Design of reverse logistics networks under uncertainty: Multi-objective approach

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ABSTRACT

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A reverse logistics network (RLN) is defined as the backward flow of products, specifically the products that are returned for recycling. Several entities are involved in a recycling process such as regional collection depots, recovery centers, remanufacturing plants, and disposal centers. The main objective of RLN design is to facilitate the reclamation of used products for the purpose of saving cost, energy, resources, and diverting waste from landfills and waterways. On this matter, decision-makers should consider different types of parameters (i.e., fixed and variable costs, the quantity of demand and return, and the quality of returned products) affecting the configuration of facility location models.

In real life, there are a variety of ambiguities associated with mentioned parameters that stem from either internal or external factors (e.g., volatility in market demand, rate of the returned products, unit transportation cost). The main objective of this dissertation is to develop multi-objective optimization models under uncertainty. In this regard, some integrated solution methodologies are introduced to address different types of uncertainty in five stewardship programs (i.e., electronic recycling association (ERA), Canadian battery association (CBA), beverage container stewardship program regulation (BCSPR), Ontario electronic stewardship (OES), wastewater management in hydraulic fracturing) in Canada.

To consider the environmental impact of such stewardship programs, the proposed mathematical models are extended to the multi-objective optimization models. In this regard, the proposed solution methodologies make decision-makers capable of optimizing the environmental aspects (e.g., green practices of third parties, carbon emissions) associated with RLNs.

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DEDICATION

I affectionately dedicate this dissertation to Maryam, my lovely, beautiful, and calming wife, along with my dearest mother and father.

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List of Acronyms

Analytic Hierarchy Process (AHP)

Absolutely More Important (AMI)

Analytic Network Process (ANP)

Beverage Container Stewardship Program Regulation (BCSPR)

Canadian Battery Association (CBA)

Collection Centers (CC)

Canadian Environmental Protection Act (CEPA)

Closed-Loop Supply Chain (CLSC)

Data Envelopment Analysis (DEA)

Economic Criteria (EC)

Equally Important (EI)

Environmental Management Systems (EMS)

End-Of-Life (EOL)

End-Of-Life Vehicles (ELVs)

Electronic Recycling Association (ERA)

Electronic Recovery Centers (ERC)

Electronic Remanufacturing Plants (ERP)

Fuzzy Analytic Network Process (FANP)

Fully Fuzzy Programming (FFP)

Fully Fuzzy Scenario-based Programming (FFSP)

Fuzzy Programming (FP)

Green Criteria (GC)

Green Closed-Loop Supply Chain Management (GCLSCM)

Green Information Technology and System (GITS)

Green Performance Evaluation in Supply Chain (GPESC)

Grey Relational Analysis (GRA)

Greater Toronto Area (GTA)

Internal Environmental Management (IEM)

Internal environmental issues (IEM)

Lead Acid Batteries (LAB)

Multi-Criteria Decision Making (MCDM)

Mixed-Integer Linear Programming (MILP)

Mixed-Integer Nonlinear Programming (MINLP)

Multi-Objective Model (MOM)

Multi-Objective Programming (MOP)

Mathematical Programming Models (MPMs)

Original Equipment Manufacturer (OEM)

Ontario Electronic Stewardship (OES)

Operations and Logistic Integration (OLI)

Partial Least Squares Structural Equation Modeling (PLS-SEM).

Quality Function Deployment (QFD)

Recovery Centers (RC)

Robust Flexible Chance-Constrained Model (RFCCM)

Reverse Logistics (RL)

Reverse Logistics Network (RLN)

Robust Optimization (RO)

Remanufacturing Plants (RP)

Simulated Deterministic (SD) Model

Strongly More Important (SMI)

Scenario-based Possibilistic Model (SPM)

Scenario-based Robust Possibilistic Model (SRPM)

Sustainable Environmental Strategies (SES)

Stochastic Mixed-Integer Linear Programming (SMILP)

Stochastic Mixed-Integer Bilinear Model (SMIBM)

Supply Chain Management (SCM)

Supplier Selection (SS)

Strategic Supplier’s Partnership (SSP)

Total Dissolved Solids (TDS)

Triangular Fuzzy Number (TFN)

Value Path Analysis (VPA)

Very Strongly More Important (VSMI)

Waste Electrical and Electronic Equipment (WEEE)

Weakly More Important (WMI)

Wastewater Treatment Plants (WWTP)

Chapter 1

1.1. Introduction

A reverse logistics network (RLN) includes some activities such as remanufacturing and refurbishing for the purpose of either creating value, or proper disposal over the entire life cycle of products (Carter and Ellram, 1998; Srivastava, 2008; Dekker et al., 2013; Govindan and Soleimani, 2017). The recovery of used products and materials is essential to support the population growth with regard to finite resources. In this regard, RLNs usually have a positive impact on saving natural resources and reducing environmental issues. Furthermore, companies are motivated to be involved in environmental stewardship due to social and environmental responsibilities (Ramos et al., 2014; Adenso-Díaz et al., 2016).

As illustrated in Fig. 1.1, a reverse stream includes several entities such as regional collection depots, recovery centers (i.e., all the required activities to recover the components of used products, such as inspection, disassembly, refurbishing), remanufacturing plants, and disposal centers. Recovery choices such as recycling are applied for the returned products. The recycling of returned products increases the total profit of the network, and it reduces environmental issues such as carbon emissions, and hazardous waste. The configuration of RLNs is a strategic decision (e.g., opening or closing the recovery center) which is impossible to be changed in the short-term (Kumar et al., 2017; Van Engeland et al., 2020).

Designing RLNs has received great attention recently. Customers return products to the regional collection depots because of different reasons. Such returns may include commercial returns, end-of-use returns, end-of-life returns, repair, and warranty returns over the product life cycle. After sorting, the returned products are transported to the recovery centers. Prior to the recovery process, inspection is conducted on every product since the quality of returned products is different. In this regard, some parts of the returned products can be used again after the recovery process, while the other components are unrecoverable and must be sent to the disposal center. The recovered components are shipped to the remanufacturing plants. Then, suppliers provide complementary parts which are required for production, to the remanufacturing plants. Therefore, RLNs should consist of all activities related to product recovery consisting of the returned product acquisition, product disassembly, inspection, refurbishing, and remanufacturing.

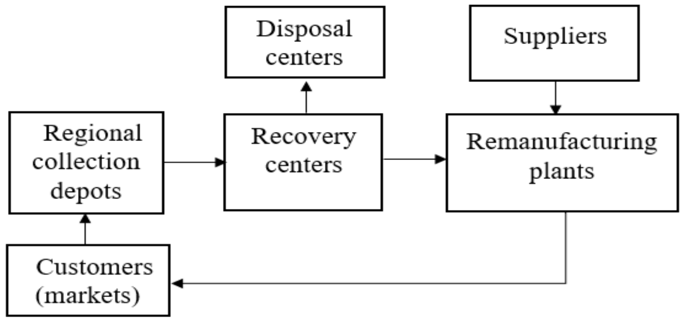

Fig. 1.1. An RL network.

1.1.1. Components of RLNs

There are two types of components (i.e., strategic and operational) that must be considered in designing of RLNs (Pokharel and Mutha, 2009). The strategic components include fixed costs (i.e., costs of required facilities and equipment), environmental impact, quality, and customer service. To optimize the RLNs, managers should ensure the full utilization of resources (e.g., equipment, labour). In addition, remanufactured products should have the same quality as virgin products, since the customers expect consistent quality from producers. Identifying and fulfilling customer expectations are the other essential parts of strategic factors in RLNs. Public awareness has led producers to integrate environmental solutions into their supply chain management practices (El Saadany et al., 2011). Once companies address such important strategic factors, they can focus on a tactical level (i.e., operational factors) of RLNs. This level of RLNs consists of the collection, transportation, sorting, inspection, warehousing, remanufacturing, and packaging. Such operational factors are different in importance based on customer expectations, resources, and capabilities of entities involved in RLNs. Accordingly, the characteristics of parameters associated with either strategic or operational components of RL systems are uncertain in the real world (Salema et al., 2007; Lee and Dong, 2009; Cardoso et al., 2013; Trochu et al., 2018).

1.1.2. Beneficial aspects of RLNs

The main objective of RLN design is to facilitate the reclamation of products at the end of their lifecycle. There is a variety of benefits associated with reclamation, refurbishing, and recycling the returned products, such as saving cost, energy, resources, and diverting waste from landfills and waterways (Sarkis et al., 2010; Grabara et al., 2014).

The presence of hazardous waste and toxic substances in some returned products may cause a serious environmental impact. RLNs lead to reduce the amount of waste discarded improperly into the air and water. Moreover, saving energy and natural resources is another ecological benefit of designing RLNs.

1.1.3. RLNs and sustainable environmental strategies

Nowadays, companies are expected to run their operations based on sustainable manners. Sustainability refers to the usage of resources in a way that future generations can benefit from them as well (Bonney and Jaber, 2011; Ahi et al., 2016).

Environmental practices are prominent parts of sustainability. On this subject, sustainable environmental strategies (SES) have been considered to design RLNs recently. SES are those applied to reduce companies' environmental impact while still leading to cost-saving. In this regard, SES are led to optimize the companies' utilization rate of resources which give rise to advance their economic performance (Marsillac, 2008).

The main factors that can promote SES are as follow:

- To prevent pollution and evaluate operation: waste and cost of operations should be measured while implementing SES. In the next step, it is required to prepare strategic plans to facilitate business environmental objectives in the long-term.
- To implement environmental management systems (EMS): it refers to the management of companies' environmental plans in a systematic manner. EMS consist of organizational structure, plans, and resources. It supports the continuous improvement of organizations by monitoring their performances.

1.1.4. Competitive advantages

Nowadays, customers are considering the environmental attributes of the products (e.g., recyclable) along with the environmental practices of companies (e.g., involving a recycling plan). Therefore, companies have been motivated to be a part of RLNs to benefit from either tangible or intangible competitive advantages of such a strategic decision (Jayaraman and Luo, 2007). For example, the recovery of used products creates values as the return on investments for returned products. In addition, companies can deliver an environmentally friendly image to the community by adopting an RLN (e.g., offering return options).

1.1.5. Developing efficient and effective RLNs

RLNs consist of planning, managing, executing, and analyzing all activities (i.e., collecting, shipping, refurbishing, and remanufacturing) associated with used products from the points of markets to the points of origin. In the current dynamic market, the efficiency and effectiveness of all entities involved in RLNs are required to be established in the long-term. The efficiency of an entity refers to the fulfillment of market demands on-time, while the effectiveness represents how well the entity is able to operate with minimum costs and environmental impact. These features are mainly associated with the network configuration that is impossible to change in the short-term (Babbar and Amin, 2018).

1.2. Considering real RLNs in Canada

The application of RLNs is expanded prominently for the purpose of optimizing environmental practices, and the costs of stewardship plans. However, the design of real RLNs is a strategic decision which can be affected by several dynamic factors. Those unpredictable factors result in some risks and complexities for the businesses in the long-term. In this dissertation, it is tried to address such uncertainties for the purpose of configuring five real RLNs in Canada as follow:

I. Electronic recycling association (ERA); Canada-Wide.

II. Canadian battery association (CBA); Manitoba, British Columbia, New Brunswick.

III. Beverage container stewardship program regulation (BCSPR); British Columbia.

IV. Ontario electronic stewardship (OES); Ontario.

V. Wastewater management in hydraulic fracturing; Alberta, British Columbia, New Brunswick, Northwest Territories.

Therefore, this proposed research has many positive economic and environmental impact on the Canadian stewardship programs.

1.3. Literature overview

The dark-blue bars in Figure 1.2 represent the number of studies that examined different aspects of RLNs, such as decision-making, environmental concerns, inventory policy, recycling, remanufacturing, sustainable development, and transportation. The green-dashed bars, on the other hand, shows the number of studies that have considered uncertainty in RLNs, which represent a very small percentage of the RLNs literature. Therefore, there is ample room to research along this line. There are some external and internal factors (e.g., supply, demand, return, transportation cost, and recycling process) that are uncertain in the real world and have a significant impact on RLN design (Salema et al., 2007; Cardoso et al., 2013).

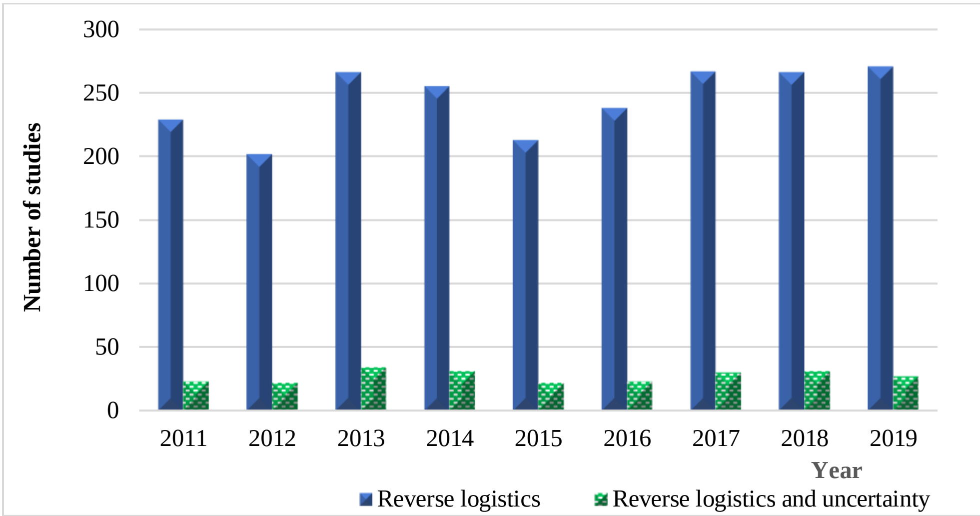

Fig. 1.2. The number of studies identified by a search of “reverse logistics” versus “reverse logistics” and “uncertainty” from 2011 to 2019 by SCOPUS on 6 December 2019.

Fig. 1.3. shows the volatility in the fuel price between January 2019 and October 2019 in Canada. Such fluctuations have a direct impact on the profitability of RLNs. The type of parameters (e.g., fuzzy or random) dictates the solution approach; however, the literature shows that most studies have considered either stochastic programming or possibilistic programming to address uncertainty in the configuration of facility location models. Therefore, we aim to develop integrated methods being capable to withstand all possible imprecise parameters.

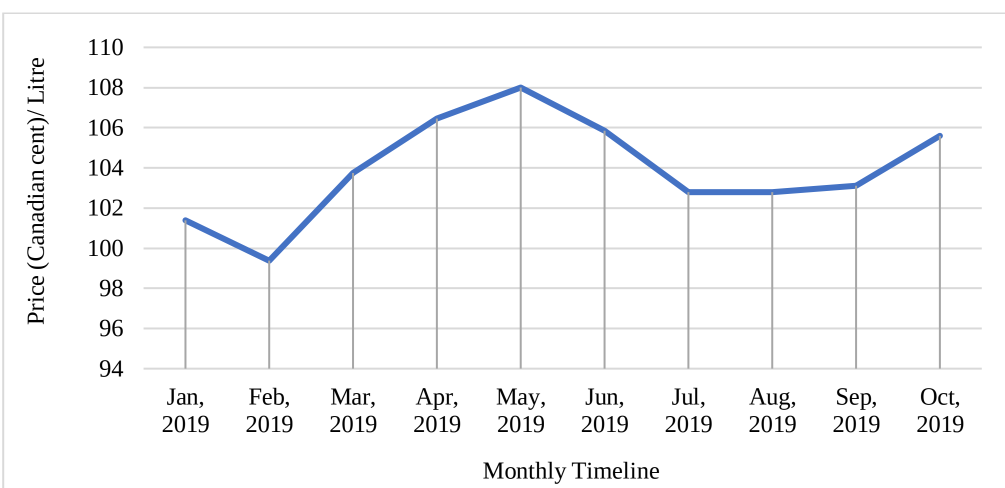

Fig. 1.3. The volatility in Canadian fuel price (The Historical Trend in Canadian Fuel Pricing, 2019)

1.4. Solution methodologies

As noted above, the type of parameter uncertainty dictates the required optimization methods (e.g., robust optimization, possibilistic, and stochastic programming). Kim et al. (2018) classified the environment of decision-making to certain, risky, and uncertain situations. Deterministic mathematical programming models (MPMs) are applicable to solve problems whose parameters are known with certainty. Stochastic MPMs are applicable when, some or all, those parameters are random with known probability distributions. Possibilistic MPMs are suitable when the system parameters are uncertain. Such models are riskier than stochastic ones, where robust optimization is attractive when the range of uncertainty is definable (i.e., ellipsoidal, polyhedral, and box uncertainty sets) (Ben-Tal et al., 2005; Bohle et al., 2010).

