}$, (3)–(9), (18)–(24), (25)–(36)

5. Computational experiments

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

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

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

5.1. Effect of flexible capacity on economic performance

The model is first solved with only profit-maximization objective, and the rate of efficiency loss is tested with $Ef^{Loss}_i = 0\%$ and $Ef^{Loss}_i = 15\%$. The calculation results are presented in Tables 5 and 6, respectively. We first compared the network performance and structure under both deterministic and stochastic environments. When non-flexible capacity is implemented, the profit achieved under deterministic environment is 6.7% higher than that of the stochastic scenario. However, when flexible capacity is implemented with $Ef^{Loss}_i = 0\%$, the profit obtained under stochastic environment is 2.2% higher. When the rate of efficiency loss increases to 15%, the deterministic scenario achieves a 1% higher profit. In addition, more facilities are opened under a stochastic environment in order to deal with the market fluctuation, and this will lead to an increase on the overall system costs due to the low facility utilization under low demand scenarios. It is observed, under market fluctuation, a highly flexible reverse logistics system may achieve a better profitability than that under a stable environment (see Table 5).

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

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

5.2. Effect of flexible capacity on economic and environmental performance

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

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

We then compared the performance of the reverse logistics system in terms of both profit expectation and environmental impact with the incorporation of flexible capacity. It is observed that the carbon emissions from reverse logistics activities increase with the increase of the profit expectation. In order to reduce the

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

Parameters	Uniform distribution	
	Product q_1	Product q_2
Amount of EOL and EOU products generation Pd^s_{wq}	4000–12,000	6000–20,000
Fixed costs of collection centers F_i	3-5 million	3-5 million
Processing costs at collection centers Oc_{iq}	50–80	50–80
Fixed costs of remanufacturing centers F_m	5-9 million	5-9 million
Processing costs at remanufacturing centers Oc_{mq}	100–120	100–120
Price of remanufactured products Pt^s_{mq}	800–1200	800–1200
Government subsidy of remanufactured products Su_{mq}	200–300	200–300

Table 4
Scenario generation for the problem.

Scenarios	Probability of occurrence	Stochastic parameters		
		Amount of EOL and EOU products collected	Price of the recovered products	Quality level
1 (Deterministic)	20%	Mean	Mean	Mean
2	10%	Low	Low	Low
3	10%	Low	Low	High
4	10%	Low	High	Low
5	10%	Low	High	High
6	10%	High	Low	Low
7	10%	High	Low	High
8	10%	High	High	Low
9	10%	High	High	High

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

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

Table 6
Selection of facilities in different scenarios.

Selection of facilities	Non-flexible capacity		Flexible capacity (Ef_i^{Lost}=0%)		Flexible capacity (Ef_i^{Lost}=15%)	
	Deterministic	Stochastic	Deterministic	Stochastic	Deterministic	Stochastic
Central collection centers	(1,0,1,1,0)	(0,0,1,1,1)	(0,0,1,1,0)	(1,0,1,1,0)	(0,0,1,1,0)	(1,0,1,1,0)
Remanufacturing centers	(1,0,0,1,0)	(0,1,0,1,0)	(1,0,0,1,0)	(0,1,0,1,0)	(1,0,0,1,0)	(0,1,0,1,0)
Recycling centers	(0,1,0,1,0)	(0,0,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)	(0,1,0,1,0)
Energy recovery centers	(1,0,0)	(1,1,0)	(1,0,0)	(0,1,0)	(0,1,0)	(0,1,0)

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

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

Thus, it is of interest to "take a closer look at" the model behavior in the segment where the performance of a flexible reverse logistics system is close to a non-flexible one. Fig. 8 illustrates the comparison of the Pareto frontiers between non-flexible configuration and flexible configuration with $Ef_i^{Loss} = 30\%$, 32.5%

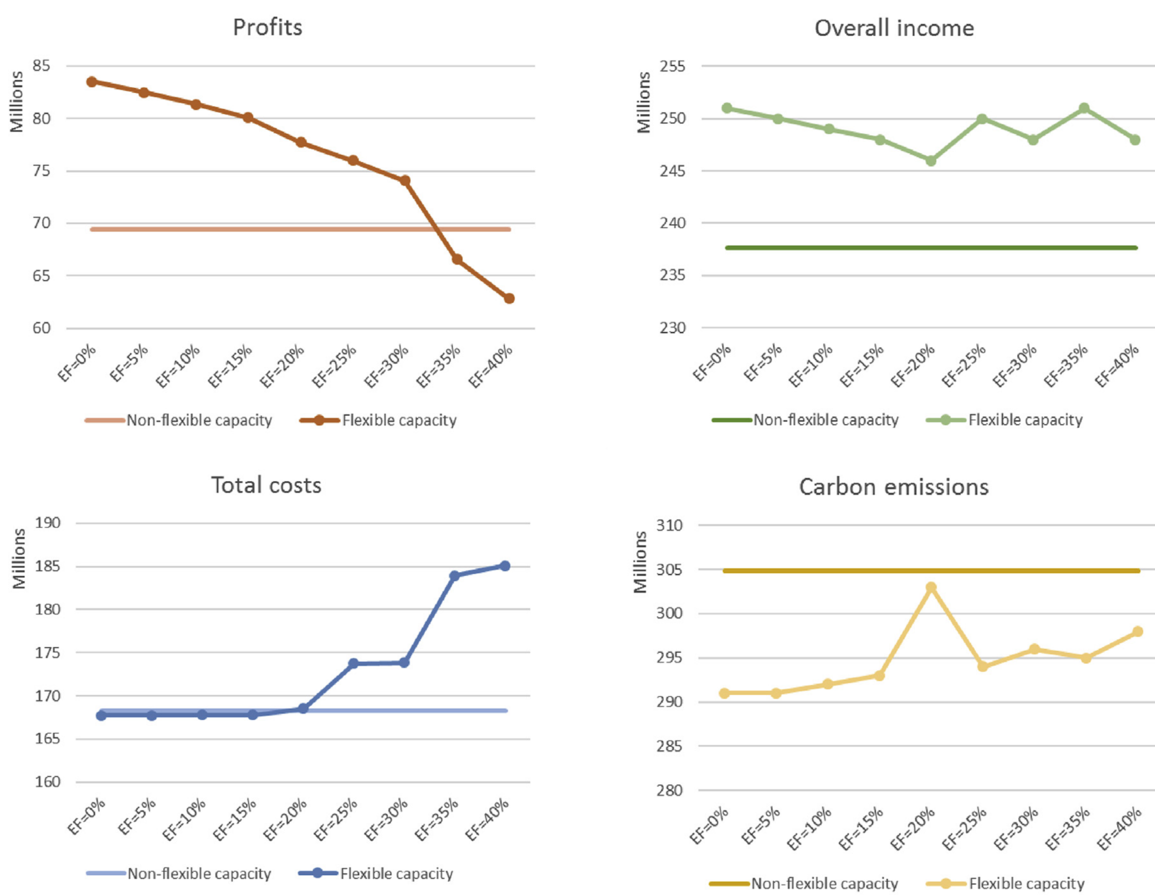

Fig. 2. Comparison of profits, overall income, total costs and carbon emissions of the different scenarios under stochastic environment.