1.4.1. A scenario-based possibilistic model (SPM)

SPM is introduced to handle imprecise parameters for different scenarios. This hybrid solution approach is developed based on the methods proposed by Cadenas and Verdegay (1997), Parra et al. (2005), Snyder (2006), Jiménez et al. (2007), Peidro et al. (2009), Amin and Zhang (2013a). The new method includes different scenarios, fuzzy coefficients, and fuzzy right-hand sides. Model (1.1) represents the general form of the proposed model.

$$\begin{aligned}
& Min\ z = \sum_{\omega} \Psi_{\omega} \tilde{c}_{\omega} x_{\omega} + \tilde{d} y && \\
& \tilde{a}_{\omega} x_{\omega} \geq \tilde{b}_{\omega} && \forall \omega \qquad (1.1) \\
& \tilde{e}_{\omega} x_{\omega} = \tilde{f}_{\omega} && \forall \omega \\
& g_{\omega} x_{\omega} \leq hy && \forall \omega \\
& x_{\omega} \geq 0, y \in \{0,1\} &&
\end{aligned}$$

ω is the number of different possible scenarios, each occurring with probability Ψ_{ω}. Furthermore, x_{ω}, y, $\tilde{c}_{\omega}$ and $\tilde{d}$ are non-negative variables, binary variables, variable, and fixed costs, respectively. It is also assumed that $\tilde{a}_{\omega}$, $\tilde{b}_{\omega}$, $\tilde{e}_{\omega}$, $\tilde{f}_{\omega}$, g_{ω}, h are matrices in the constraints.

1.4.2. A scenario-based robust possibilistic model (SRPM)

SPM is enhanced to an SRPM to handle uncertainty associated with flexible constraints and capacity of resources based on the methods applied by Cadenas and Verdegay (1997), Peidro et al. (2009), Pishvaee and Khalaf (2016).

$$
\begin{aligned}
&Max\ z = \sum_{\omega} \Psi_{\omega} \left(\tilde{p}_{\omega} - \tilde{c}_{\omega} \right) x_{\omega} - \tilde{d}y \\
&\tilde{a}_{\omega} x_{\omega} \tilde{\leq} \tilde{b}_{\omega} && \forall \omega && (1.2) \\
&\tilde{e}_{\omega} x_{\omega} = \tilde{f}_{\omega} && \forall \omega \\
&g_{\omega} x_{\omega} \tilde{\leq} \tilde{h} y && \forall \omega \\
&x_{\omega} \geq 0, y \in \{0,1\}
\end{aligned}
$$

Where $\tilde{p}_{\omega}$ is the selling price and the other parameters have the same definitions as described in Subsection 1.4.1. The symbol $\tilde{\leq}$ is the fuzzy version of $\leq$ that denotes the left-hand side of the soft constraint is required to be less than or similar to the right-hand side value (Peidro et al., 2009).

1.4.3. A fully fuzzy scenario-based programming (FFSP)

FFSP can be applied where the parameters and decision variables are assumed to be imprecise in different scenarios. This solution approach is developed and integrated based on the methods introduced by Snyder (2006) and Ezzati et al. (2015). The general form of the FFSP problem is defined by Model (1.3).

$$
\begin{aligned}
&Max(Min)\, \tilde{\rho}^{T} \tilde{\chi} \\
&s.t.\, \tilde{\xi}\, \tilde{\chi} = \tilde{\beta} && (1.3)
\end{aligned}
$$

Where $\tilde{\rho}^T = [\tilde{\rho}_j]_{1*\acute{n}}$, $\tilde{\chi} = [\tilde{\chi}_j]_{\acute{n}*1}$, $\tilde{\xi} = [\tilde{\xi}_{ij}]_{\eta*\acute{n}}$, $\tilde{\beta} = [\tilde{\beta}_i]_{\eta*1}$, $\tilde{\rho}_j, \tilde{\xi}_{ij}, \tilde{\beta}_i \in TF\,(\mathrm{R})^+$, $\grave{\imath} = 1, 2, \ldots, \eta$ and $\hat{\jmath} = 1, 2, \ldots, \acute{n}$. Where $\tilde{\rho}^T\chi = ((\rho^T\chi)^l, (\rho^T\chi)^c, (\rho^T\chi)^u)$, $\tilde{\xi}\tilde{\chi} = ((\xi\chi)^l, (\xi\chi)^c, (\xi\chi)^u)$, $\tilde{\beta} = ((\beta)^l, (\beta)^c, (\beta)^u)$, $\tilde{\chi} = ((\chi)^l, (\chi)^c, (\chi)^u)$, $(\chi)^l \geq 0$.

1.4.4. A robust flexible chance-constrained model (RFCCM)

A novel RFCCM is developed to deal with different sources of uncertainty. To describe the solution approach, Model (1.4) is considered (Ben-Tal and Nemirovski, 2000; Ben-Tal et al., 2005; Pishvaee and Khalaf, 2016).

$$
\begin{aligned}
& Min\ Z \\
& s.t. \\
& px + qy \le Z \qquad \forall p \in u_{box}^{p} \\
& Ax \ge d \\
& Bx \tilde{\le} F y \\
& y \in \{0,1\}, x \in R^{+}.
\end{aligned}
\tag{1.4}
$$

In Model (1.4), vector *p* shows variable costs, *q* is related to the fixed costs of opening or holding a facility. *A*, *B*, *F*, *d* are defined as the matrices used in the constraints. Besides, all binary and non-negative decision variables are defined by *y* and *x*, respectively. In this approach, all parameters of variable costs are assumed to be varied in a specified bounded box, while *d* complies with the normal distribution.

1.5. Organization of the dissertation

Chapter 1 included the introduction and overview of RLNs, Canadian stewardship programs, and methodologies. Table 1.1 illustrates the titles and publication status of Chapter 2 to Chapter 6. Conclusions, research contributions, and future research recommendations of this dissertation are discussed in Chapter 7.

Table 1.1
Journal publications during the PhD program

Chapter	Papers	Status
2.	**Tosarkani, B. M.,** Amin, S. H. (2018). A multi-objective model to configure an electronic reverse logistics network and third-party selection, Journal of Cleaner Production, 198C, 662-682.	Published
3.	**Tosarkani, B. M.,** Amin, S. H. (2019). An environmental optimization model to configure a hybrid forward and reverse supply chain network under uncertainty. Computers & Chemical Engineering, 121, 540-555.	Published
4.	**Tosarkani, B. M.,** Amin, S. H., Zolfagharinia, H. (2020). A scenario-based possibilistic model for a multi-objective electronic reverse logistics network, International Journal of Production Economics, 224, 107557.	Published
5.	**Tosarkani, B. M.,** Amin, S. H. An ecological multi-objective model to configure a sustainable beverage container reverse logistics network.	Under review
6.	**Tosarkani, B. M.,** Amin, S. H. (2020). A robust optimization model for designing a wastewater treatment network under uncertainty: Multi-objective approach. Computers & Industrial Engineering, 146, 106611.	Published

Chapter 2. A multi-objective model to configure an electronic reverse logistics network and third party selection

2.1. Introduction

Nowadays, reverse logistics (RL) is an essential part of green closed-loop supply chain management (GCLSC) due to environmental regulatory compliance (Noman and Amin, 2017). Prakash and Barua (2016) categorized RL into the main activities of waste logistics and recovery logistics. According to environmental regulation and agreement, policy-makers are stimulated to configure efficient RLs to utilize resources effectively. Furthermore, there is a significant profit associated with RL due to the recovery value of the returned products. In the forward supply chain, economic aspects are considered as a single objective, while in RL both economic and environmental aspects are emphasized. Customers may return products due to different reasons. Returns may include commercial return, end of use return, end of life return, repair, and warranty return over the product life cycle. Therefore, RL may include activities related to product recovery consisting of the returned product acquisition, product disassembly, remanufacturing, and remarketing. In this sense, green practices of entities involving in the RL can be the vital factors to reduce environmental issues.

Electronic recycling association (ERA) is a non-profit organization in Canada committed to reducing electronic waste through the recycling and recovery of unwanted computers, laptops, and other electronic equipment. It aims to avoid unwanted computers and other electronic equipment of being destroyed. Hence, all Canadian users are offered to benefit from the ERA's services including the recovery and reuse of electronics. However, used computers and electronic equipment may not be recoverable. In such cases, ERA cooperates with reliable partners to ensure all materials are recycled based on environmental compliance.

2.1.1. Review of some studies related to the environmental multi-criteria decision making (MCDM)

As public awareness increases with respect to environmental issues, companies are stimulated to enhance their green performance. This factor is very important in third party RL selection. Third parties' selection is a strategic decision in which different criteria are taken into account. The criteria associated with potential third parties may have conflicts. To handle the conflicts, decision-makers utilize various MCDM techniques such as the analytic hierarchy process (AHP) and the analytic network process (ANP) (Govindan et al., 2015a).

The roles of MCDM models are significant in industries and businesses. Some researchers have considered environmental factors in MCDM techniques (e.g., Bai and Sarkis, 2010). Büyüközkan and Çifçi (2012) examined green supply chain management (GSCM) to offer an environmental framework for supplier selection in the automotive industry. DEMATEL, ANP, and TOPSIS methods were integrated with fuzzy sets theory to assist in the decision-making process. Amindoust et al. (2013) applied data envelopment analysis (DEA) for supplier selection considering environmental competency in a pocket and box manufacturer. In their investigation, some criteria consisting of air pollution, environmental cost, and management system, green research and development were taken into account. Yazdani (2014) studied green supplier selection in the automotive industry. AHP was applied to determine the weights of criteria, then fuzzy TOPSIS was utilized to rank the suppliers. Hashemi et al. (2015) proposed an integrated framework consisting of economic and environmental criteria. They applied ANP to deal with interdependencies among criteria. In addition, grey relational analysis (GRA) was used to address the uncertainty in the problem.

Some researchers have considered green practices in different echelons of supply chains. Uygun and Dede (2016) proposed a model to evaluate GSCM through the application of ANP and TOPSIS. The proposed model includes 5 criteria and 17 sub-criteria. They include regulations, environmental performance, and economic performance as the sub-criteria of green design; supplier-customer collaboration, enforcement of stakeholders and quality regulation as the sub-criteria of green purchasing; green manufacturing, green packaging and green stock politics as the sub-criteria of green transformation; organization of the green logistics network, quality of service, and quality of technology as the sub-criteria of green logistic; reducing activities, recycling, remanufacturing, reusing, and disposal as the sub-criteria of reverse logistic.

Kusi-Sarpong et al. (2016) introduced a framework to evaluate the impact of GSCM on organizational sustainable performance in the mining industry. The proposed GSCM factors include green information technology and system (GITS), strategic supplier's partnership (SSP) operations and logistic integration (OLI), internal environmental management (IEM), eco-innovation practice (EOL), and end-of-life practices (EOL). Miroshnychenko et al. (2017) investigated the impact of green practices comprised of ISO 14001, pollution prevention, and green product development on financial performance. They determined nitrogen dioxide, emission reduction, waste reduction, water and energy efficiency, and toxic chemical reduction as the factors to measure pollution prevention index, while environmental products and eco-product design have been considered as the indicators of green product index.

Sharma et al. (2017) utilized the AHP method to rank 13 green performance factors and 79 sub-factors for GSCM in the agro-industry. According to their findings, environmental management and design, regulatory pressure, and green purchasing were determined as the most effective green performance indicators. Vanalle et al. (2017) indicated that environmental practice and economic performance have a positive relationship. They utilized partial least squares structural equation modeling (PLS-SEM). Internal environmental issues (IEM), eco-design, green purchasing, collaboration with customers regarding environmental issues, and investment recovery were determined as the indicators for GSCM practice in their study.

Sari (2017) introduced a framework to evaluate GSCM by utilizing the Monte Carlo simulation and the AHP method. The green practices in inbound operation, production, outbound operation, and reverse logistics have been considered to assess the performance of GSCM. For such evaluation, designing recyclable products and utilization of cleaner technology have been assigned as the sub-factors for green production operation. Choosing suppliers based on environmental criteria, green purchasing, and cooperation with suppliers to develop environmental practices were determined as the indicators for green inbound operation. Carvalho et al. (2017) proposed a model to determine the best set of green performance and lean supply chain management practices with the aim of promoting eco-efficiency in the automotive industry. In their proposed framework, ISO 14001 and environmentally friendly packaging have been considered as the indicators for green performance. Zhao et al. (2017) proposed a multi-objective model for the optimization of a GSCM network. They minimized the risk arising from hazardous materials, and carbon emission. Tramarico et al. (2017) utilized the AHP method to evaluate GSCM through four top-level criteria including plan, source, make, and deliver in the chemical industry. In their proposed framework, the sub-criterion of the plan has been considered as the planning for demand based on a long-term basis and planning for material with the best use of resources. Sub- criterion of the source has been identified as the usage of recycled raw material and merchandising based on renewable energy. Besides, the sub-criterion of make has comprised of reducing the scrap rate, reducing the greenhouse gas emission, recycling and reusing water, and sub-criterion of delivery has been chosen as the application of full truckload for distribution and reducing the environmental impact through the transportation management. Scur and Barbosa (2017) examined the application of green practices in the home appliance industry. Their proposed framework for green practices consists of internal environmental management, green purchasing and manufacturing, eco-design, and waste management. According to their findings, waste management was the most widely applied practice among research participants.

2.1.2. Integration of MCDM with optimization models

To balance economic, social and environmental performances, there have been some attempts to combine green criteria with network design. Fattahi and Fayyaz (2010) stated that many objectives including satisfaction of water consumers, national benefit, and social hazard should be involved in urban water management. They applied the compromise programming technique to optimize water distribution cost, leakage water, and social satisfaction level estimated by the AHP method. Haleh and Hamidi (2011) mentioned that the allocation of orders to suppliers have a significant impact on the efficiency of the supply chain. They applied a fuzzy MCDM to allocate orders to the suppliers. Then, fuzzy linear programming was utilized to optimize the multi-objective model. He et al. (2012) proposed an optimization model consisting of qualitative and quantitative parameters to maximize the customer service level, and minimize the logistics cost. They used mixed-integer linear programming (MILP) integrated with fuzzy AHP to deal with MCDM. Amin and Zhang (2013a) applied MILP to minimize the total cost. Thereafter, the model was developed to consider the environmental factors measured by the AHP approach. Jadidi et al. (2014) developed an MCDM model that included compromise programming, goal programming, and TOPSIS to minimize price, rejects, and lead time.

Boukherroub et al. (2015) proposed an integrated approach to optimize a multi-objective problem including economic and environmental performance in a lumber industry case. Shakourloo et al. (2016) examined a closed-loop supply chain (CLSC) network consisting of some elements such as producer and remanufacturer. They integrated fuzzy AHP with MILP to minimize the waste of processes, and maximize the total profit of the network. Entezaminia et al. (2016) investigated the relationship between green principals and economic performance in an RL network. In their proposed model, environmental criteria consisting of recyclability, biodegradability, energy consumption, and product risk have been ranked by AHP. Hamdan and

Cheaitou (2017) proposed a model to solve a supplier selection and order allocation problem. They applied fuzzy TOPSIS, AHP, and a bi-objective optimization model to select the best supplier. Tosarkani and Amin (2018a) utilized fully fuzzy MILP to configure a battery CLSC with regard to the environmental performance of battery producers and recovery centers. A review of some related papers has been provided in Table 2.1.

According to the literature review, there are some research gaps that should be addressed. According to our knowledge, third party RL selection with RL network configuration (at the same time) has been ignored in academic papers. As a result, an integrated model should be developed. In addition, there is not a single scientific paper in the literature about fuzzy ANP for third part RL selection in Canada. Besides, there is not a single publication that has considered profit, environmental practice, defect rate, and on-time delivery as objectives in RL network optimization.

Table 2.1
Review of some studies utilizing MCDM techniques and optimization model

Authors	Method(s)	MOP*	Type of industry	Criteria**	Approach***
Haleh and Hamidi (2011)	Fuzzy MCDM and linear programming	√		EC	SS
Büyüközkan and Çifçi (2012)	DEMATEL, ANP, and TOPSIS		Automotive industry	GC	SS
Amindoust et al. (2013)	DEA		Pocket and box manufacturer	GC	SS
Yazdani (2014)	AHP, Fuzzy TOPSIS		Automotive industry	GC	SS
Jadidi et al. (2014)	Compromise and goal programming, TOPSIS	√		EC	SS
Hashemi et al. (2015)	ANP, GRA		Automotive industry	GC and EC	SS
Uygun and Dede (2016)	Fuzzy DEMATEL ANP and TOPSIS			GC	GPESC
Kusi-Sarpong et al. (2016)	Fuzzy DEMATEL and ANP		Mining industry	GC	GPESC
Hamdan and Cheaitou (2017)	Fuzzy TOPSIS, AHP, MOP	√		GC and EC	SS
Miroshnychenko et al. (2017)	Empirical examination		Several industries	GC and EC	GPESC
Sharma et al. (2017)	AHP analysis		Agro industry	GC	GPESC
Sari (2017)	Monte Carlo simulation and AHP method			GC	SS
Scur and Barbosa (2017)	Interview		Home appliance industry	GC	GPESC
Tramarico et al. (2017)	AHP analysis		Chemical industry	GC	GPESC
Our paper	Fuzzy ANP, MILP, MOP	√	Electronic industry	GC and EC	Third parties selection and network configuration

* multi-objective programming (MOP), ** Green criteria (GC), Economic criteria (EC),
*** Supplier selection (SS), Green performance evaluation in supply chain (GPESC)

2.1.3. Aims and contributions of this research

In this research, a multi-objective programming model for an electronic RL network is proposed. Initially, a fuzzy ANP method is developed and applied to rank the electronic suppliers, recovery centers, and remanufacturing plants. Then, an optimization model is introduced for the network to maximize the total profit, green practices, and on-time delivery along with the minimization of defect rate.

Unlike the most of the papers that have focused on the reverse logistics partner selection, this paper provides an integrated model comprising the reverse logistics partner selection and network configuration, simultaneously. This point is one of the unique contributions of this study. The other main research contributions of this study are as follows:

- Configuring and optimizing a multi-echelon, multi-component, multi-product electronic RL network in multiple periods.
- Developing and utilizing a fuzzy ANP model to estimate the qualitative environmental factors in the model.
- Developing a mathematical model to consider multiple objectives consisting of the total profit of RL, the environmental performance of third parties, on-time delivery, and defect rate.
- Determining the trade-off surface for the proposed multi-objective model.

Section 2.2 is allocated to the problem statement. The solution approach is discussed in Section 2.3. It includes the definition and application of the fuzzy ANP, the proposed optimization model, the distance technique and ε-constraint method, the parameters' values, and associated solutions. In Section 2.4, the value path analysis is provided. Finally, conclusions are discussed in Section 2.5.

2.2. Problem statement

Nowadays, there is a growing concern related to discarded electronic appliances. Electronic recycling association (ERA) in Canada has attempted to decrease electronic waste since 2004. ERA considers all activities such as recovery, refurbishment, and reuse to reduce environmental issues. In this way, they have partnered with certified recovery organizations across Canada.

There is a variety of questions regarding the configuration of green networks. In Fig. 2.1, a multi-echelon, multi-component, multi-product electronic RL network is shown. This electronic RL includes suppliers, remanufacturing plants, markets, regional collection centers, recovery centers, and disposal center.

The regional collection center(s) collect unwanted computers, laptops, and printers from markets, and ship them to the recovery center(s). The returned electronic appliances are disassembled to the main components in the recovery center(s). The recycled components are transferred to the remanufacturing plant(s), and unrecoverable components are sent to the disposal center. The remanufacturing plant(s) order for complimentary components to assemble with recycled material received from the recovery center(s). The remanufactured electronic appliances are shipped back to the markets. To address the environmental concerns, the green performance of third parties should be measured. In this research, it is intended to answer the following questions with regard to the optimization of total profit, the environmental performance of third parties, on-time delivery, and defect rate.

- Which supplier(s) must be selected?
- Which place(s) must be selected for remanufacturing plant(s)?
- Which regional collection center(s) must be chosen?
- Which recovery center(s) are required to collect unwanted electronic appliances?
- How many complementary components must be purchased from supplier(s)?
- How many products and components are shipped in every echelon of the RL?

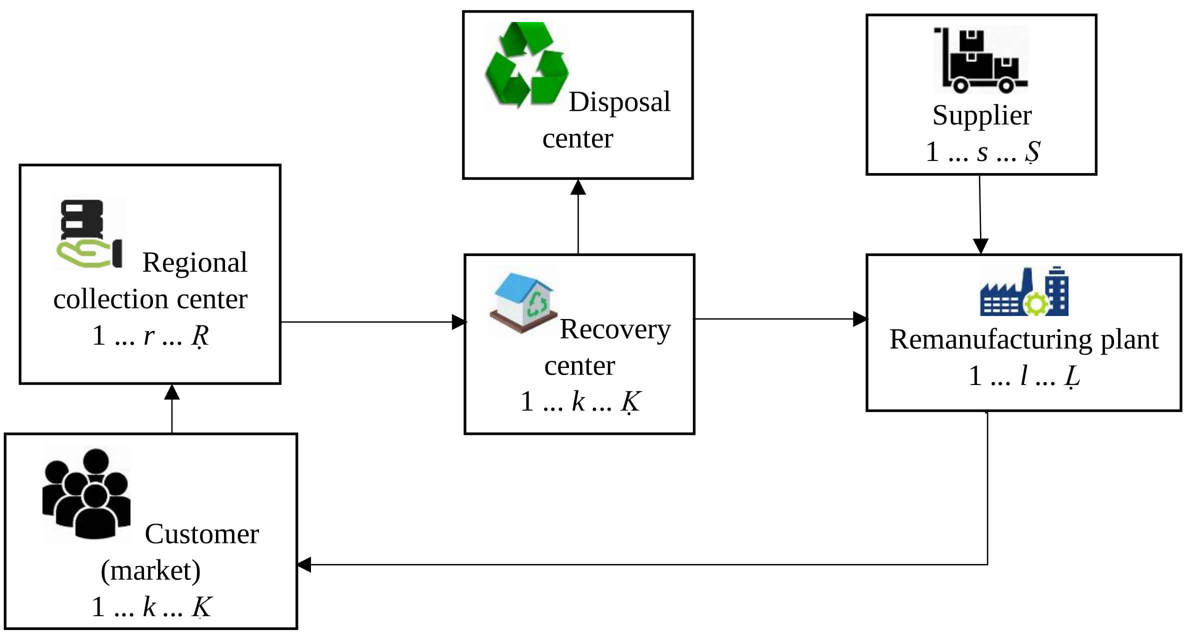

Fig. 2.1. The proposed electronic RL.

2.3. Solution approach

The overall solution framework is provided in Fig. 2.2. In the 1st Step, it is aimed to rank the third parties based on green performance. Fuzzy ANP is applied in this step. In the 2nd Step, MILP is applied and is developed to formulate the mathematical model. In the 3rd Step, the non-dominated solutions are computed.

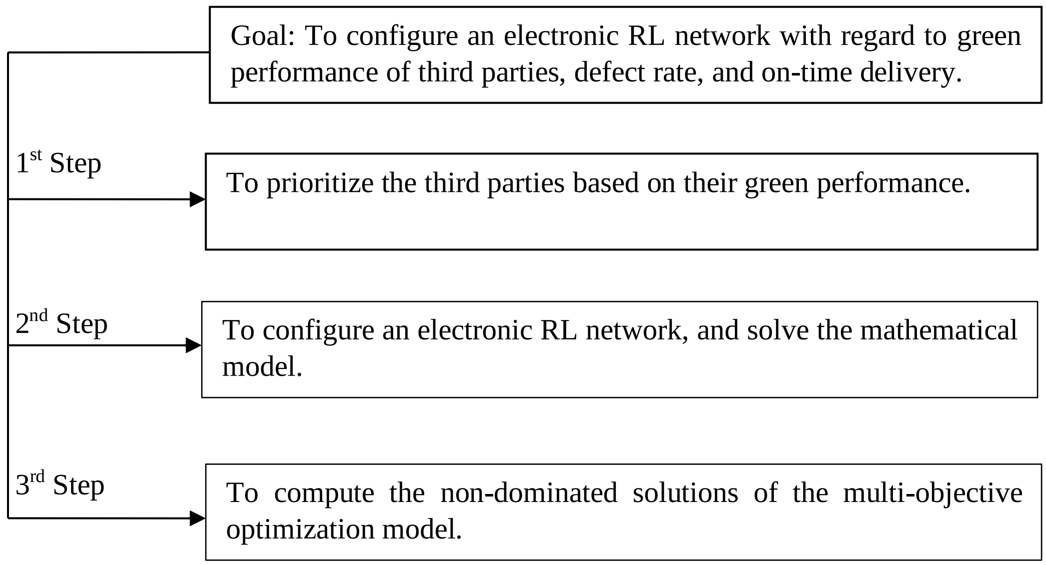

Fig. 2.2. The proposed framework to solve the multi-objective problem

2.3.1. Fuzzy ANP

Saaty (1996) proposed the analytic network process (ANP) to cope with a possible interdependency among criteria incorporating into MCDM problems. ANP has some advantages compared to other MCDM techniques including structuring problems as networks, considering the relationships among different elements, and using pairwise comparisons (Aragonés-Beltrán et al., 2014; Sun et al., 2018). ANP is widely applied in decision-making, particularly in contradictory circumstances. Many researchers have utilized ANP in different fields, such as information system project selection (Lee and Kim, 2000), financial crisis prediction (Niemira and Saaty, 2004), textile industry (Yüksel and Dagdeviren, 2007), electronic industry (Gencer and Gürpinar, 2007; Vinodh et al., 2011), pharmaceutical industry (Kirytopoulos et al., 2008), transportation-mode selection (Tuzkaya and Önüt, 2008), purchasing decision (Demirtas and Ustun, 2009), municipal solid waste disposal selection (Khan and Faisal, 2008; Aragonés-Beltrán et al., 2010), personnel selection (Lin, 2010), evaluation of power plants (Atmaca and Basar, 2012), selection of solar-thermal power plant investment projects (Aragonés-Beltrán et al., 2014), risk assessment for asset maintenance decision-making (Chemweno et al., 2015), selection of maintenance projects in railway infrastructure (Montesinos-Valera et al., 2017), and safety assessment in oil drilling projects (Sun et al., 2018). Fuzzy sets theory can be utilized with ANP to deal with uncertainty in expert's judgment. As illustrated in Fig. 2.3, a triangular fuzzy number (TFN) can be indicated by a membership function which is between 0 and 1.

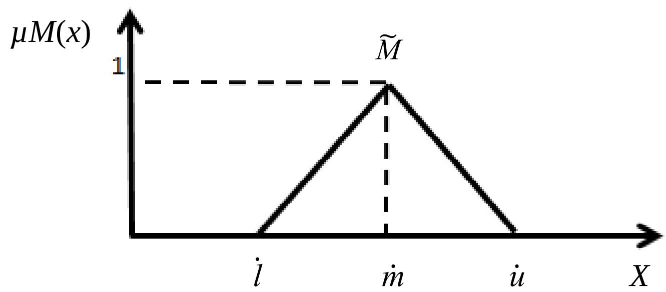

Fig. 2.3. A triangular fuzzy number $\widetilde{M}$.

If $\widetilde{M}$ is assumed as a TFN by three components such as $\widetilde{M} = (\dot{l},\dot{m},\dot{u})$, the associated membership function is shown by Eq. (2.1).

$$\mu M(x) = \begin{cases} 0,\ x < \dot{l}, \\ \dfrac{x-\dot{l}}{\dot{m}-\dot{l}},\ \dot{l} \le x \le \dot{m}, \\ \dfrac{\dot{u}-x}{\dot{u}-\dot{m}},\ \dot{m} \le x \le \dot{u}, \\ 0,\ x > \dot{u}, \end{cases} \tag{2.1}$$

To apply the pairwise comparisons through the fuzzy ANP method, Chang's extent examination is utilized (Chang, 1996).

Step 1: Eq. (2.2) indicates the value of the fuzzy synthetic extent considering the i^{th} object. In this way, the value of $\sum_j \widetilde{M}_{gi}^{j}$ can be obtained from Eq. (2.3).

$$\dot{S}_i = \sum_j \widetilde{M}_{gi}^{j} \otimes \left[\sum_i \sum_j \widetilde{M}_{gi}^{j} \right]^{-1} \tag{2.2}$$

$$\sum_j \widetilde{M}_{gi}^{j} = \left(\sum_j \dot{l}_j, \sum_j \dot{m}_j, \sum_j \dot{u}_j \right) \tag{2.3}$$

Where all $\widetilde{M}_{gi}^{j}$ are assumed triangular fuzzy numbers.

Step 2: To compare the fuzzy numbers, it is required to calculate the degree of possibility for $\widetilde{M}_1 \geq \widetilde{M}_2$, which can be defined by Eq. (2.4).

$$V(\widetilde{M}_1 \geq \widetilde{M}_2) = \sup_{x \geq y} [\min(\mu\widetilde{M}_1(x), \mu\widetilde{M}_2(y))] \tag{2.4}$$

According to assumptions, if there is a pair of (x, y) and $x \geq y$, while $\mu\widetilde{M}_1(x) = \mu\widetilde{M}_2(y) = 1$, then $V(\widetilde{M}_1 \geq \widetilde{M}_2) = 1$. It is assumed that $\widetilde{M}_1 = (\dot{l}_1, \dot{m}_1, \dot{u}_1)$ and $\widetilde{M}_2 = (\dot{l}_2, \dot{m}_2, \dot{u}_2)$ are convex fuzzy numbers. Therefore, Eq. (2.5) can be written as follows.

$$V(\widetilde{M}_1 \geq \widetilde{M}_2) = 1 \qquad \text{if } \dot{m}_1 \geq \dot{m}_2,$$

$$V(\widetilde{M}_2 \geq \widetilde{M}_1) = hgt(\widetilde{M}_1 \cap \widetilde{M}_2) = \mu\widetilde{M}_1(d) \tag{2.5}$$

As illustrated by Fig. 2.4, $\dot{d}$ is the ordinate of the highest intersection point D between $\mu\widetilde{M}_1$ and $\mu\widetilde{M}_2$, which can be obtained from Eq. (2.6).

$$V(\widetilde{M}_2 \geq \widetilde{M}_1) = hgt(\widetilde{M}_1 \cap \widetilde{M}_2) = \frac{\dot{l}_1 - \dot{u}_2}{(\dot{m}_2 - \dot{u}_2) - (\dot{m}_1 - \dot{l}_1)} \tag{2.6}$$

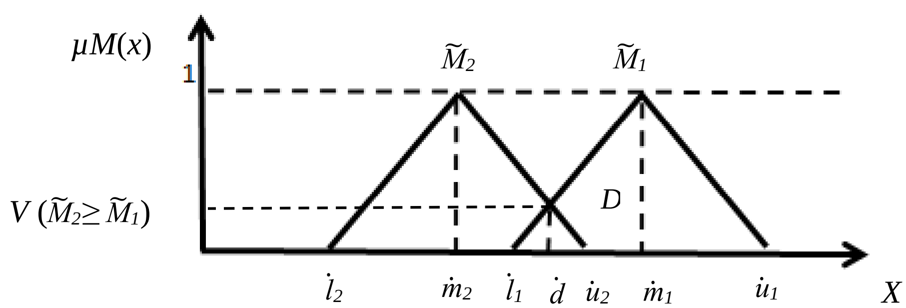

Fig. 2.4. The intersection between $\widetilde{M}_1$ and $\widetilde{M}_2$.