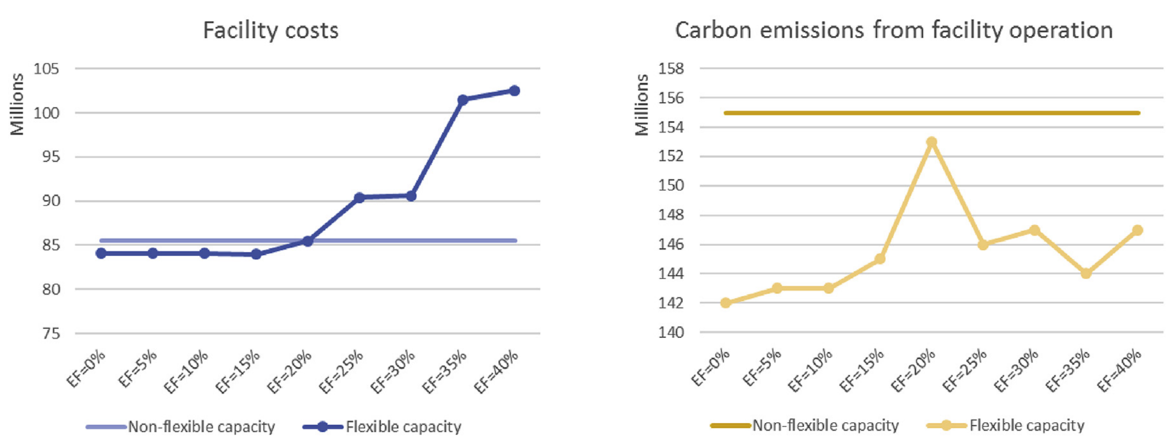

Fig. 3. Comparison of costs and carbon emissions related to facility operations of different scenarios under stochastic environment.

and 35%, respectively. When $Ef_i^{Loss} = 32.5\%$, the performance of the reverse logistics system with both capacity settings is very close to each other. In this case, the flexible reverse logistics system favors more on profit-focused scenarios. While, on the other hand, the non-flexible configuration has a slightly better performance on the emission-focused scenarios.

6. Managerial implications

The planning of a sustainable reverse logistics system is a complex decision-making problem that aims at optimizing the trade-off between economic benefits and environmental influence. Furthermore, in the planning horizon of a reverse logistics system, there are many uncertainties related the quantity and quality of the

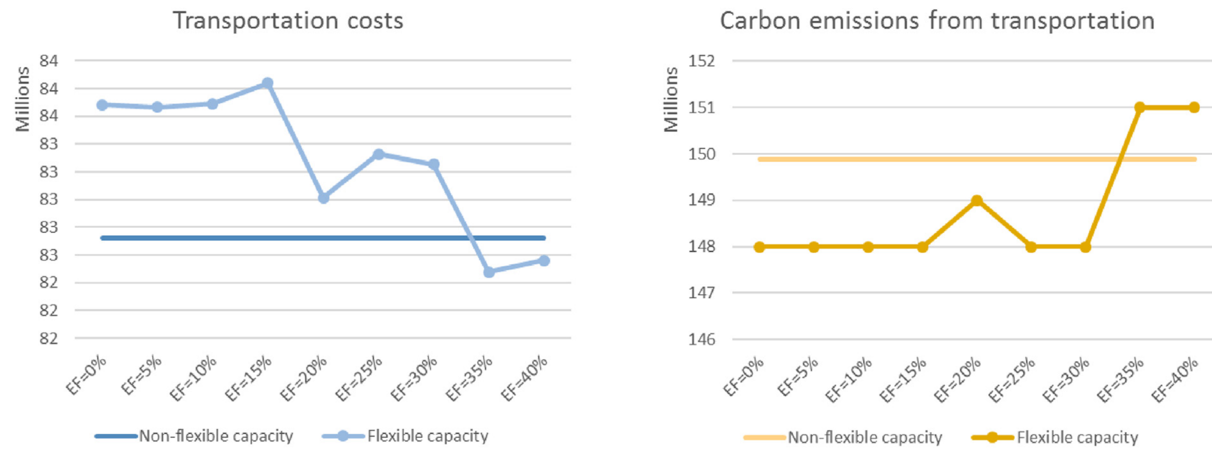

Fig. 4. Comparison of costs and carbon emissions related to transportation of different scenarios under stochastic environment.

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

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

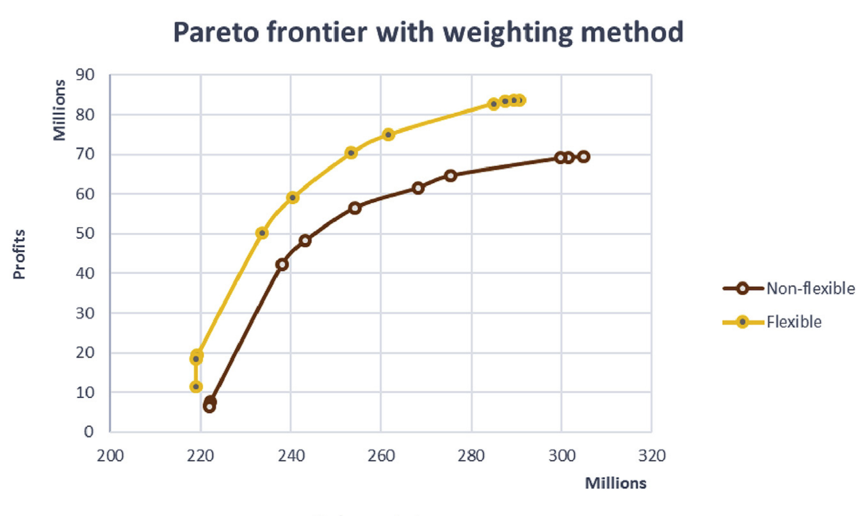

Fig. 5. Pareto frontier determined by weighting method.

reverse flow, and market fluctuation, which make the problem becoming more complicated. The latest modelling efforts and computational analysis on sustainable reverse logistics network design under uncertainty have shown a significant improvement on the understanding of the trade-offs among economic, environmental and social sustainability (Feitó-Cespón et al., 2017; Talaei et al., 2016), implications from the customer satisfaction (Özkır and Başlıgil, 2013), on-site/off-site separations (Rahimi and Ghezavati, 2018), as well as computational performance (Govindan et al., 2016b; Soleimani et al., 2017). In this paper, the managerial implications regarding the impact of flexibility on sustainable reverse logistics network design under uncertainty is

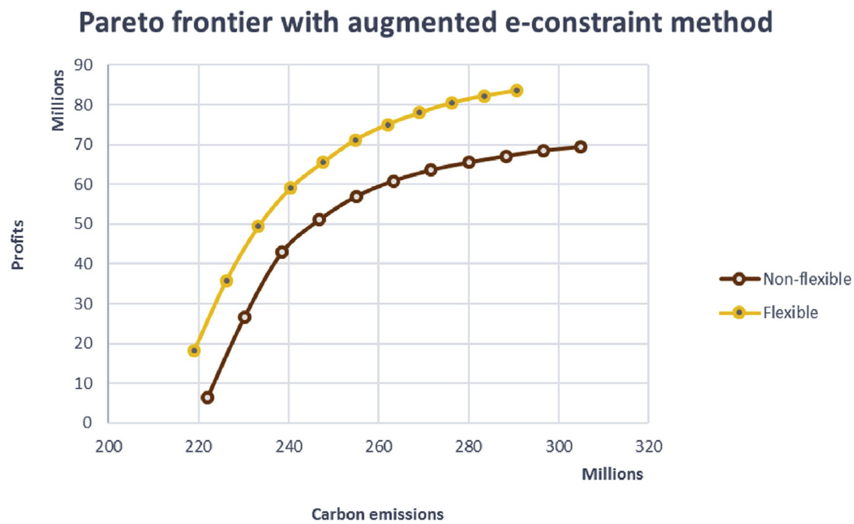

Fig. 6. Pareto frontier determined by augmented ε-constraint method.

focused.