In order to apply the comparisons between $\widetilde{M}_1$ and $\widetilde{M}_2$, it is required to have both values of $V(\widetilde{M}_1 \geq \widetilde{M}_2)$ and $V(\widetilde{M}_2 \geq \widetilde{M}_1)$. Generally, if there are k TFNs, the degree of possibility can be estimated as follows:

$$V(\widetilde{M} \geq \widetilde{M}_1, \widetilde{M}_2, \ldots, \widetilde{M}_k) = V[(\widetilde{M} \geq \widetilde{M}_1) \text{ and } (\widetilde{M} \geq \widetilde{M}_2) \text{ and} \ldots \text{ and, } (\widetilde{M} \geq \widetilde{M}_k)]$$

$$= \min V(\widetilde{M} \geq \widetilde{M}_i),\ i = 1, 2, \ldots, k \tag{2.7}$$

$$d'(\dot{A}_i) = \min V(\dot{S}_i \geq \dot{S}_k), \tag{2.8}$$

The weight vector can be written by Eq. (2.9) for $k = 1, 2, \ldots, n$ and $k \neq i$

$$W' = (d'(\dot{A}_1), d'(\dot{A}_2), \ldots, d'(\dot{A}_n))^T, \tag{2.9}$$

Where $\dot{A}_i$ ($i = 1, 2, \ldots, n$) are n elements. Thereafter, Eq. (2.9) is replaced by Eq. (2.10) after normalization.

$$W = (d(\dot{A}_1), d(\dot{A}_2), \ldots, d(\dot{A}_n))^T, \tag{2.10}$$

2.3.1.1. ANP framework for electronic suppliers, recovery centers, and remanufacturing centers based on green performance

Based on Chang's method (1996), we determine the relative importance of each criterion in the proposed MCDM structures. To apply the pairwise comparisons, the fuzzy linguistic scale indicated by Fig. 2.5, is utilized. As illustrated in Fig. 2.6, 2.7, and 2.8 some criteria have been identified based on related studies (Yücenur et al., 2011; Bhattacharya et al., 2014; Malviya and Kant, 2016; Sari, 2017; Sharma et al., 2017; Tosarkani and Amin, 2018a).

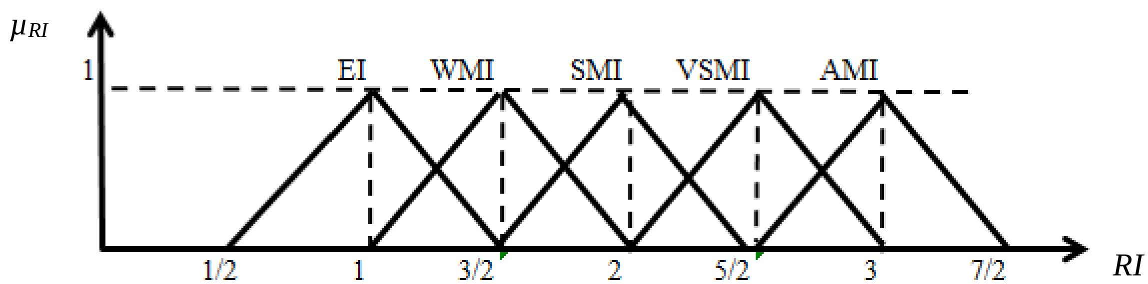

Fig. 2.5. Linguistic scale for relative importance

Step 1: At first, it is assumed that there are no relationships among the criteria. The pairwise comparisons are done in accordance with the defined instruction. The results are provided in Tables 2.A.1, 2.B.1, and 2.C.1in Appendices 2.A, 2.B, and 2.C.

Step 2: It is probable that there is an inner dependency between criteria. To avoid this problem, pairwise comparisons among the criteria are required to be completed by considering the effect of each criterion on every other (see Tables 2.A.2 to 2.A.5, 2.B.2 to 2.B.5, and 2.C.2 to 2.C.5).

Step 3: $W_{Criteria}$ is supposed to be determined based on the matrices W_1 and W_2 obtained in Steps 1 and 2. The results are provided in Tables 2.A.6, 2.B.6, and 2.C.6.

Step 4: The priority of each sub-criterion is required to be measured based on pairwise comparisons (see Tables 2.A.7 to 2.A.10, 2.B.7 to 2.B.10, and 2.C.7 to 2.C.10).

Step 5: As illustrated in Tables 2.A.11, 2.B.11, and 2.C.11, the overall priorities of sub-criteria can be calculated by multiplying $W_{Criteria}$ and $W_{Sub\text{-}criteria}$ obtained in Steps 3 and 4, respectively.

Step 6: The priorities of the electronic suppliers, recovery centers, and remanufacturing plants with regard to each sub-criterion are computed by pairwise comparisons (see Tables 2.A.12 to 2.A.21, 2.B.12 to 2.B.21, and 2.C.12 to 2.C.21). The results are represented by W_4 (see Tables 2.A.22, 2.B.22, and 2.C.22).

Step 7: As illustrated in Tables 2.2, 2.3, and 2.4, the overall ranking of the electronic suppliers, recovery centers, and remanufacturing plants based on green performance are calculated by multiplying $W_{Sub\text{-}criteria}$ (overall) and W_4 obtained in Steps 5, and 6.

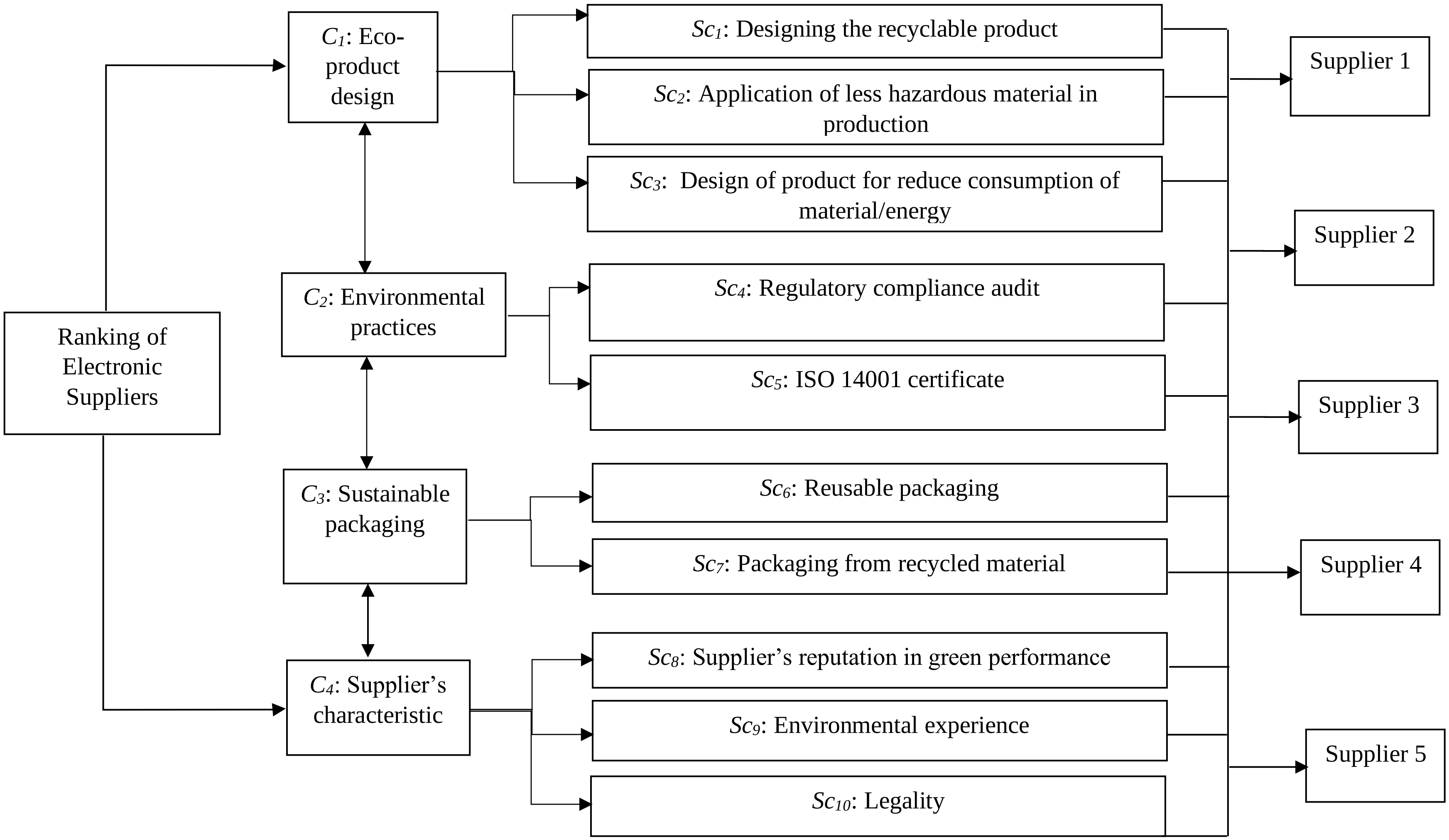

Fig. 2.6. The ANP model for ranking suppliers

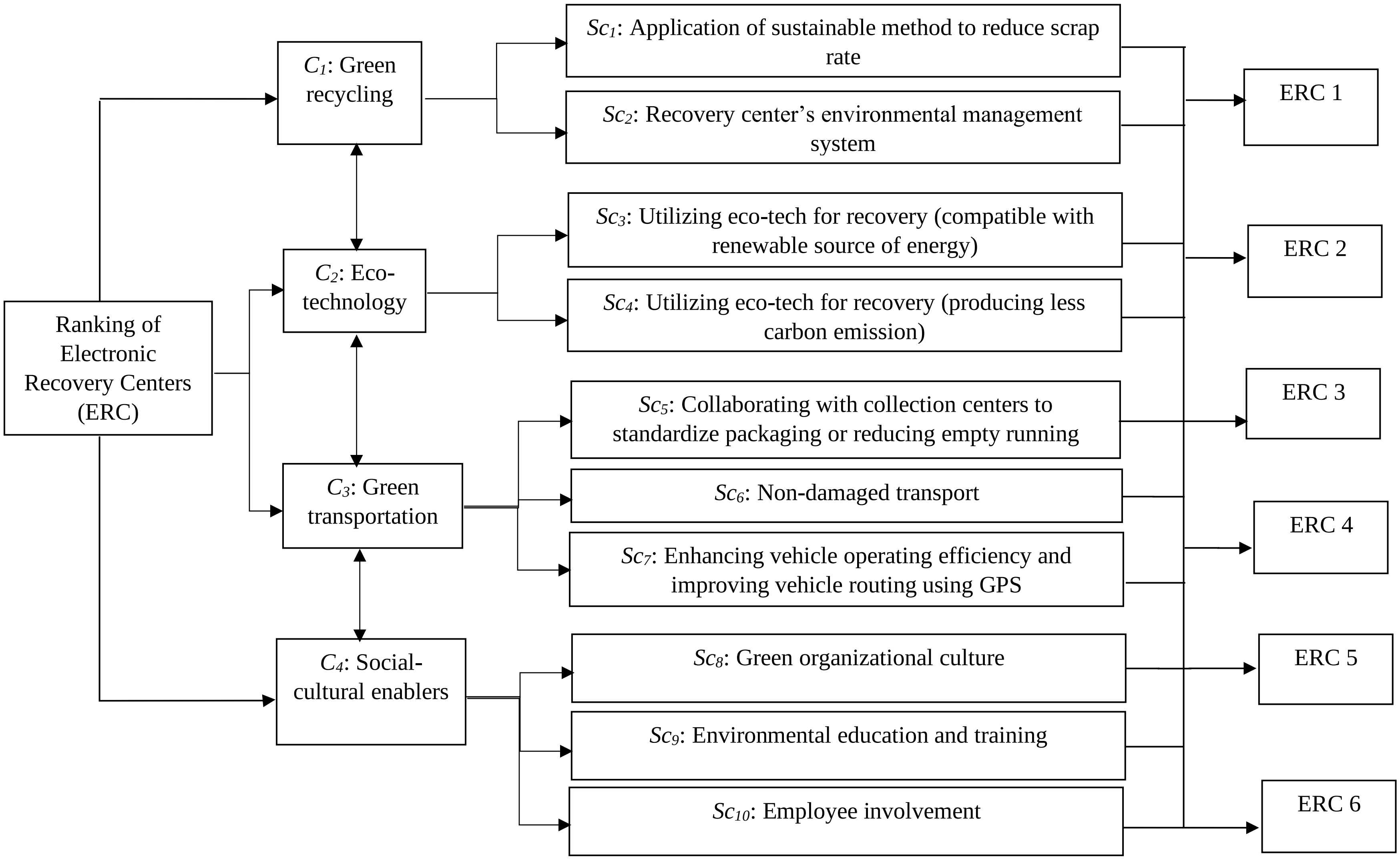

Fig. 2.7. The ANP model for ranking electronic recovery centers (ERC)

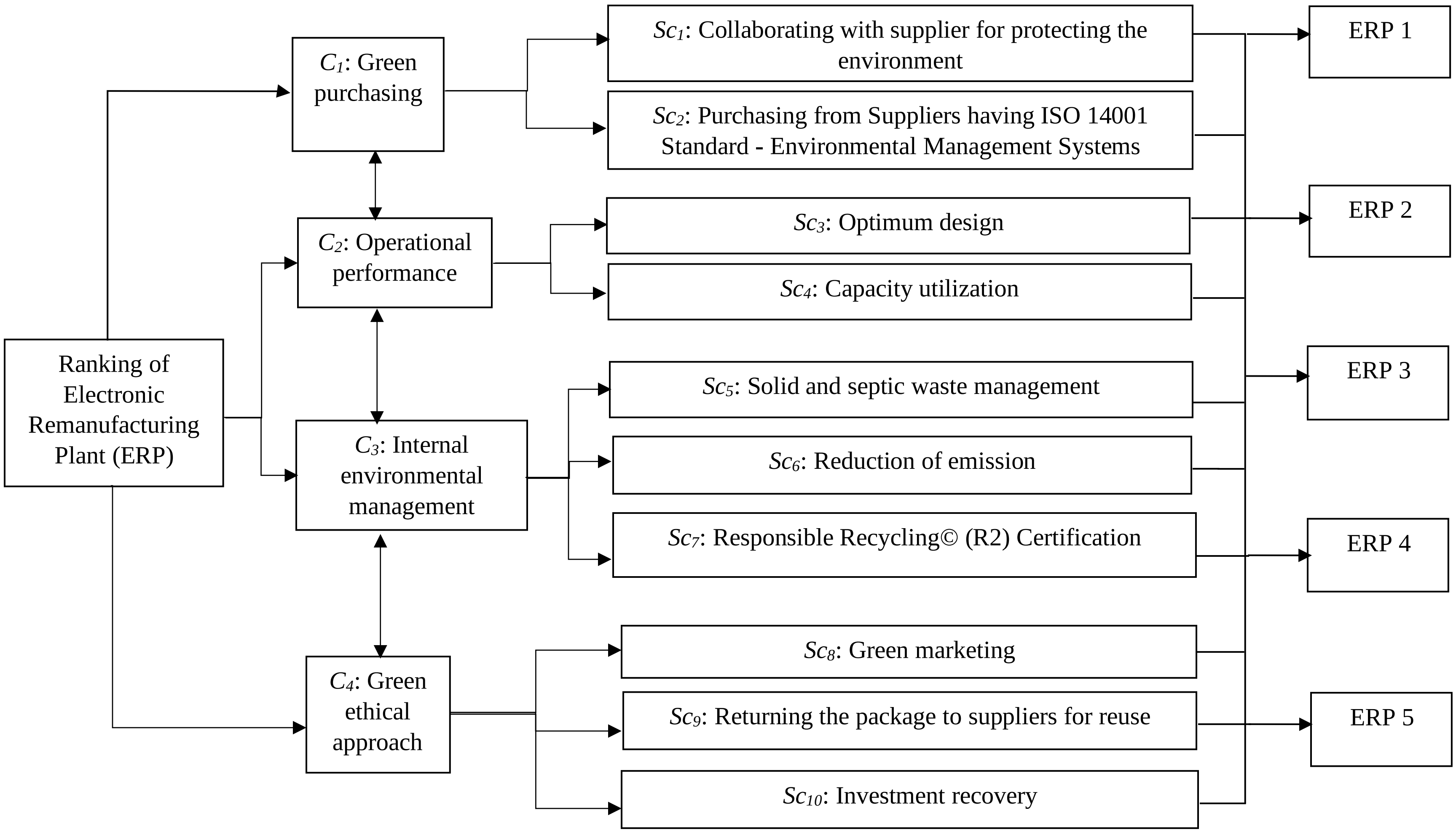

Fig. 2.8. The ANP model for ranking electronic remanufacturing plants (ERP)

2.3.1.2. Ranking the suppliers, recovery centers, and remanufacturing plants based on Fuzzy ANP approach

It is assumed that there are 5 electronic suppliers, 6 recovery centers, and 5 remanufacturing centers in the proposed network. The overall environmental weights are provided in Tables 2.2, 2.3, 2.4. The details of the calculations are provided in Appendices 2.A, 2.B, and 2.C.

Table 2.2
Results of the fuzzy ANP method for the suppliers

Suppliers	ANP	ANP priority
1	0.214	2
2	0.251	1
3	0.173	4
4	0.199	3
5	0.162	5

Table 2.3
Results of the fuzzy ANP method for the recovery centers

Recovery centers	ANP	ANP priority
1	0.193	2
2	0.198	1
3	0.156	4
4	0.169	3
5	0.155	5
6	0.130	6

Table 2.4
Results of the fuzzy ANP method for the remanufacturing plants

Remanufacturing centers	ANP	ANP priority
1	0.257	1
2	0.233	2
3	0.192	3
4	0.155	5
5	0.162	4

2.3.2. Optimization model

A multi-objective mixed-integer linear programming model is employed to optimize the proposed network. The following sets, parameters, and decision variables are utilized:

Sets

J = set related to products ($j \in J$)

$\d{N}$ = set related to components ($n \in \d{N}$)

$\d{S}$ = set related to suppliers ($s \in \d{S}$)

$\d{M}$ = set related to markets ($m \in \d{M}$)

$\d{R}$ = set related to regional collection centers ($r \in \d{R}$)

$\d{K}$ = set related to recovery centers ($k \in \d{K}$)

$\d{L}$ = set related to remanufacturing plants ($l \in \d{L}$)

$\d{T}$ = set related to periods ($t \in \d{T}$)

Parameters

A_s = fixed-cost associated with supplier s

B_r = fixed-cost associated with regional collection center r

C_k = fixed-cost associated with recovery center k

D_l = fixed-cost associated with remanufacturing plant l

R_j = selling price of product j

E_{sn} = purchasing cost of component n from supplier s

F_j = cost of disassembly related to product j

G_j = cost of remanufacturing related to product j

L_n = disposal cost related to component n

O_n = unit cost of transportation related to component n from suppliers to remanufacturing plants

P_j = unit cost of transportation related to product j from markets to regional collection centers

H_j = unit cost of transportation related to product j from regional collection centers to recovery centers

M_n = unit cost of transportation related to component n from recovery centers to remanufacturing plants

N_j = unit cost of transportation related to product j from remanufacturing centers to markets

θ_η = unit cost of transportation related to component n from recovery centers to disposal center

e_{sl} = the distance between locations s and l

e_k = the distance between recovery center k and disposal center

d_{mjt} = demand of customer (market) m for product j related to period t

ε_n = disposal fraction of the component *n*

z_{mjt} = returned product *j* related to customer (market) *m* related to period *t*

$h_{l\eta}$ = number of capacity of remanufacturing center *l* for component *n*

u_{rj} = number of capacity of regional collection center *r* for product *j*

n_{kj} = number of capacity of recovery center *k* for product *j*

$g_{s\eta}$ = number of capacity of supplier *s* for component *n*

I_{jn} = number of component *n* in product *j*

α_{sn} = green performance allocating to the supplier *s* via providing of component *n*

β_{ln} = green performance allocating to the remanufacturing plant *l* via assembling of component *n*

ς_{kn} = green performance allocating to the recovery center *k* to recycle component *n* via disassembling the returned electronic appliances

γ_{sn} = defect rate of component *n* providing by supplier *s*

η_{lj} = defect rate of product *j* providing by remanufacturing plant *l*

ν_{kn} = defect rate of component *n* recycled by recovery center *k*

ω_{sn} = on-time delivery of component *n* providing by supplier *s*

δ_{lj} = on-time delivery of product *j* providing by remanufacturing plant *l*

μ_{kn} = on-time delivery of component *n* recycled by recovery center *k*

Decision Variables

V_{slnt} = number of component *n* shipped to remanufacturing plant *l* by supplier *s* related to period *t*

W_{lmjt} = number of product *j* remanufactured by remanufacturing plant *l* for customer (market) *m* related to period *t*

X_{mrjt} = number of returned product *j* from customer *m* to regional collection center *r* related to period *t*

Y_{rkjt} = number of product *j* shipped by regional collection center *r* to recovery center *k* related to period *t*

Z_{klnt} = number of component *n* shipped to remanufacturing plant *l* from recovery center *k* related to period *t*

λ_{knt} = number of component *n* shipped to disposal center from recovery center *k* related to period *t*

T_l = 1, if the remanufacturing plant is selected at potential site *l*, 0, otherwise.

Q_r = 1, if the regional collection center located in site r is utilized to collect the products, 0, otherwise.

S_k = 1, if the recovery center located in site k is utilized to recycle the used products, 0, otherwise.

U_s = 1, if the supplier s is selected, 0, otherwise.

$$Max\ z_1 = \sum_l\sum_m\sum_j\sum_t \left(R_j - \left(G_j + N_j e_{lm}\right)\right)W_{lmjt} - \sum_s\sum_l\sum_n\sum_t \left(E_{sn} + O_n e_{sl}\right)V_{slnt} - \sum_m\sum_r\sum_j\sum_t P_j e_{mr} X_{mrjt} -$$
$$\sum_r\sum_k\sum_j\sum_t \left(F_j + H_j e_{rk}\right)Y_{rkjt} - \sum_k\sum_n\sum_t \left(L_n + \theta_n e_k\right)\lambda_{knt} - \sum_k\sum_l\sum_n\sum_t M_n e_{kl} Z_{klnt} -$$
$$\sum_s A_s U_s - \sum_r B_r Q_r - \sum_k C_k S_k - \sum_l D_l T_l$$

$$Max\ \ z_2 = \sum_s\sum_n \alpha_{sn}\left(\sum_l\sum_t V_{slnt}\right) + \sum_l\sum_n \beta_{ln}\left(\sum_s\sum_t V_{slnt} + \sum_k\sum_t Z_{klnt} + \sum_m\sum_j\sum_t \left(W_{lmjt}\right) I_{jn}\right) +$$
$$\sum_k\sum_n \varsigma_{kn}\left(\sum_r\sum_j\sum_t \left(Y_{rkjt}\right) I_{jn} + \sum_l\sum_t Z_{klnt} + \sum_t \lambda_{knt}\right)$$

$$Min\ \ z_3 = \sum_s\sum_l\sum_n\sum_t \gamma_{sn} V_{slnt} + \sum_l\sum_m\sum_j\sum_t \eta_{lj} W_{lmjt} + \sum_k\sum_l\sum_n\sum_t \nu_{kn} Z_{klnt}$$

$$Max\ \ z_4 = \sum_s\sum_l\sum_n\sum_t \omega_{sn} V_{slnt} + \sum_l\sum_m\sum_j\sum_t \delta_{lj} W_{lmjt} + \sum_k\sum_l\sum_n\sum_t \mu_{kn} Z_{klnt}$$

s.t.

$$\sum_k Z_{klnt} + \sum_s V_{slnt} = \sum_m\sum_j \left(W_{lmjt}\right) I_{jn} \qquad \forall n,l,t \qquad (2.11)$$

$$\sum_l W_{lmjt} = d_{mjt} \qquad \forall m,j,t \qquad (2.12)$$

$$\sum_r X_{mrjt} = z_{mjt} \qquad \forall m,j,t \qquad (2.13)$$

$$\sum_k Y_{rkjt} = \sum_m X_{mrjt} \qquad \forall r,j,t \qquad (2.14)$$

$$\varepsilon_n \sum_r\sum_j \left(Y_{rkjt}\right) I_{jn} \le \lambda_{knt} \qquad \forall k,n,t \qquad (2.15)$$

$$\sum_l Z_{klnt} + \lambda_{knt} = \sum_r\sum_j \left(Y_{rkjt}\right) I_{jn} \qquad \forall n,k,t \qquad (2.16)$$

$$\sum_{k}\sum_{n} Z_{klnt} + \sum_{s}\sum_{n} V_{slnt} \le T_l \sum_{n} h_{ln} \qquad \forall l,t \qquad (2.17)$$

$$\sum_{m}\sum_{j} X_{mrjt} \le Q_r \sum_{j} u_{rj} \qquad \forall r,t \qquad (2.18)$$

$$\sum_{r}\sum_{j} Y_{rkjt} \le S_k \sum_{j} n_{kj} \qquad \forall k,t \qquad (2.19)$$

$$\sum_{l}\sum_{n} V_{slnt} \le U_s \sum_{n} g_{sn} \qquad \forall s,t \qquad (2.20)$$

$$S_k, Q_r, T_l, U_s \in \{0,1\} \qquad \forall l,r,k,s \qquad (2.21)$$

$$V_{slnt}, W_{lmjt}, X_{mrjt}, Y_{rkjt}, Z_{klnt}, \lambda_{knt} \ge 0 \qquad \forall s,l,n,m,j,r,k,t \qquad (2.22)$$

The first objective function is aimed to maximize the total profit of electronic RL. For such purpose, it is intended to maximize the subtraction of fixed and variable costs from the revenue of selling products. The second objective function is utilized to maximize the green performance associated with electronic suppliers, recovery centers, and remanufacturing plants. Three qualitative parameters of α_{sn}, β_{ln}, and ς_{kn} have been measured by the fuzzy ANP method in Section 2.3. The third objective function is utilized to minimize the defect rate of components provided by supplier(s) and recovery center(s) along with electronic appliances remanufactured by plant(s). To this aim, the percentage of defect rate related to each entity is considered. The fourth objective function is used to maximize on-time delivery. Accordingly, the delivery performance report of each entity involving in the RL network can be applied.

Constraint (2.11) implies that the number of components related to the remanufactured products (W_{lmjt}) must be equal to the summation of the components either purchasing from the suppliers (V_{slnt}) or coming from the electronic recovery centers (Z_{klnt}). Constraints (2.12) and (2.13) are related to the market's demand and collection rate of unwanted electronic appliances, respectively. Constraint (2.14) indicates that every product entering regional collection centers must be transferred to the recovery centers. The disposal fraction of the used products is represented by Constraint (2.15). As specified by Constraint (2.16), the number of components associated with the returned products entering the recovery center(s) must be equal to the summation of the recycled components and unrecoverable materials sending to a disposal center. Constraints (2.17), (2.18), (2.19), and (2.20) are linked with the capacities of the remanufacturing plants, regional collection centers, recovery centers, and electronic suppliers, respectively. Finally, Constraints (2.21) and (2.22) show the binary and non-negative decision variables.

2.3.3. Distance method

To achieve non-dominated solutions neighboring to ideal values, the distance method can be applied for multi-objective problems (Branke and Miettinen, 2008). Suppose that the objective functions are minimization. As illustrated by Eq. (2.23), $z_i^*$and w_i are defined as the ideal values and distance metrics, respectively. To find z_i^*, each objective function is required to be solved individually with respect to the defined constraints (Mirzapour Al-E-Hashem et al., 2011). In this research, there are four objective functions including the total profit of RL, green performance associated with electronic suppliers, recovery centers, and remanufacturing plants, defect rate, and on-time delivery. The objective function for the proposed multi-objective RL network can be written as Eq. (2.24).

$$z = \left(\sum_i w_i^\tau \left(\frac{z_i - z_i^*}{z_i^*} \right)^\tau \right)^{\frac{1}{\tau}} \qquad \forall\ i = 1, 2\ldots, \infty \tag{2.23}$$

$$Max\ z = \left(w_1^\tau \left(\frac{z_1 - z_1^*}{z_1^*} \right)^\tau + w_2^\tau \left(\frac{z_2 - z_2^*}{z_2^*} \right)^\tau - w_3^\tau \left(\frac{z_3 - z_3^*}{z_3^*} \right)^\tau + w_4^\tau \left(\frac{z_4 - z_4^*}{z_4^*} \right)^\tau \right)^{\frac{1}{\tau}} \tag{2.24}$$

s.t.

Eqs. (2.11) – (2.22)

2.3.4. ε-constraint method

To reach the Pareto solutions through the ε-constraint method, the most important objective is assumed as the main objective and the other objectives are written as the constraints (Collette and Siarry, 2003). As indicated by Eq. (2.25), the total profit is considered as the principal objective, and the other objectives consisting of the green performance, defect rate, and on-time delivery are written as the new constraints.

$$Max\ z = z_1 \tag{2.25}$$

s.t.

$z_2 \geq \varepsilon_2$

$z_3 \leq \varepsilon_3$

$z_4 \geq \varepsilon_4$

Eqs. (2.11) – (2.22)

2.3.5. Parameters' value and solutions

The optimization model is solved for the electronic RL network. In this study, it is assumed that there are 5 suppliers, 5 locations for the remanufacturing plant, 22 markets, 10 locations for regional collection centers, 6 locations for the recovery centers, and 1 location for the disposal center. The values of the other parameters applied in the optimization model are indicated in Table 2.5. In the real-life, the demand associated with specific product varies in different months or seasons based on the type of the product. Therefore, configuring a multi-period model is necessary for the effective decision-making process in real life. In this application, two periods have been considered that represent two seasons.