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

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

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

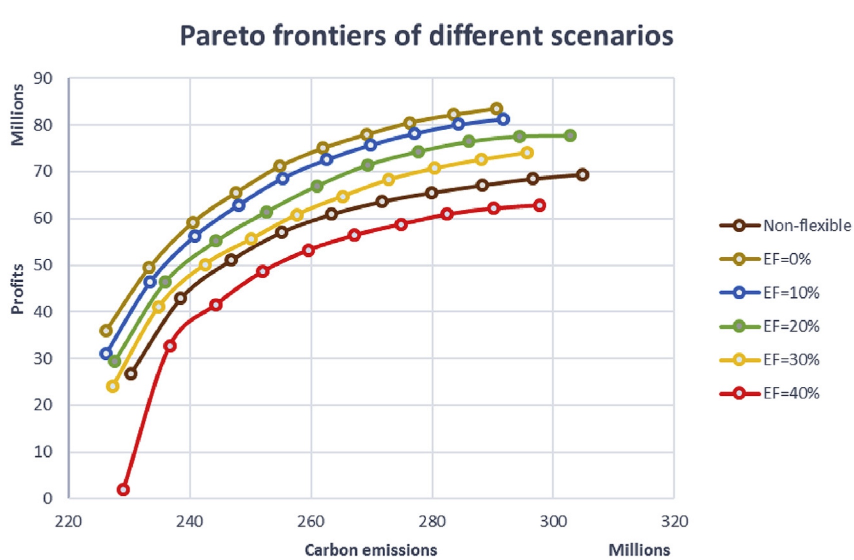

Fig. 7. Pareto frontiers determined by augmented ε-constraint method of different scenarios (Ef_i^{Loss}=0%, 10%, 20%, 30% and 40%).

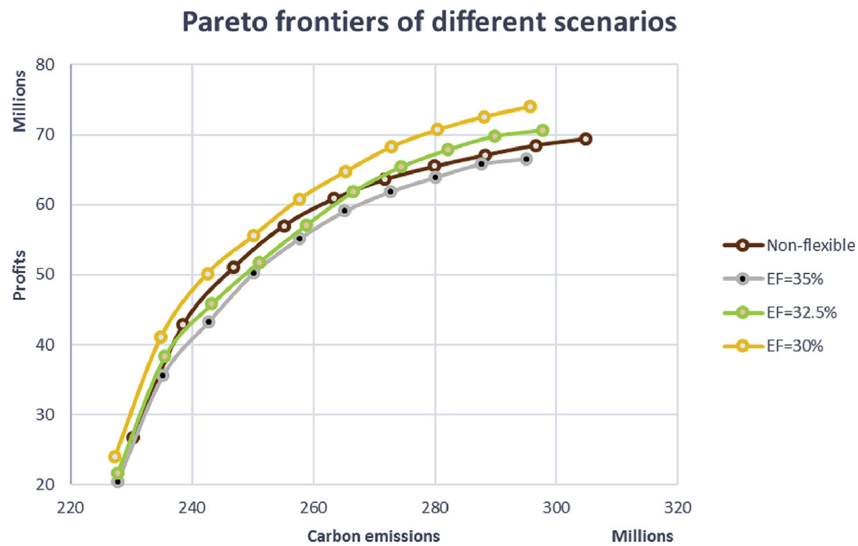

Fig. 8. Pareto frontiers determined by augmented ε-constraint method of different scenarios (Ef_i^{Loss}=30%, 32.5% and 35%).

distributed non-dominant efficient solutions, while weighting method requires less computational time.

7. Conclusion

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

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

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

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

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.07.019.

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Paper III

A stochastic programming approach with improved multi-criteria scenario-based solution method for sustainable reverse logistics design of waste electrical and electronic equipment (WEEE)

Hao Yu and Wei Deng Solvang

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Author's Contribution

Hao Yu has contributed substantially in the proposal of research idea, literature review, modelling, programming, experimental analysis, and writing of the paper.

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A carbon-constraint 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

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Hao Yu has contributed substantially in the proposal of research idea, literature review, modelling, programming, experimental analysis, and writing of the paper.

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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*, Wei Deng Solvang

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

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A B S T R A C T

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.

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

* Corresponding author.
E-mail addresses: hao.yu@uit.no (H. Yu), wei.d.solvang@uit.no (W.D. Solvang).

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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 pollution 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

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

The [*] is significant, and it provides the selection of relevant options in the table, and it provides information of which literature is classified in which categories.

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.

3. Development of mathematical model

The proposed reverse logistics network structure is given in Fig. 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.

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).

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:

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

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.

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

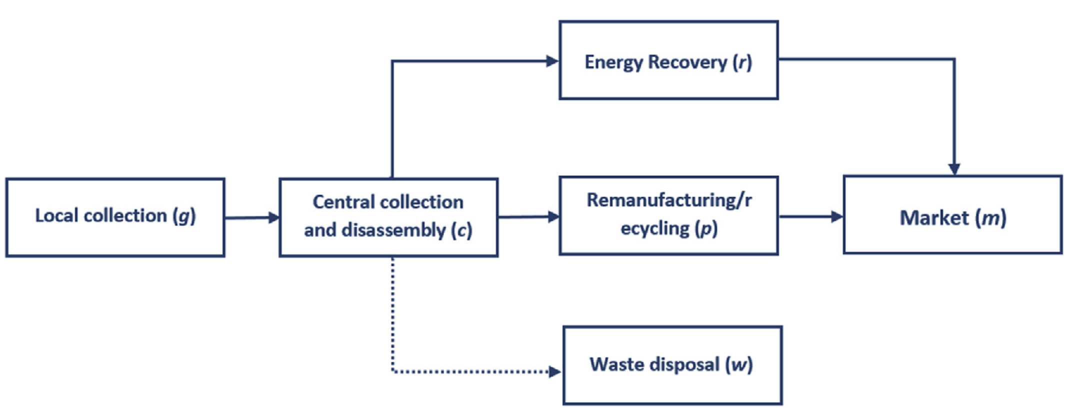


Fig. 1. Reverse logistics network.

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

$$\text{Income} = \sum_{r\in R}\sum_{t\in T} Pen_{rt}^s Qen_{rt}^s + \sum_{p\in P}\sum_{t\in T} Ppd_{pt}^s Qpd_{pt}^s \quad \forall s\in S \tag{3}$$

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

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.

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

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

$$\text{Processing cost} = \sum_{c\in C}\sum_{t\in T} Po_{ct} Qcd_{ct}^s + \sum_{p\in P}\sum_{t\in T} Po_{pt} Qpd_{pt}^s + \sum_{r\in R} \times \sum_{t\in T} Po_{rt} Qen_{rt}^s + \sum_{w\in W} Po_w Qwm_w^s \quad \forall s\in S \tag{7}$$

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

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.

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

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

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

$$Qen^s_{rt} = \sum_{c \in C} Qt^s_{crt}, \ \forall r \in R, \forall t \in T, \ \forall s \in S \quad (13)$$

$$Qwm^s_w = \sum_{c \in C} Qt^s_{cwt}, \ \forall w \in W, \forall t \in T, \ \forall s \in S \quad (14)$$

Eqs. (15) and (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.

$$\sum_{p \in P} Qt^s_{cpt} \le \partial_{tp} Qcd^s_{ct}, \ \forall c \in C, \forall t \in T, \ \forall s \in S \quad (15)$$

$$\sum_{r \in R} Qt^s_{crt} \le \partial_{tr} Qcd^s_{ct}, \ \forall c \in C, \forall t \in T, \ \forall s \in S \quad (16)$$

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

$$Qcd^s_{ct} \le MCp_{ct}, \ \forall c \in C, \forall t \in T, \ \forall s \in S \quad (17)$$

$$Qpd^s_{pt} \le MCp_{pt}, \ \forall p \in P, \forall t \in T, \ \forall s \in S \quad (18)$$

$$Qen^s_{rt} \le MCp_{rt}, \ \forall r \in R, \forall t \in T, \ \forall s \in S \quad (19)$$

$$Qwm^s_w \le MCp_w, \ \forall w \in W, \forall, \ \forall s \in S \quad (20)$$

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

$$\sum_{g \in G} Qt^s_{gct} \le X^s_c Q, \ \forall c \in C, \ \forall t \in T, \forall s \in S \quad (21)$$

$$\sum_{c \in C} Qt^s_{cpt} \le X^s_p Q, \ \forall p \in P, \ \forall t \in T, \forall s \in S \quad (22)$$

$$\sum_{c \in C} Qt^s_{crt} \le X^s_r Q, \ \forall r \in R, \ \forall t \in T, \forall s \in S \quad (23)$$

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.

$$\begin{aligned} Ruq^s_{ems} \ge & \sum_{c \in C} \sum_{t \in T} EP_{ct} Qcd^s_{ct} + \sum_{p \in P} \sum_{t \in T} EP_{pt} Qpd^s_{pt} + \sum_{r \in R} \\ & \times \sum_{t \in T} EP_{rt} Qen^s_{rt} + \sum_{w \in W} EP_w Qwm^s_w + \sum_{g \in G} \sum_{c \in C} \\ & \times \sum_{t \in T} Et_{gct} Qt^s_{gct} + \sum_{c \in C} \sum_{p \in P} \sum_{t \in T} Et_{cpt} Qt^s_{cpt} + \sum_{c \in C} \sum_{r \in R} \\ & \times \sum_{t \in T} Et_{crt} Qt^s_{crt} + \sum_{c \in C} \sum_{w \in W} \sum_{t \in T} Et_{cwt} Qt^s_{cwt} + \sum_{p \in P} \sum_{m \in M} \\ & \times \sum_{t \in T} Et_{pmt} Qt^s_{pmt} + \sum_{r \in R} \sum_{m \in M} \sum_{t \in T} Et_{rmt} Qt^s_{rmt}, \ \forall s \in S \end{aligned} \quad (24)$$

In addition to the aforementioned constraints, the first-level decision variables X^s_c, X^s_p and X^s_r are binary variables, which belongs to the set of $\{0, 1\}$, and second-level decision variables Qcd^s_{ct}, Qpd^s_{pt}, Qen^s_{rt}, Qwm^s_w, Qt^s_{gct}, Qt^s_{cpt}, Qt^s_{crt}, Qt^s_{cwt}, Qt^s_{pmt} and Qt^s_{rmt} 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 Fig. 2(A), solutions A and B are the candidate solutions of the stochastic optimization problem through scenarios $s_1, s_2,\ldots, s_n$. 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 $\mu\pm3\sigma$ (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.

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 Fig. 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. Fig. 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 Fig. 3 illustrates the procedures of the solution method. First, the absolute

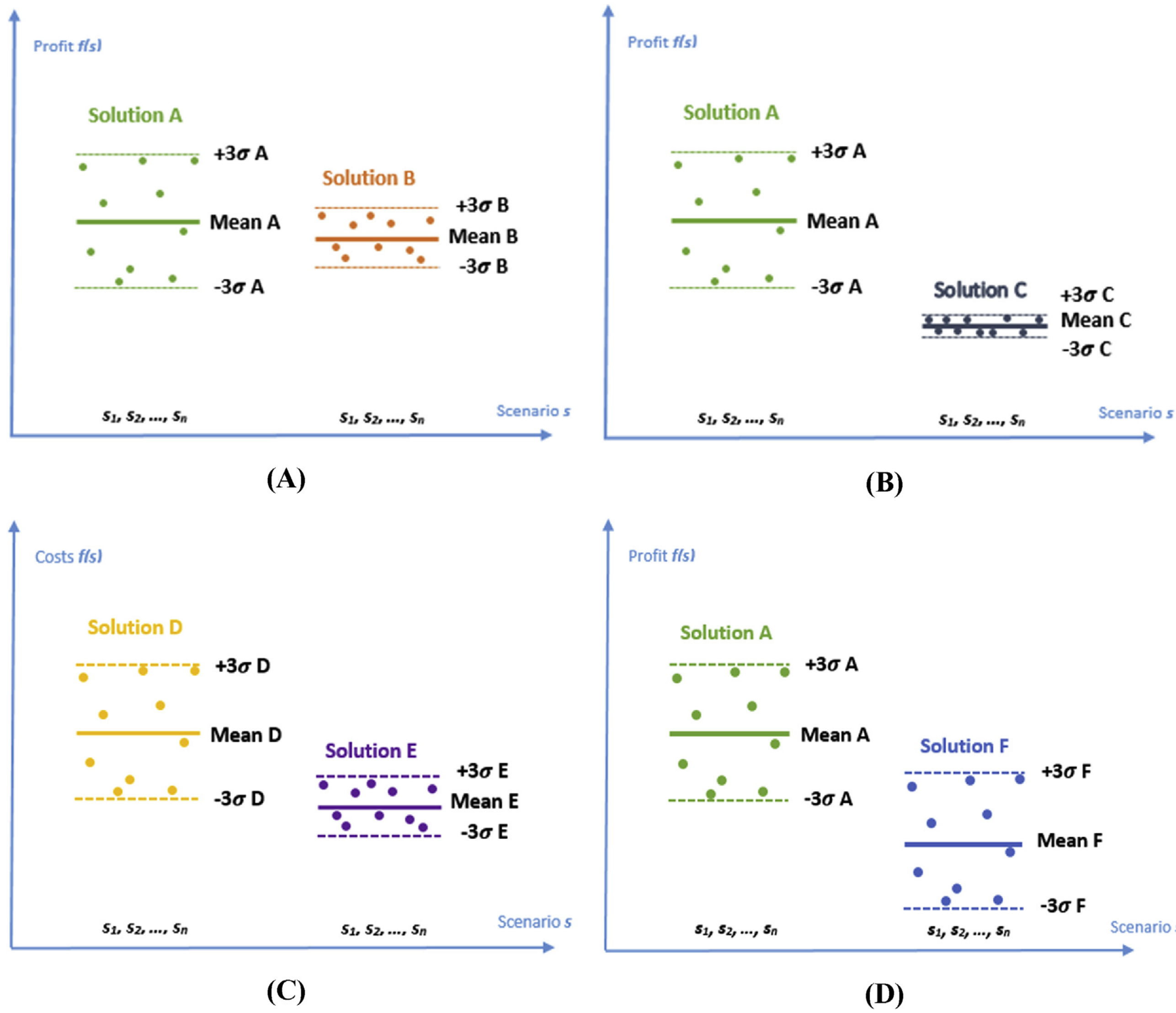


Fig. 2. Schematic of the benefit and problems of the multi-criteria scenario-based solution method: **(A)** Typical max-mean and min-standard deviation problem; **(B)** The problem of weak-reliable solution; **(C)** The incapability to resolve cost-minimization problem; **(D)** The problem of performance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

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, 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.