Table 2.5
Parameters' values applied to solve the proposed model

$J = 3$	$A_s = 1{,}000$, $B_r = 1{,}500$, $C_k = 10{,}000$, $D_l = 400{,}000$	$\gamma_{1n}=0.1$, $\gamma_{2n}=0.1$, $\gamma_{3n}=0.35$, $\gamma_{4n}=0.1$, $\gamma_{5n}=0.35$
$\underset{\cdot}{N} = 5$	$R_j = 100$, $G_j = 35$, $F_j = 15$	$\eta_{1j}=0.1$, $\eta_{2j}=0.1$, $\eta_{3j}=0.1$, $\eta_{4j}=0.35$, $\eta_{5j}=0.35$
$\underset{\cdot}{S} = 5$	$P_j = H_j = N_j = 0.097$	$\nu_{1n}=0.1$, $\nu_{2n}=0.1$, $\nu_{3n}=0.1$, $\nu_{4n}=0.1$, $\nu_{5n}=0.35$, $\nu_{6n}=0.35$
$\underset{\cdot}{M} = 22$	$O_n = M_n = \theta_\eta = 0.0194$	$\omega_{1n}=0.25$, $\omega_{2n}=0.25$, $\omega_{3n}=0.2$, $\omega_{4n}=0.2$, $\omega_{5n}=0.1$
$\underset{\cdot}{R} = 10$	$E_{sn} = (5)_{5*5}$	$\delta_{1j}=0.35$, $\delta_{2j}=0.35$, $\delta_{3j}=0.1$, $\delta_{4j}=0.1$, $\delta_{5j}=0.1$
$\underset{\cdot}{K} = 6$	$\alpha_{1n}=0.214$, $\alpha_{2n}=0.251$, $\alpha_{3n}=0.173$, $\alpha_{4n}=0.199$, $\alpha_{5n}=0.162$	$\mu_{1n}=0.30$, $\mu_{2n}=0.30$, $\mu_{3n}=0.1$, $\mu_{4n}=0.1$, $\mu_{5n}=0.1$, $\mu_{6n}=0.1$
$\underset{\cdot}{L} = 5$	$\beta_{1n}=0.257$, $\beta_{2n}=0.233$, $\beta_{3n}=0.192$, $\beta_{4n}=0.155$, $\beta_{5n}=0.162$	$L_n = 5$, $\varepsilon_n=0.2$
$\underset{\cdot}{T} = 2$	$\varsigma_{1n}=0.193$, $\varsigma_{2n}=0.198$, $\varsigma_{3n}=0.156$, $\varsigma_{4n}=0.169$, $\varsigma_{5n}=0.155$, $\varsigma_{6n}=0.130$	

To solve the proposed model, IBM ILOG CPLEX 12.7.1.0 is applied. In the distance technique, each objective was solved separately with respect to the defined constraints (2.11-2.22) to determine z_i^* (where i = 1, 2, 3, 4). Then, different pairs of w_i are applied on account of achieving the non-dominated solutions between the four defined objectives. The final optimization problem (including 550 constraints, 2,954 decision variables, 26 binary variables, and 21,092 non-zero coefficients) was solved in 0.37 seconds. As illustrated by Tables 2.6 and 2.8, by altering the w_i associated with each objective, the non-dominated solutions and the binary variables were changed. Subsequently, such entities (U_2, S_1, T_1) were selected when the second objective function had a higher distance metric.

In the ε-constraint method, the higher priority function was assumed as the main objective (total profit), and other objective functions were treated as the constraints. The mathematical model (including 750 constraints, 2,954 decision variables, 26 binary variables, and 25,092 non-zero coefficients) was solved in 0.53 seconds. It was intended to reach Pareto solutions by trying different parameters (ε_i, where i = 2, 3, 4). As indicated in Table 2.7, some trade-off solutions have been obtained. Furthermore, Tables 2.6 and 2.7 illustrate that a solution related to one objective cannot be improved, unless the values of other objectives become deteriorated.

Table 2.6
Non-dominated solutions obtained by the distance technique

	Assigned weights				Objective values			
Row	W_1	W_2	W_3	W_4	Z_1	Z_2	Z_3	Z_4
1	0.85	0.05	0.05	0.05	4,751,300	463,640	79,200	213,840
2	0.10	0.70	0.05	0.15	3,714,300	530,380	79,200	211,200
3	0.15	0.15	0.50	0.20	4,522,500	494,660	79,200	213,840
4	0.10	0.15	0.10	0.65	4,283,800	517,780	79,200	213,840

Table 2.7
Non-dominated solutions obtained by the ε-constraint method

	Epsilon values			Objective values			
Row	ε_2	ε_3	ε_4	Z_1	Z_2	Z_3	Z_4
1	420,000	165,000	110,000	4,761,613	440,250	165,000	151,800
2	435,000	80,000	115,000	4,761,415	458,090	79,200	203,280
3	530,000	80,000	120,000	3,776,820	530,000	79,200	211,410
4	520,000	79,200	150,000	4,191,800	520,000	79,200	213,840

Table 2.8
Priority of third party in accordance with different objectives

Non-dominated solution	Supplier (U_s)	Recovery center (S_k)	Remanufacturing plant (T_l)
Distance method # 1	U_1	S_2	T_2
Distance method # 2	U_2	S_1	T_1
Distance method # 3	U_1	S_1	T_1
Distance method # 4	U_2	S_2	T_1
ε-constraint # 1	U_1	S_3	T_2
ε-constraint # 2	U_1	S_3	T_2
ε-constraint # 3, 4	U_2	S_2	T_1

2.4. The value path analysis

To illustrate the balance among different objectives in MOP models, value path analysis (VPA) can be applied (Schilling et al., 1983, Wadhwa and Ravinsdran, 2007; Amin and Zhang, 2014). As indicated in Table 2.9, the value of each non-dominated solution is defined as the objective's value related to the certain alternative divided by its minimum value among all alternatives. Such ratios are utilized as the normalized scales to indicate the advantages of the associated alternative compared with other alternatives. Fig. 2.9 shows the results. To interpret Fig. 2.9, it is inclined to have a greater normalized value in the case of maximization. On the contrary, the objective's value is more desirable if its normalized value becomes close or equal to 1 in the case of minimization. According to the properties of VPA, if two value paths intersect, then neither of them is dominated. Otherwise, one path (alternative) must lie below the other one that is called an inferior solution. As depicted in Fig. 2.9, all value paths are intersected and are therefore non-dominated.

Table 2.9
The results based on different objectives

Alternatives	Total profit	Environmental performance	Defect rate	On-time delivery
Distance method # 1	1.279191	1.053129	1	1.408696
Distance method # 2	1	1.204725	1	1.391304
Distance method # 3	1.217591	1.123589	1	1.408696
Distance method # 4	1.153326	1.176104	1	1.408696
ε-constraint # 1	1.281968	1	2.083333	1
ε-constraint # 2	1.281914	1.040522	1	1.33913
ε-constraint # 3	1.016832	1.203861	1	1.392688
ε-constraint # 4	1.128557	1.181147	1	1.408696

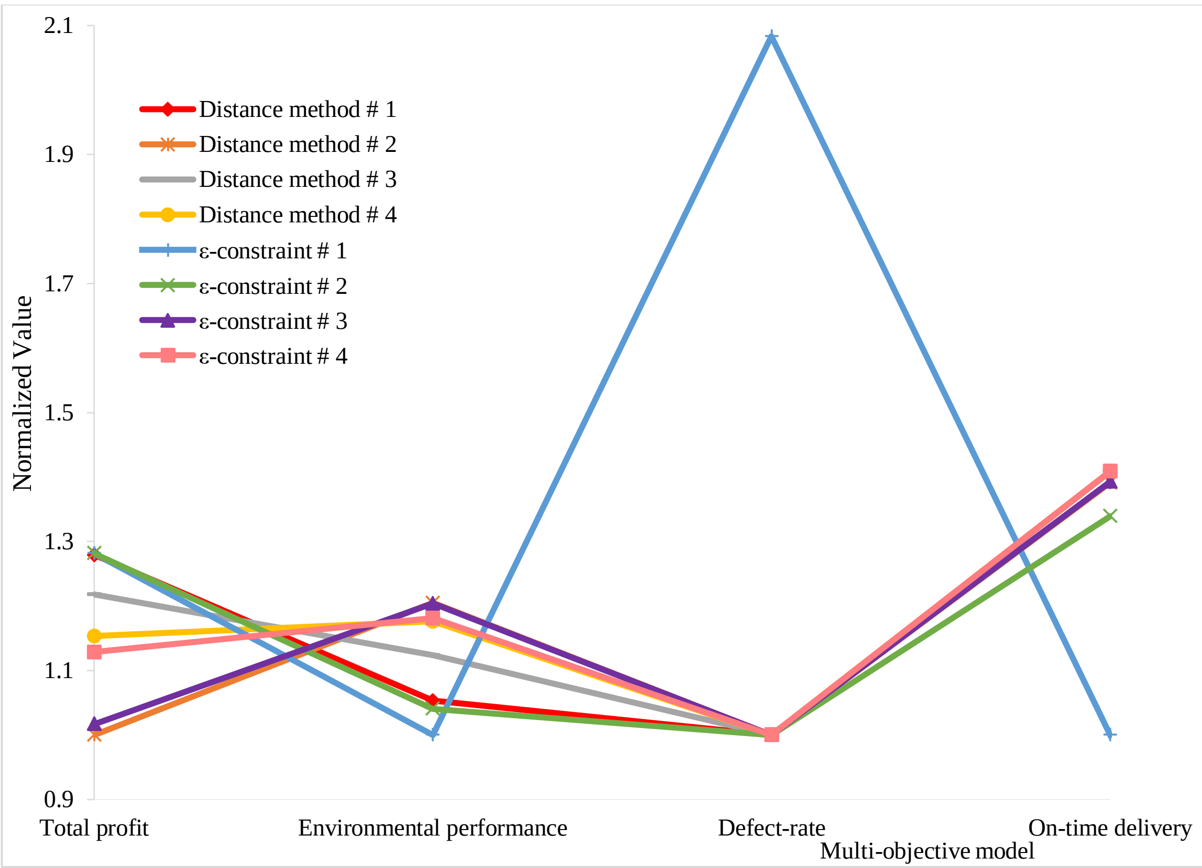

Fig. 2.9. The value path analysis

2.5. Conclusions

In this research, a multi-objective model has been proposed for the selection of third parties in an electronic RL network in addition to network configuration. The selection of third party RL provider and optimizing related RL network at the same time is one of the important contributions of this research. The proposed multi-component, multi-product, multi-period model includes multiple echelons including electronic suppliers, remanufacturing plants, markets, regional collection centers, and recovery centers. The main objective has been defined as the maximization of total profit for the RL. In this sense, revenue due to the selling price of products along with variable costs (including costs of transportation, remanufacturing, disassembly, disposal, and purchasing raw material), and fixed costs play prominent roles.

To reduce environmental issues, the green performance of electronic suppliers, remanufacturing plants, and recovery centers have been taken into account. Three different frameworks including four criteria and ten sub-criteria have been proposed to rank 5 suppliers, 6 recovery centers, and 5 remanufacturing plants. There are a variety of qualitative determinants representing the green performance of each party. Hence, the ANP method has been applied to change the qualitative factors to the measurable parameters. To avoid ambiguity in the expert's judgments, the fuzzy sets theory has been combined with the ANP method. 2nd supplier, 1st and 2nd recovery centers, and 1st remanufacturing plant were among the best parties based on green performance. The obtained results have been utilized to represent the green performance of the third parties in the second objective function.

There is a great deal of concern associated with resource shortage and economic volatility. Hence, reducing the defect rate can be a crucial objective to eliminate the impact of such fluctuations on the network. To identify the optimal network, the defect rate of components has been considered. Furthermore, on-time delivery is one of the major challenges among the parties in RL networks. According to the capacity constraints and uncertain material supplies, each entity is supposed to cooperate with others to optimize the network. Therefore, on-time delivery has been taken into account as one of the objectives in this study.

The multi-objective mathematical model has been solved through the application of distance technique and ε-constraint method. To solve the proposed multi-objective model, each problem has been solved separately, then the distance method has been applied to find the non-dominated solutions. In addition, the ε-constraint method has been used to reach Pareto solutions. It is commonsensical that different trade-off solutions can be obtained by changing the relative weight of each objective. To our knowledge, this research is among the first studies that has utilized a multi-objective mathematical model to identify the third party in an electronic RL network with network configuration. In order to display and analyze the non-dominated solutions, VPA has been employed. It has been shown that all obtained results are acceptable due to the properties of VPA.

There are some related methods that can be applied for future research. In this study, a multi-objective mathematical model has been proposed. However, in some cases, there is imprecise information to deal with in optimization. Therefore, other methods such as robust optimization and fuzzy programming are recommended to be utilized to address uncertainty. Besides, to solve a large multi-objective RL problem, metaheuristic algorithms can be applied to reach good solutions.

Chapter 3. An environmental optimization model to configure a hybrid forward and reverse supply chain network under uncertainty

3.1. Introduction

Management of returned products such as lead-acid batteries (LAB) is a challenge for communities. There is a great deal of concern related to battery recycling on account of incremental usage. Hence, it is required to have a comprehensive plan to collect returned LAB; otherwise discarded batteries in the environment may damage habitat on account of containing toxic materials. Accordingly, configuring the closed-loop supply chain (CLSC) network focusing on the recovery of used batteries has become as a necessary part of the business. A worthy example of a battery CLSC network can be observed in Winnipeg, Manitoba. Canadian Battery Association (CBA) manages the recycling of LAB across Canada. CBA intends to provide related information and programs to support safe storage, shipment, and recycling of returned LAB to reduce environmental issues. As a result of CBA stewardship program, 6,756,500 kg of used LAB have been recovered during 2016 (CBA annual report, 2016). To continue such sustainable plans, the profitability of CLSC should be taken into account. With this respect, configuring the locations of involved facilities is a strategic decision and affects the expected profit of networks. There is often imprecise information challenging decision-makers of battery CLSCs in real life. Most of the parameters contributing to optimize a mathematical model are imprecise, and policy-makers are required to adapt their approaches with such uncertainties (Jung et al., 2004; Mele et al., 2007; Jung and Jeong, 2012; Marufuzzaman et al., 2014; Cardoso et al., 2016; von Westarp and Schinas, 2016; Englberger et al., 2016; Ramezanian and Behboodi, 2017; Amin and Baki, 2017; Amin et al., 2017; Zamar et al., 2017; Banaeian et al., 2018; Amin et al., 2018; Papen and Amin, 2019). Furthermore, transportation strategies have a significant impact on reducing the total cost and environmental issues associated with CLSC networks. On this matter, finished products can be delivered to the markets in a single shipment after production, or delivered in multiple batches. Such strategies are determined by decision-makers based on incurred costs of inventory, transportation, loss of opportunity, and environmental concerns (i.e., CO_2 emissions). In this study, a multi-objective FFSP approach is employed, since it is aimed to handle nondeterministic decision variables and parameters with regard to environmental compliance of third parties.

3.1.1. Review of studies used fuzzy programming in facility location design

Since a CLSC network is supposed to operate in a dynamic environment, dealing with uncertainty is one of the main difficulties in facility location design. There are some methods that can be utilized in unpredictable situations, such as fuzzy methods (e.g., fuzzy goal programming, fuzzy intervals, and fuzzy integer programming). Zarandi et al. (2011) designed a network distribution for a CLSC. They solved the proposed model by a fuzzy goal programming method. Pishvaee and Razmi (2012) developed a fuzzy multi-objective model (MOM) for a green supply chain. They applied an interactive fuzzy approach to minimize the total cost of supply chain and environmental issues. Costantino et al. (2012) utilized a fuzzy programming approach to examine the sustainable CLSC. They aimed to minimize the total cost, the consumption rate of energy, and CO_2 emissions in the case of a desktop computer supply chain. Vahdani et al. (2013) proposed an optimization model for a multi-echelon, multi-product CLSC in the iron and steel industry. They applied fuzzy programming to solve the mathematical model. Ramezani et al. (2014) designed a multi-product, multi-period CLSC. They proposed a fuzzy MOM to maximize the profit and the quality along with the optimization of delivery time. In the proposed fuzzy model, the coefficients were assumed to be fuzzy due to the uncertain environment. They employed a fuzzy optimization approach to convert the fuzzy multi-objective model to the equivalent crisp version.