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) and (30)–(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

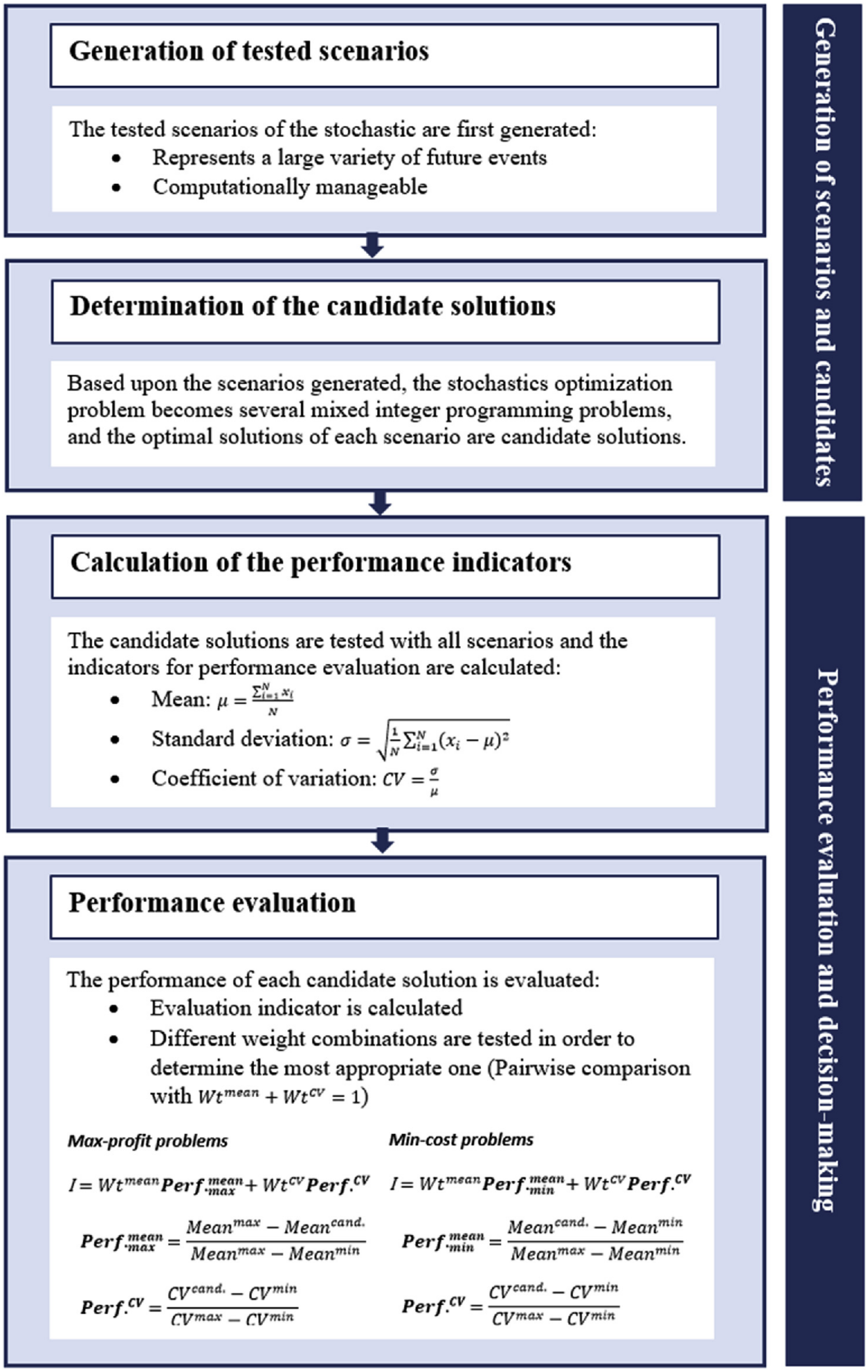


Fig. 3. Augmented multi-criteria scenario-based risk-averse solution method.

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 $\boldsymbol{Perf}_{\cdot max}^{mean}/\boldsymbol{Perf}_{\cdot min}^{mean}$ 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 $\boldsymbol{Perf}_{\cdot}^{CV}$ in order emphasize the reliability in the decision-making.

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

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

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

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

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

$$Wt^{mean} + Wt^{CV} = 1 \tag{32}$$

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.

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 Fig. 4.

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 2.20 GHz 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 Figs. 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

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

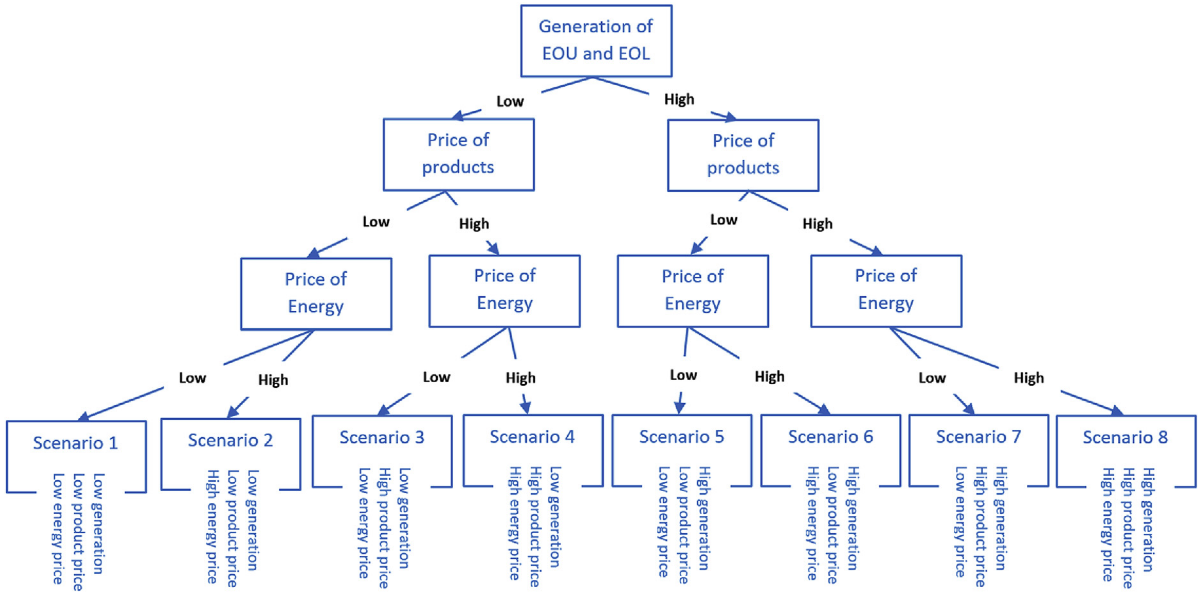


Fig. 4. Scenario tree related to the numerical experiment.

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	27,454	1, 2, 4, 6, 7, 8	2, 4, 5	1, 2, 3, 5
Basic	3724	20,284	1, 2, 4, 6, 7	4, 5	2, 3, 5
Worst-case	1208	13,047	1, 2, 6, 7	4, 5	3, 5
s1	2462	15,570	2, 4, 6, 7, 8	3, 4	3, 4
s2	3506	15,192	1, 2, 6, 7, 8	3, 4	4, 5
s3	3397	15,718	2, 5, 6, 7, 8	4, 5	3, 4
s4	4387	15,614	1, 2, 6, 7, 8	4, 5	2, 4
s5	3098	22,502	2, 4, 6, 7, 8	2, 3, 4	1, 3, 4
s6	4510	22,825	1, 2, 4, 6, 7, 8	2, 3, 4	2, 4, 5
s7	4299	22,567	2, 4, 6, 7, 8	1, 4, 5	1, 3, 4
s8	5617	22,405	2, 4, 6, 7, 8	1, 4, 5	2, 4, 5

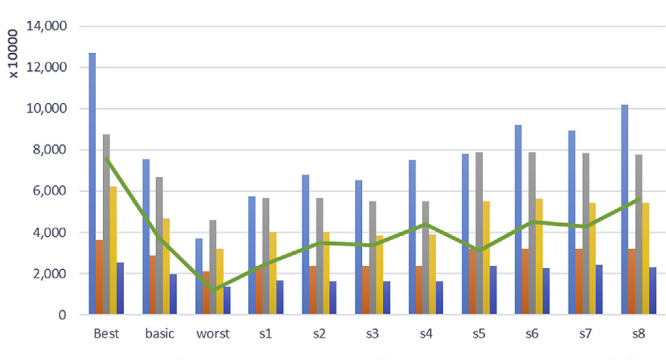


Fig. 5. Comparison of the revenue, profit and cost components of the candidate solutions (results are normalized by dividing by10^4).

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.

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 Figs. 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,

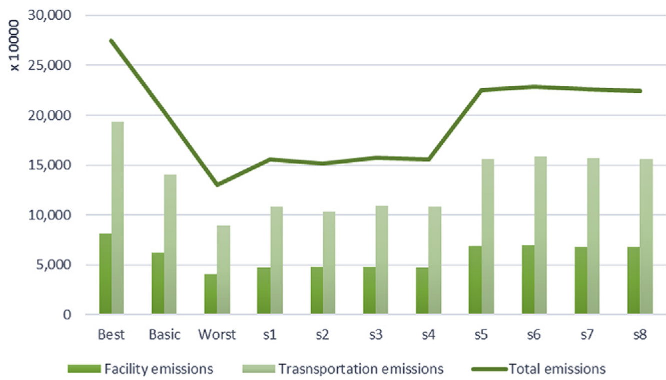


Fig. 6. Comparison of the total emissions, facility emissions and transport emissions of the candidate scenarios (results are normalized by dividing by10^4).

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.

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.

As shown in Table 4, each candidate solution represents the best profit expectation in its own scenario. The best profit expectation

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%

The shaded values are important, because they are selected optimal values with respect to different evaluation criteria.

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.

The performance of the candidate solutions is evaluated through both $\frac{1}{cv}$ and weighted sum and the result is shown in Fig. 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 Fig. 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.

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,

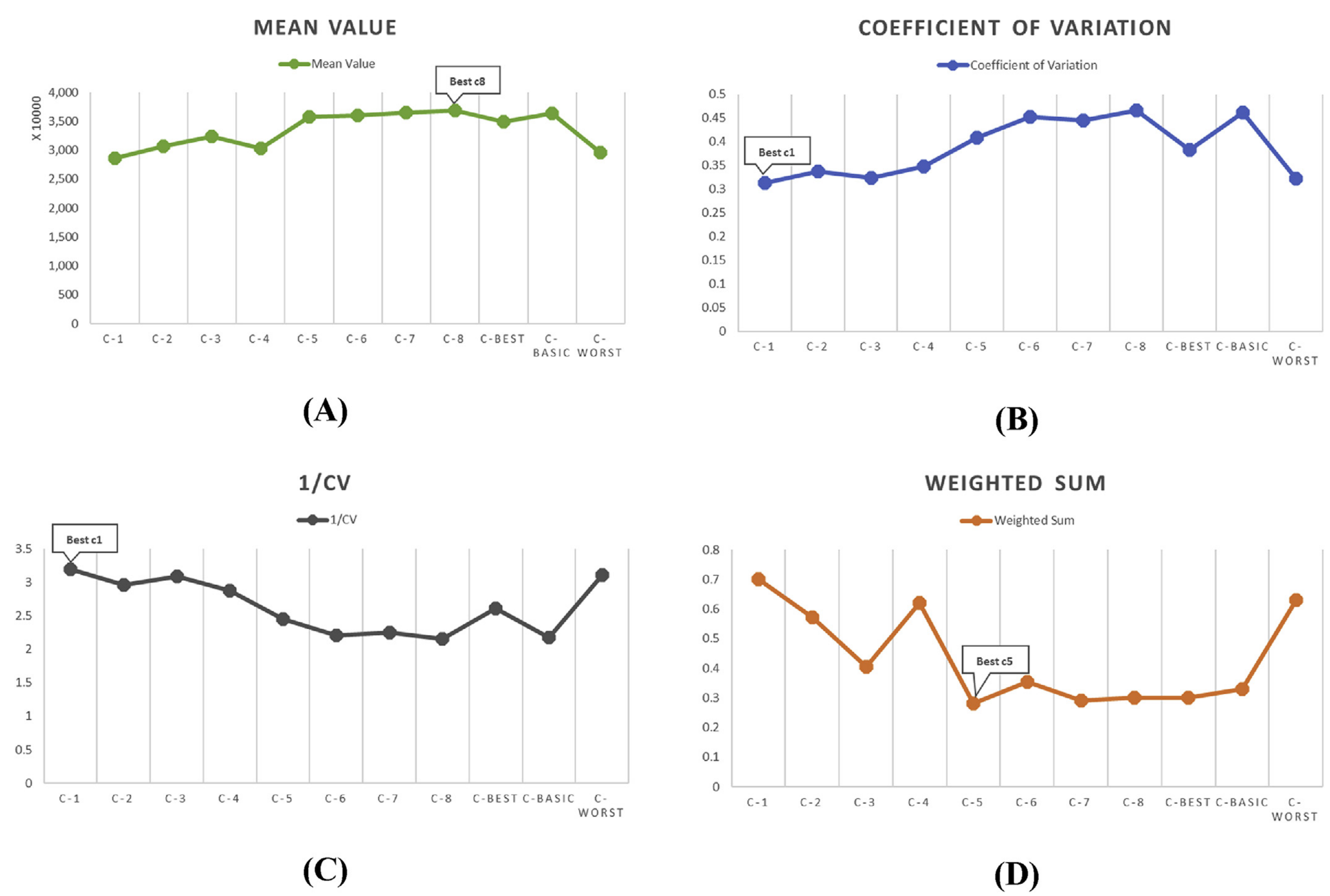


Fig. 7. Performance of the candidate solutions through all the test scenarios: **(A)** Comparison of mean value; **(B)** Comparison of standard deviation; **(C)** Performance evaluation with $\frac{1}{cv}$; **(D)** Performance evaluation with the weighted sum.