Jindal and Sangwan (2014) employed fuzzy mixed-integer linear programming (MILP) for a multi-facility, multi-product CLSC in a single period. They aimed to maximize the proposed model under uncertainty of demand along with all types of possible costs related to CLSC. Alimoradi et al. (2014) developed a fuzzy MILP model to deal with uncertain returned products for a single-period, multi-product CLSC. Fallah-Tafti et al. (2014) designed a multi-period CLSC network with regard to uncertain costs and demand. A novel interactive fuzzy programming was employed to find the non-dominated solutions of MOM. Mirakhorli (2014) discussed about designing a CLSC which may have an impact on the performance of a logistics network. He applied interactive fuzzy programming to address the fuzzy multi-objective optimization model.

Subulan et al. (2015) proposed a MOM for a tire CLSC network. They utilized an interactive fuzzy goal programming to solve their model. They believed that designing the efficient CLSC through the application of fitting disposal methods along with appropriate collection and storage can diminish the environmental impact of used products. Dai and Zheng (2015) designed a multi-echelon, multi-product CLSC under uncertain demand and disposal rate. They applied stochastic and fuzzy programming to maximize the total profit of the model. Mohajeri and Fallah (2016) considered the recovery of end-of-life products in a notebook CLSC. On this matter, they aimed to minimize the total cost along with CO_2 emissions during the distribution, delivery, and recycling of the products. Fuzzy programming was applied to deal with uncertain parameters (recovery rate, landfilling rate, and demand) in a realistic CLSC network. Pham and Yenradee (2017) suggested an alternative approach to configure a manufacturing network under uncertainty. They applied the possibilistic theory to deal with uncertain parameters. The deterministic and fuzzy models were applied and compared in their study. They proved that fuzzy model can be more accurate in comparison with the deterministic approach. Ghomi-Avili et al. (2018) proposed a fuzzy bi-objective model to configure a CLSC network. They addressed the environmental issues by designing the reverse flow and controlling the CO_2 emissions. Ghaderi et al. (2018) introduced a multi-objective robust fuzzy programming model to configure a bioethanol supply chain.

3.1.2. Review of studies used stochastic programming in facility location design

To design CLSCs, stochastic programming can be employed in optimization models to deal with imprecise information when the probability of each scenario is known. Hu and Bidanda (2009) utilized stochastic dynamic programming to design a network based on the product life cycle. They determined the optimal strategy to maximize the whole profit. Paksoy et al. (2011) proposed a MOM to examine the efficiency and environmental practices in a multi-product CLSC. Stochastic programming was utilized to investigate the trade-off solution in a proposed realistic network. Amin and Zhang (2013b) introduced a three-stage model for CLSC. They introduced stochastic mixed-integer non-linear programming to design the CLSC network with regard to uncertain demand. Litvinchev et al. (2014) discussed about designing an RL network including locations of distribution and inspection centers along with remanufacturing facilities. They employed stochastic programming to formulate a multi-product CLSC with respect to scenario-based demand. Zeballos et al. (2014) utilized stochastic programming for a multi-period, multi-product CLSC. Multiple scenarios were utilized to consider the effects of uncertain demand and raw material supplies. In the proposed model, a scenario tree approach was applied to indicate all possible discrete events. Each node of the scenario tree represented a possible outcome estimated by a given probability of occurrence.

Francie et al. (2015) employed stochastic programming for a printer cartridge CLSC. They aimed to minimize the total cost as a result of waiting customers and holding inventories related to the finished and returned products. Vahdani and Mohammadi (2015) utilized stochastic programming and robust optimization to solve a bi-objective optimization model under uncertainty. Soleimani et al. (2016) believed that an integrated approach is necessary for designing and planning decision levels to achieve the best performance of CLSC. They also mentioned that real markets can be unpredictable for demand and price parameters. A MILP was applied for a multi-product, multi-period CLSC in order to deal with stochastic demand and products' price. Entezaminia et al. (2016) examined the connection between green principals and economic indicators. Biodegradability, energy consumption, and recyclability were determined as the environmental factors in their proposed model. Zhalechian et al. (2016) designed a sustainable CLSC considering economic, environmental, and social aspects. They considered CO_2 emissions, fuel consumption, and wasted energy as the environmental issues, creating job opportunities as the social aspects, and economic growth rate. The stochastic-possibilistic programming was applied to address the uncertainty of the proposed CLSC. Keyvanshokooh et al. (2016) proposed a profit optimization model for a CLSC network by considering economic, environmental, and social concerns. They developed a hybrid robust-stochastic programming method to deal with different types of uncertainties in transportation cost, demand, and return. Feitó-Cespón et al. (2017) utilized a stochastic programming and multi-criteria programming to configure a sustainable supply chain network under uncertainty. The application of performance indicators was discussed to evaluate the results. Zahiri et al. (2018) applied stochastic programming to optimize a bi-objective model comprising the total cost and freshness of products in a blood supply chain. Tsao et al. (2018) designed a sustainable supply chain network by application of an interactive method based on stochastic programming and fuzzy multi-objective model.

Based on the mentioned papers, there are still some missing parts that can be investigated. In the majority of studies, one or two sources of uncertainty such as demand and return have been taken into account. Since the configuration of CLSC is a strategic decision, all possible ranges for the objective function and decision variables are preferred to be computed in uncertain situations. To handle uncertainty in several sources, appropriate integrated solution approaches should be developed. A classification of the reviewed mathematical models has been provided in Table 3.1.

Table 3.1
Classification of some solution approaches to address imprecise parameters in CLSCs

Authors	Imprecise parameters	Multi-product	Type of products	Multi-period	Multi-objective	Solution approaches	Real locations
Amin and Zhang (2013b)	Demand	✓			✓	MILP, QFD, Stochastic programming	
Zeballos et al. (2014)	Demand, raw material supplies	✓		✓		Stochastic programming	
Vahdani and Mohammadi (2015)	Costs, capacity	✓			✓	Stochastic programming, Robust optimization	
Soleimani et al. (2016)	Demand, product's price	✓		✓		Stochastic programming	
Feitó-Cespón et al. (2017)	Stochastic variable (demand and waste generation)	✓				Stochastic programming	
Zahiri et al. (2018)	Demand, donation	✓	Blood products	✓	✓	Stochastic programming	
Fallah-Tafti et al. (2014)	Costs and demand	✓		✓	✓	Fuzzy programming	
Mirakhorli (2014)	Demand, return				✓	Interactive fuzzy programming	
Ramezani et al. (2014)	All parameters	✓		✓	✓	Fuzzy optimization approach	
Jindal and Sangwan (2014)	Demand, variable costs	✓				Fuzzy programming	
Mohajeri and Fallah (2016)	Recovery rate, landfilling rate, demand		Notebook (laptop) industry			Fuzzy programming	✓
Pham and Yenradee (2017)	Demand, fixed and variable costs	✓	Toothbrush industry	✓		Fuzzy programming	
Ghaderi et al. (2018)	Input parameters (costs, environmental and social impact)		Bioethanol	✓	✓	robust fuzzy programming	✓
Proposed model	All parameters and decision variables	✓	Battery	✓	✓	Integration of fully fuzzy programming and stochastic programming	✓

3.1.3. Aims and contributions of research

Approximately 8,500,000 kg of LAB sold in Manitoba are under the supervision of CBA. 88% of sold LAB are related to the vehicles and commercial trucks, and the rest (12%) is associated with motive LAB (i.e., forklift, and stationary LAB for power backup). The consumers can benefit from CBA recovery program (CBA stewardship program, 2016).

In this study, a bi-objective environmental optimization model for an LAB CLSC network in Winnipeg, Manitoba, Canada is introduced. In reality, some parameters such as cost of raw materials, production, transportation, market's demand, rate of returned LAB, efficiency in recovery of returned LAB may go up or down. Thus, proposing an appropriate model compatible with real-life is required. Furthermore, environmental compliance of third parties (i.e., suppliers, plants, and battery recovery centers) involved in CBA's program should be taken into account. In this research, a bi-objective model consisting of LAB CLSC profit as the first objective, and green performances of third parties as the second objective is developed. Moreover, the impact of fluctuation in fuel price in a network in Winnipeg is considered. Besides, An FFSP method is developed to estimate the possible ranges of objective functions and decision variables. The significant research contributions of this paper are expressed as follows:

- To propose and develop an integrated model including fully fuzzy programming and stochastic programming. To our knowledge, this hybrid method is new in the optimization literature. This method enables us to deal with different types of imprecise parameters.
- To design and configure an LAB CLSC network in Winnipeg, Canada. Google Maps are utilized to compute real distances between the involved third parties.
- To extend the proposed hybrid model to the bi-objective one for the purpose of considering the environmental compliance of third parties.

The structure of this study is arranged as follows. Section 3.2 includes the problem statement. Thereafter, the fully fuzzy stochastic programming is developed in Section 3.3. Then, the proposed model is extended to the multi-objective model in Section 3.4. The distance technique and value path analysis are introduced and utilized in Section 3.5. Finally, Section 3.6 is devoted to the conclusions.

3.2. Problem definition

Fig. 3.1 illustrates the recovery process of returned LAB. The recovered components can be applied to make new LAB and other products such as cleaners. For this purpose, the returned LAB is disassembled to lead, plastic, and battery acid. The lead and heavy materials are gathered and shaped to lead ingots which are then melted down to produce lead plates for using in new LAB. Similarly, plastic cases can be remanufactured for a new battery, while the LAB's acid is converted to sodium sulphate using in detergent. The CBA's stewardship plan provides recovery program for LAB's consumers. Fig. 3.2 illustrates municipal areas in Winnipeg where the application of our proposed model is investigated.

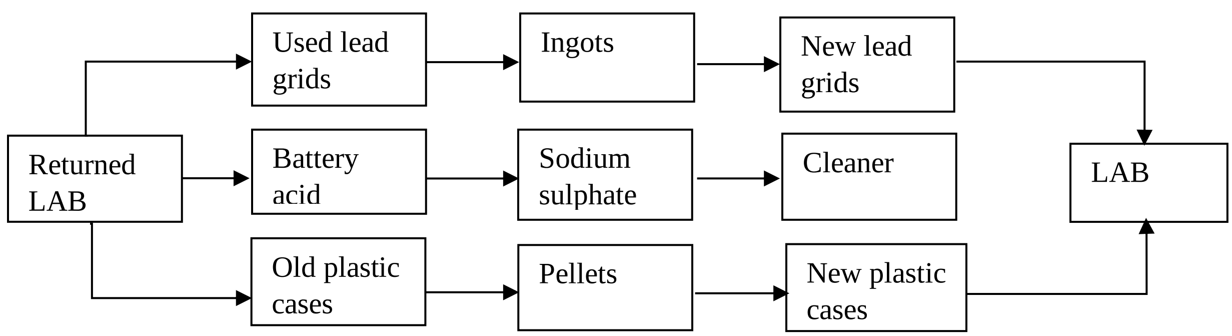

Fig. 3.1. The recycling method of lead-acid battery (CBA stewardship program, 2016)

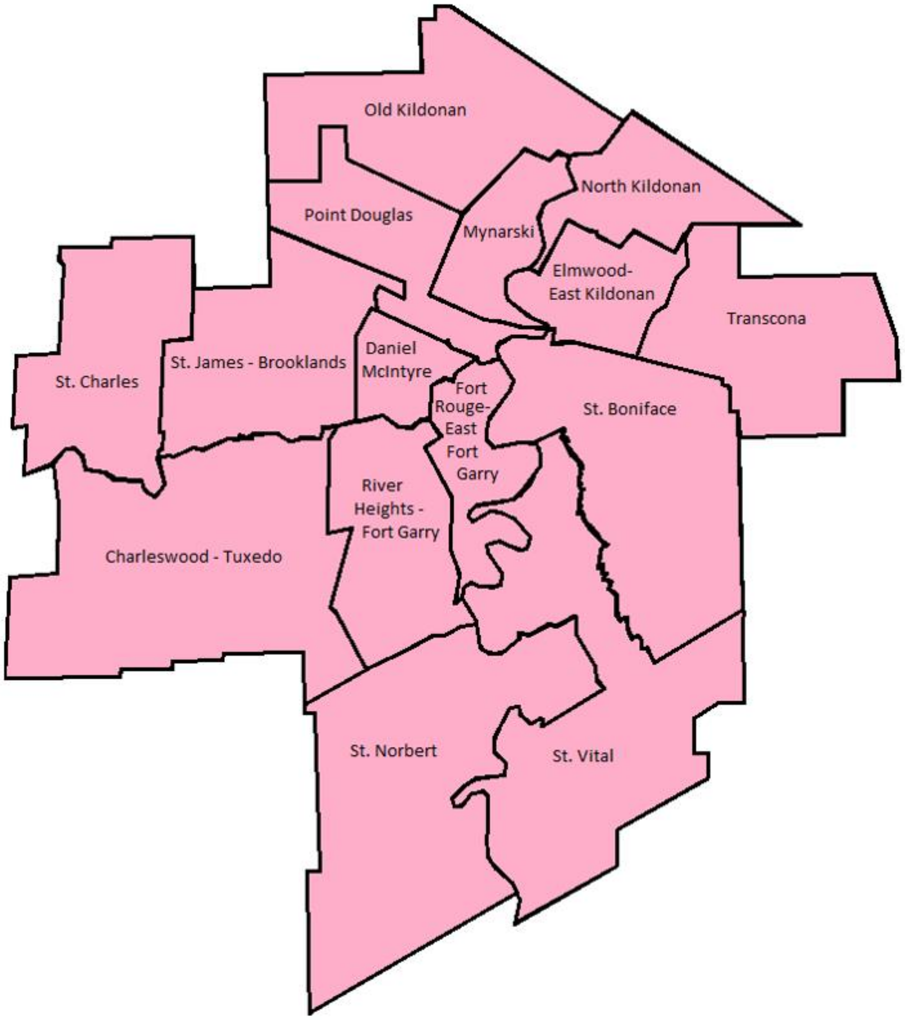

Fig. 3.2. Municipal districts in Winnipeg

In the competitive global market, decision-makers are vigilant in estimating the total profit. Hence, it is necessary to consider the possible optimal ranges of decision variables and objective function based on imprecise parameters. Market demand is one of the most prominent parameters affecting the total expected profit of CLSCs (Listeş and Dekker, 2005; Amin and Zhang, 2013a). There are some other factors that have influences on the profitability of the LAB CLSC such as rate of the returned LAB, selling price, fixed, and variable costs. Therefore, configurations of the optimal networks depend on uncertain parameters significantly.

Fig. 3.3 illustrates a multi-echelon LAB CLSC. The forward flow includes supplier(s), plant(s), demand markets, and reverse flow includes LAB recovery center(s) and a disposal center. Plant(s) produce(s) the LAB made of electrolyte, lead, plastic, as the main components. The main components for production are provided by suppliers (raw materials), and LAB recovery centers (recycled materials). Thereafter, the LAB are shipped to fulfill the markets, and some of them are held as inventories in the plants. In the reverse flow, end-of-life LAB are returned to the LAB recovery centers based on CBA's stewardship plan. CBA believes that the recovery rate should be maximized in addition to collecting the used LAB. The most elements of batteries can be utilized in the production of new batteries after recovery, and the rest of the slag which is non-hazardous can be disposed into the landfill (CBA stewardship program, 2016). The returned LAB is decomposed to the recovered and unrecovered materials in LAB recovery centers. The recovered components are shipped to the locations supervised by CBA members (i.e., plants), and the waste components are transported to the disposal center. Accordingly, CBA examines the best answers for various questions including; Which supplier(s) should be selected? Which plant(s), and LAB recovery center(s) should be chosen? How many LAB's components are supposed to be purchased from supplier(s) with regard to the recovery process? How many LAB should be produced to fulfill the markets?