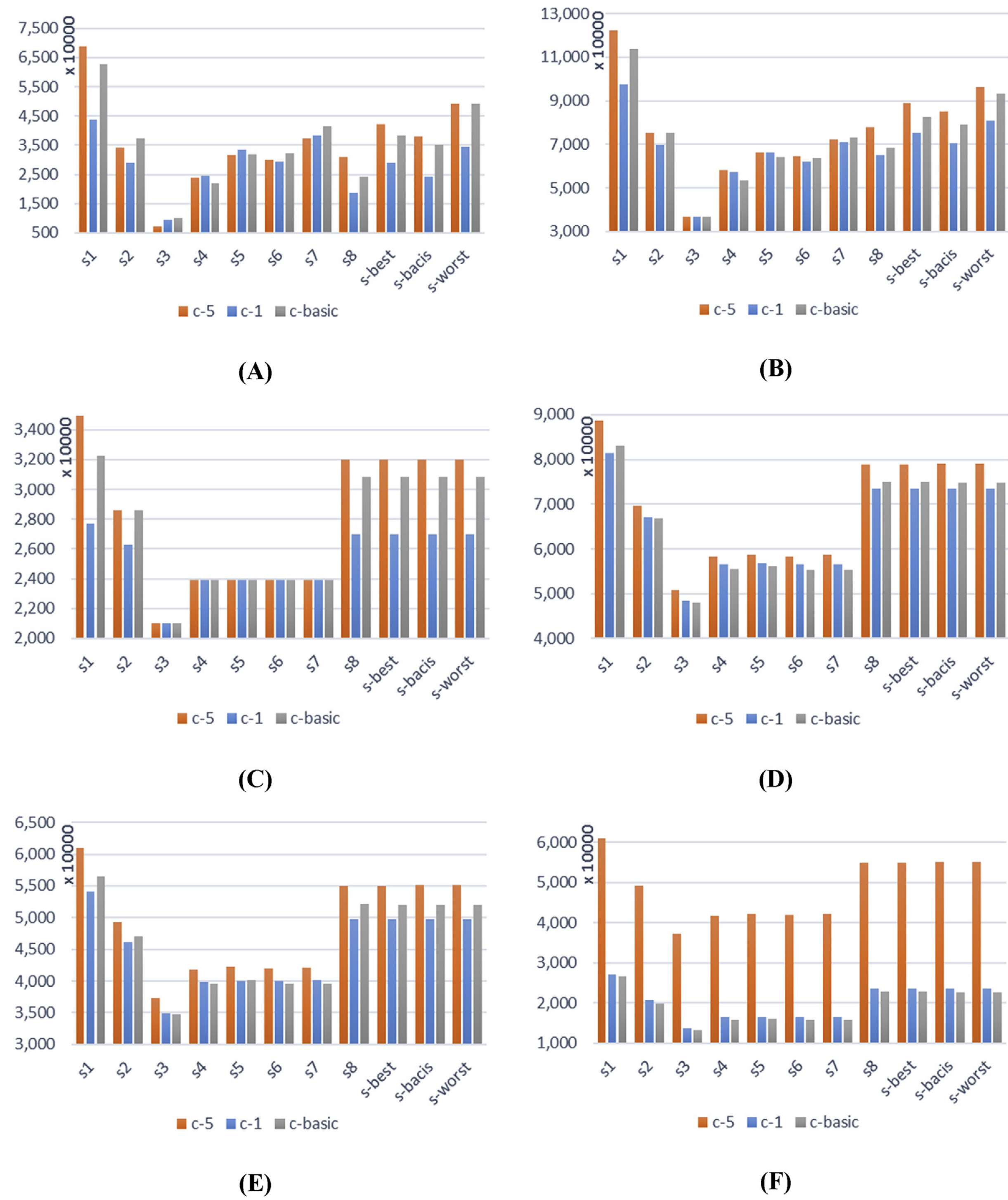


Fig. 8. Comparison of candidate solutions 1 and 5 through all the scenarios (results are normalized by dividing by10^4): **(A)** Profit expectation; **(B)** Total revenue; **(C)** Subsidy; **(D)** Total costs; **(E)** Facility costs; **(F)** Transportation costs.

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 Fig. 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 5 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. Figs. 9 and 10 present the comparison of the average cost expectation and average carbon emissions of the test problems. As shown in Fig. 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.

Fig. 10 shows the comparison of the two uncapacitated scenarios. As shown in Fig. 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. Fig. 9(B) shows the average carbon emissions reduce by 11.9% and 20.6% in the test problems, respectively. This illustrates that opening a smaller number of facilities with large capacity is another way to reduce the carbon emissions from the reverse logistics activities. Also, the result shows the facility expansion may improve both economic and environmental performance of the reverse logistics system, and the upper limit of the increased investment can be suggested to the decision-makers from the analysis.

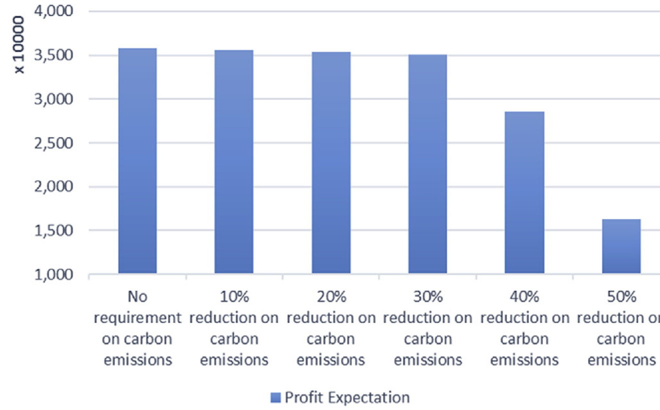


Fig. 9. Average profit expectation over the incremental requirement for the reduction of carbon emissions (results are normalized by dividing by10^4).

Figs. 11 and 12 illustrate the comparisons 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 different test problems, but the total costs change dramatically 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 configuration has significant importance in determining both economic and environmental performance of the reverse logistics system.

Table 5
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

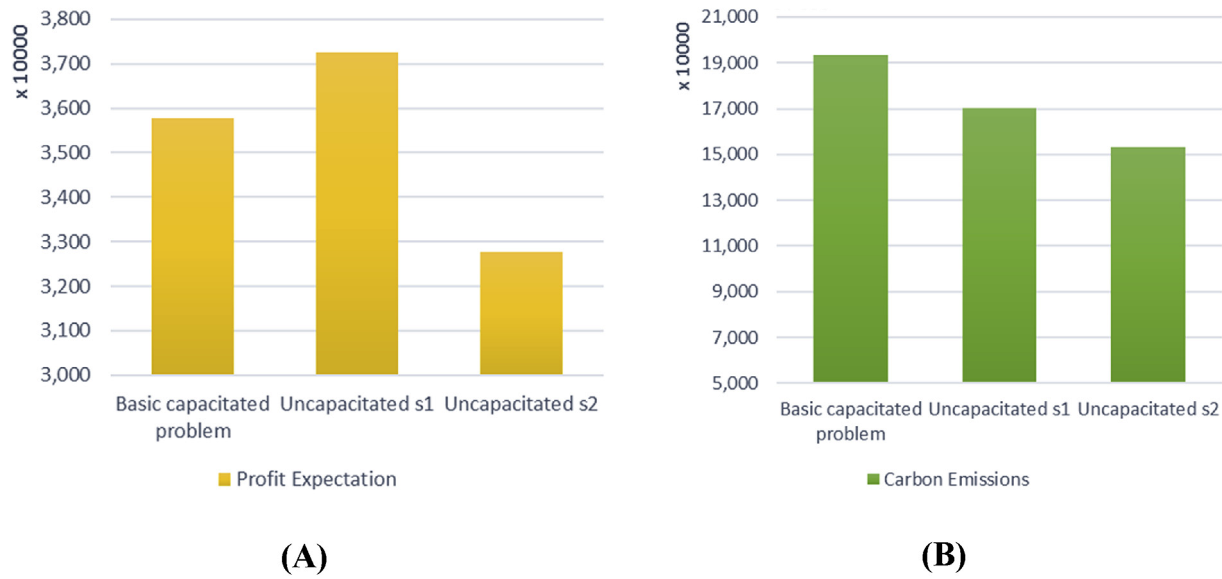


Fig. 10. Comparison of the basic capacitated problem and uncapacitated scenarios 1 and 2 (results are normalized by dividing by10^4): **(A)** Average profit expectation; **(B)** Average carbon emissions.

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.

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 6. The ratio of subsidy/profit illustrates the relative importance of the subsidy in the overall 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 surplus 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 obtained 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 extremely important role to promote the reuse, recycling and recovery of EOU and EOL products.

As shown in Table 6, the government subsidy is important to guarantee 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 addition, 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 profitability of the reverse logistics system.

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

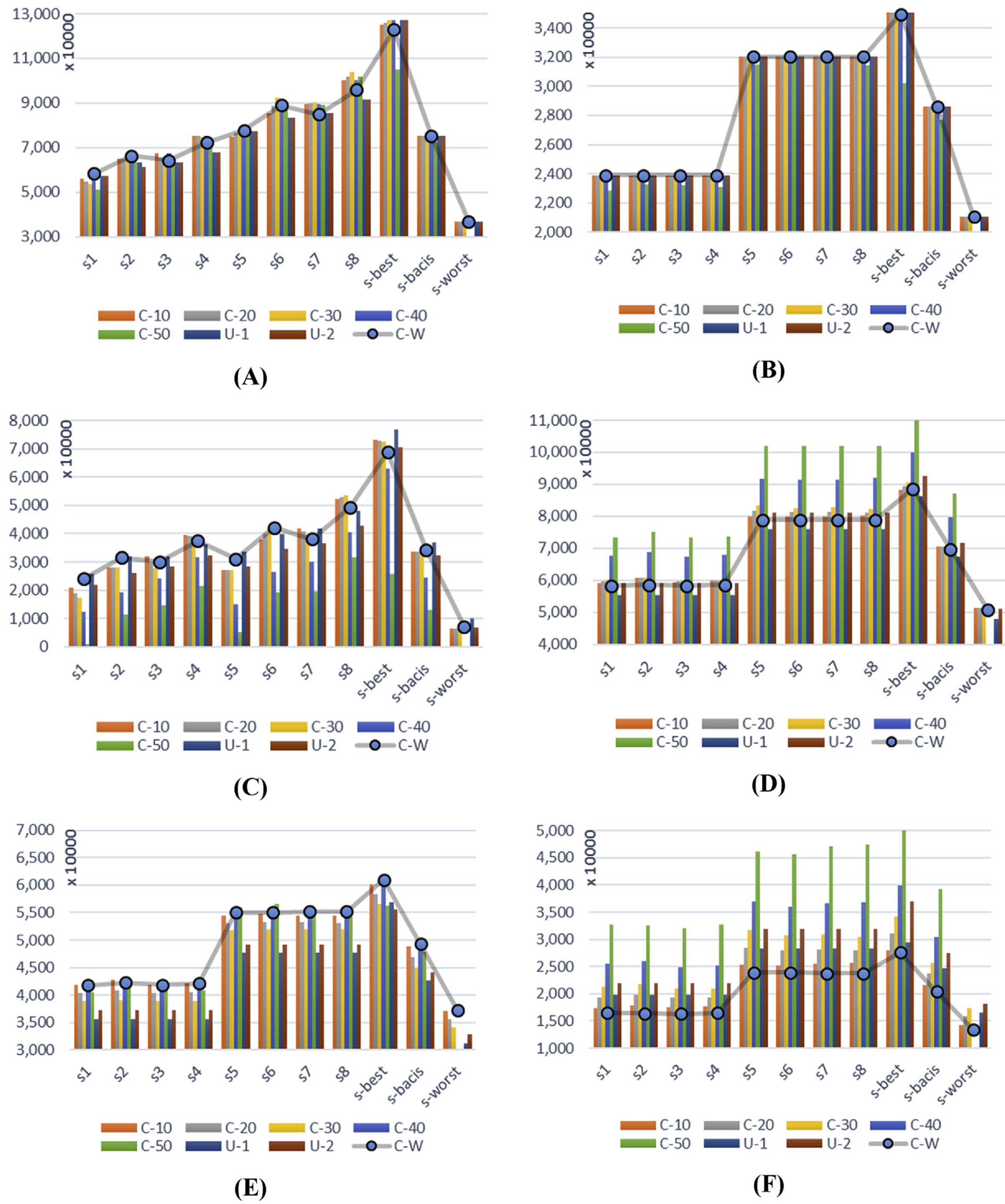
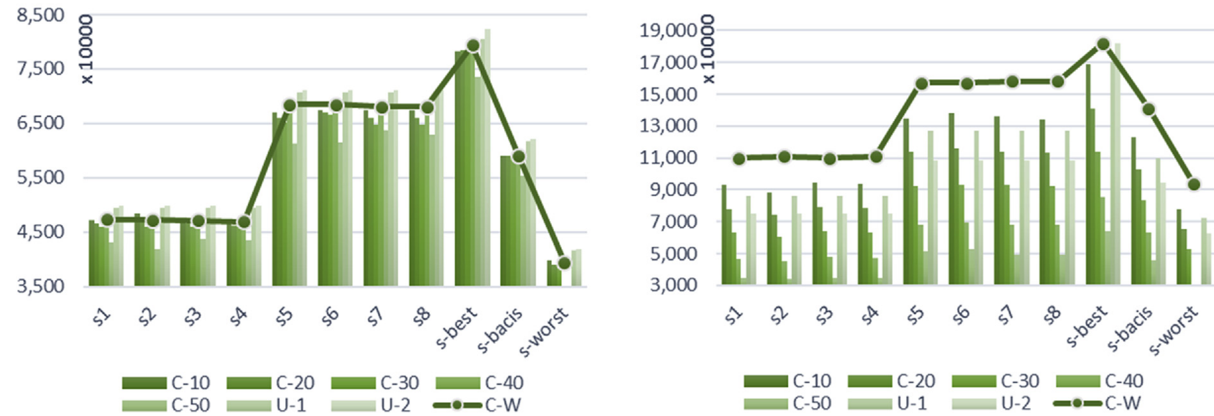


Fig. 11. Comparison of the optimal solutions with respect to the changing parameters in the sensitivity analysis (results are normalized by dividing by10^4): **(A)** Profit expectation; **(B)** Total revenue; **(C)** Subsidy; **(D)** Total costs; **(E)** Facility costs; **(F)** Transportation costs.

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



(A) **(B)**

Fig. 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.

Table 6
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%

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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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2017.07.066.

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Paper V

A multi-objective location-allocation optimization for sustainable management of municipal solid waste

Hao Yu and Wei Deng Solvang

Environment, Systems and Decisions, 2017, 37, 289-308.

Doi: 10.1007/s10669-017-9632-y

Author's Contribution

Hao Yu has contributed substantially in the proposal of research idea, literature review, modelling, programming, experimental analysis, and writing of the paper.

Not included in the electronic version

Paper VI

An improved multi-objective programming with augmented ε-constraint method for hazardous waste location-routing problems

Hao Yu and Wei Deng Solvang

International Journal of Environmental Research and Public Health, 2016, 13, 548.

Doi: 10.3390/ijerph13060548

Author's Contribution

Hao Yu has contributed substantially in the proposal of research idea, literature review, modelling, programming, experimental analysis, and writing of the paper.

Not included in the electronic version