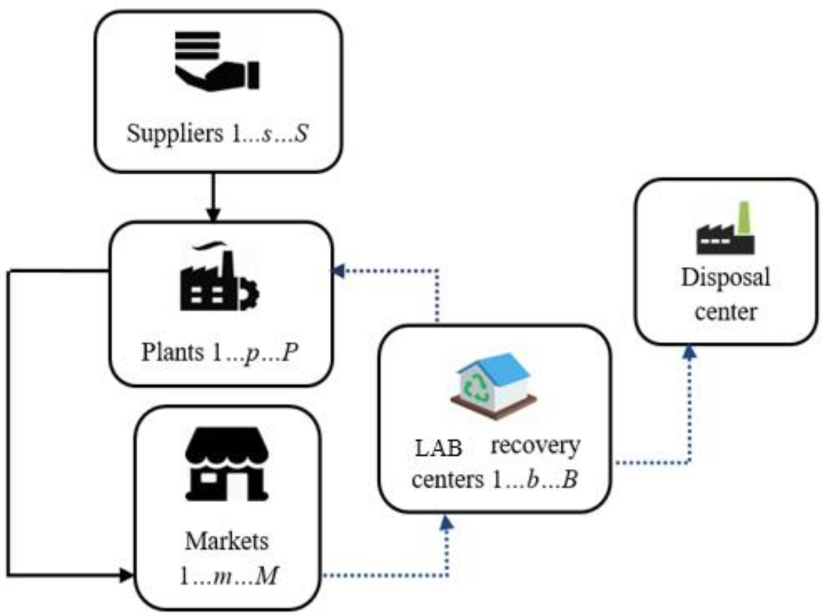

Fig. 3.3. The LAB CLSC network

3.3. Optimization model

We develop and integrate fuzzy concepts and stochastic programming to reach a range of profit for the LAB CLSC under the uncertainty of the parameters and decision variables. In this paper, triangular fuzzy numbers (TFNs) are utilized. TFNs are effective numbers that can handle uncertainty in the parameters (Cadenas and Verdegay, 1997; Zimmermann, 2012; Gani and Assarudeen, 2012; Zadeh et al., 2014; Wei et al., 2017; Faizi et al., 2018). The required sets, parameters, non-negative and binary variables are introduced in this section.

Sets

S = set associated with suppliers ($s \in S$)

P = set associated with locations of plants ($p \in P$)

J = set associated with LAB ($j \in J$)

M = set associated with demand markets ($m \in M$)

B = set associated with locations of LAB recovery centers ($b \in B$)

N = set associated with components ($n \in N$)

Ŧ = set associated with time periods ($t \in$ Ŧ)

Ω = set associated with scenarios ($\omega \in \Omega$)

Parameters

Φ_ω= probability of scenario ω

$\tilde{L}_j$ = TFN associated with selling price of LAB j

$\tilde{C}_j$ = TFN associated with production cost of LAB j

$\tilde{D}_n$ = TFN associated with shipment cost of component n per Km between suppliers and plants

$\tilde{A}_j$ = TFN associated with shipment cost of LAB j per Km between plants and demand markets

$\tilde{E}_j$ = TFN associated with shipment cost of LAB j per Km between demand markets and LAB recovery centers

$\tilde{F}_n$ = TFN associated with shipment cost of component n (recycled material) per Km between LAB recovery centers and plants

$\tilde{G}_n$ = TFN associated with shipment cost of component n (unrecoverable material) per Km between LAB recovery centers and disposal center

$\tilde{\delta}_s$ = TFN associated with fixed-cost of agreement with supplier s

$\tilde{H}_p$ = TFN associated with fixed cost of agreement with plant p

$\tilde{Q}_b$ = TFN associated with fixed cost of agreement with LAB recovery center b

$\tilde{O}_n$ = TFN associated with saving cost of component n due to LAB recovery

$\tilde{\theta}_n$ = TFN associated with disposal cost of components n

$\tilde{K}_{sn}$ = TFN associated with cost of purchasing components n from supplier s

$\tilde{h}_j$= TFN associated with holding cost of LAB j

$\tilde{g}_{pn}$ = TFN associated with capacity of plant p for components n

$\tilde{k}_{sn}$ = TFN associated with capacity of supplier s for components n

$\tilde{l}_{bj}$ = TFN associated with capacity of LAB recovery center b for LAB j

Z_{sp} = the distance between location s and p

Z_{pm} = the distance between location p and m

Z_{mb} = the distance between location m and b

Z_{bp} = the distance between location b and p

Z_l = the distance between location of LAB recovery center b and the disposal center

V_{jn} = quantity of component n in LAB j

$\tilde{d}_{mjt}$ = TFN associated with demand from market m for LAB j in period t

$\tilde{r}_{mjt}$ = TFN associated with return from market m for LAB j in period t

$\alpha_{n\omega}$ = disposal ratio associated with components n related to scenario ω

Variables

$\tilde{W}_{spn\omega t}$ = TFN of componént n provided by supplier s for plant p related to scenario ω in period t

$\tilde{I}_{pj\omega t}$ = TFN of LAB j held as the inventory in plant p related to scenario ω in period t

$\tilde{R}_{pmj\omega t}$ = TFN of LAB j sold by plant p to market m related to scenario ω in period t

$\tilde{Y}_{pj\omega t}$ = TFN of LAB j produced by plant p related to scenario ω in period t

$\tilde{U}_{mbj\omega t}$ = TFN of returned LAB j from demand market m to LAB recovery center b related to scenario ω in period t

$\tilde{X}_{bpn\omega t}$ = TFN of component n (i.e., recovered material) from LAB recovery center b to plant p related to scenario ω in period t

$\tilde{\lambda}_{bn\omega t}$ = TFN of component n (i.e., unrecovered material) from LAB recovery center b to disposal center related to scenario ω in period t

q_s = 1, if a supplier is selected at potential site s, 0, otherwise

c_p = 1, if a plant is chosen at site p, 0, otherwise

e_b = 1, if a LAB recovery center is chosen at site b, 0, otherwise

$$
Max\ \ z_1 = \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega \tilde{L}_j \tilde{R}_{pmj\omega t} -
$$

$$
\left(
\begin{array}{l}
\sum_s \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(\tilde{K}_{sn} + \tilde{D}_n Z_{sp}\right) \tilde{W}_{spn\omega t} + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega \tilde{C}_j \tilde{Y}_{pj\omega t} \\
+ \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega \tilde{A}_j Z_{pm} \tilde{R}_{pmj\omega t} + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega \tilde{h}_j \tilde{I}_{pj\omega t} + \sum_m \sum_b \sum_j \sum_\omega \sum_t \Phi_\omega \tilde{E}_j Z_{mb} \tilde{U}_{mbj\omega t} + \\
\sum_b \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(-\tilde{O}_n + \tilde{F}_n Z_{bp}\right) \tilde{X}_{bpn\omega t} + \sum_b \sum_n \sum_\omega \sum_t \Phi_\omega \left(\tilde{\theta}_n + \tilde{G}_n Z_l\right) \tilde{\lambda}_{bn\omega t} + \sum_s \tilde{\delta}_s q_s + \sum_p \tilde{H}_p c_p + \sum_b \tilde{Q}_b e_b
\end{array}
\right)
$$

s.t.

$$
\tilde{I}_{pj\omega t} = \tilde{I}_{pj\omega(t-1)} - \sum_m \tilde{R}_{pmj\omega t} + \tilde{Y}_{pj\omega t} \qquad \forall p, j, \omega, t \qquad (3.1)
$$

$$
\tilde{Y}_{pj\omega t} + \tilde{I}_{pj\omega t} \ \ \geq \sum_m \tilde{R}_{pmj\omega t} \qquad \forall p, j, \omega, t \qquad (3.2)
$$

$$
\sum_b \tilde{X}_{bpn\omega t} + \sum_s \tilde{W}_{spn\omega t} = \sum_j \left(\tilde{Y}_{pj\omega t}\right) V_{jn} \qquad \forall p, n, \omega, t \qquad (3.3)
$$

$$
\sum_p \tilde{R}_{pmj\omega t} \leq \tilde{d}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.4)
$$

$$
\sum_p \tilde{R}_{pmj\omega t} \geq \sum_b \tilde{U}_{mbj\omega t} \qquad \forall m, j, \omega, t \qquad (3.5)
$$

$$
\sum_b \tilde{U}_{mbj\omega t} = \tilde{r}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.6)
$$

$$
\alpha_{n\omega} \sum_m \sum_j \left(\tilde{U}_{mbj\omega t}\right) V_{jn} \leq \tilde{\lambda}_{b\omega nt} \qquad \forall b, n, \omega, t \qquad (3.7)
$$

$$
\sum_m \sum_j \left(\tilde{U}_{mbj\omega t}\right) V_{jn} = \sum_p \tilde{X}_{bpn\omega t} + \tilde{\lambda}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.8)
$$

$$
\sum_s \sum_n \tilde{W}_{spn\omega t} + \sum_b \sum_n \tilde{X}_{bpn\omega t} \leq c_p \sum_n \tilde{g}_{pn} \qquad \forall p, \omega, t \qquad (3.9)
$$

$$
\sum_m \sum_j \tilde{U}_{mbj\omega t} \ \ \leq e_b \sum_j \tilde{l}_{bj} \qquad \forall b, \omega, t \qquad (3.10)
$$

$$
\sum_p \sum_n \tilde{W}_{spn\omega t} \leq q_s \sum_n \tilde{k}_{sn} \qquad \forall s, \omega, t \qquad (3.11)
$$

$$
q_s, c_p, e_b \in \{0,1\} \qquad \forall s, p, b \qquad (3.12)
$$

$$
\tilde{W}_{spn\omega t}, \tilde{R}_{pmj\omega t}, \tilde{Y}_{pj\omega t}, \tilde{X}_{bpn\omega t}, \tilde{U}_{mbj\omega t}, \tilde{\lambda}_{bn\omega t}, \tilde{I}_{pj\omega t} \geq 0 \qquad \forall s, p, n, \omega, t, j, m, b \qquad (3.13)
$$

The total expected profit of the LAB CLSC is maximized in the objective function. The first part of the objective determines the revenue of selling LAB to the markets. The second part is associated with the purchasing and shipping cost of LAB's components (raw materials) from the supplier(s) to the plant(s). Cost of manufacturing, holding (inventory), and transportation between the plant(s) and the markets are imposed on the production phase. The next part includes the transportation cost of used LAB from markets to LAB recovery center(s). The used LAB are decomposed to unrecycled materials and recovered components. Product recovery increases cost-saving. The disposal and shipping cost of unrecoverable materials are considered in the model. Furthermore, the total fixed-cost of agreement with supplier(s), plant(s), LAB recovery center(s) are taken into account.

Constraint (3.1) balances the inventory in period t with last period inventory (t - 1), and difference among the number of LAB produced ($\tilde{Y}_{pj\omega t}$) and sold ($\tilde{R}_{pmj\omega t}$) in period t. Constraint (3.2) forces plant(s) to produce and hold inventory that is required for selling to the markets. Constraint (3.3) implies that the number of products' components ($\tilde{Y}_{pj\omega t}*V_{jn}$) produced by plant(s) should be equal to the quantities of components either purchased from suppliers ($\tilde{W}_{spn\omega t}$) or shipped back by LAB recovery center(s) ($\tilde{X}_{bpn\omega t}$). Constraint (3.4) refers to the number of selling LAB in period t. Constraint (3.5) implies that the number of returned LAB from markets must be less than or equal to the number of LAB selling by plant(s) in period t. In other words, the forward flow is greater than or equal to the reverse flow. Constraint (3.6) represents the number of returned LAB from markets. Constraint (3.7) determines the disposal ratio of used LAB. Constraint (3.8) designates the balance between the components of used LAB before and after the recovery process. Constraints (3.9), (3.10), and (3.11) are associated with limitations in the capacity of plant(s), LAB recovery center(s), and supplier(s), respectively. Constraints (3.12) and (3.13) show the 0-1 and decision variables.

3.3.1. A fully fuzzy stochastic model in CLSC

In this paper, we develop and employ an integrated method including fuzzy and stochastic programming for finding a solution with respect to uncertain circumstances. Rosenhead et al. (1972) categorized the environment of decision-making to certain, uncertain, and risky situations. In risky situations, uncertain parameters comply with probability distributions which are known by decision-makers. Stochastic programming is applied in risky conditions. However, in uncertain situations, parameters are imprecise, and there is not sufficient evidence about the probability distributions. Fuzzy programming can be applied for such uncertain conditions. In our FFSP model, parameters and decision variables are supposed to be imprecise, and different scenarios are considered for the disposal fraction of the returned LAB. To this aim, a solution approach is developed and is integrated based on the methods introduced by Snyder (2006) and Ezzati et al., (2015). The general form of FFSP problem is defined as follows:

$$\begin{aligned} &Max(Min)\,\tilde{\rho}^T\tilde{\chi} \\ &s.t.\,\tilde{\xi}\,\tilde{\chi}=\tilde{\beta} \end{aligned} \tag{3.14}$$

Where $\tilde{\rho}^T = [\tilde{\rho}_j]_{1*\acute{n}}$, $\tilde{\chi} = [\tilde{\chi}_j]_{\acute{n}*1}$, $\tilde{\xi} = [\tilde{\xi}_{ij}]_{\eta*\acute{n}}$, $\tilde{\beta} = [\tilde{\beta}_i]_{\eta*1}$, $\tilde{\rho}_j, \tilde{\xi}_{ij}, \tilde{\beta}_i \in TF\,(\mathrm{R})^+$, $\grave{\imath} = 1, 2, \ldots, \eta$ and $\hat{\jmath} = 1, 2, \ldots, \acute{n}$. Where $\tilde{\rho}^T\chi = ((\rho^T\chi)^l, (\rho^T\chi)^c, (\rho^T\chi)^u)$, $\tilde{\xi}\tilde{\chi} = ((\xi\chi)^l, (\xi\chi)^c, (\xi\chi)^u)$, $\tilde{\beta} = ((\beta)^l, (\beta)^c, (\beta)^u)$, $\tilde{\chi} = ((\chi)^l, (\chi)^c, (\chi)^u)$, $(\chi)^l \geq 0$. Then, Model (3.14) can be transformed to Model (3.15) when there are Ω scenarios with probability of Φ_ω for each scenario.

$$\begin{aligned} &Max(Min)\sum_{\omega}\Phi_\omega\Big(\big(\rho_\omega{}^T\chi_\omega\big)^l,\big(\rho_\omega{}^T\chi_\omega\big)^c,\big(\rho_\omega{}^T\chi_\omega\big)^u\Big) \\ &s.t.\Big(\big(\xi_\omega\chi_\omega\big)^l,\big(\xi_\omega\chi_\omega\big)^c,\big(\xi_\omega\chi_\omega\big)^u\Big)=\Big(\big(\beta_\omega\big)^l,\big(\beta_\omega\big)^c,\big(\beta_\omega\big)^u\Big) \qquad \forall\omega, \end{aligned} \tag{3.15}$$

The phases to achieve the optimal solution of Model (3.15) are summarized as follows:

Phase 1: Model (3.15) is converted to the three separate crisp objectives with respect to the defined constraints:

$$\begin{aligned} &Max(Min)\sum_{\omega}\Phi_\omega\big(\rho_\omega{}^T\chi_\omega\big)^c \\ &Min(Max)\sum_{\omega}\Phi_\omega\Big(\big(\rho_\omega{}^T\chi_\omega\big)^u-\big(\rho_\omega{}^T\chi_\omega\big)^l\Big) \\ &Max(Min)\sum_{\omega}\Phi_\omega\Big(\big(\rho_\omega{}^T\chi_\omega\big)^l+\big(\rho_\omega{}^T\chi_\omega\big)^u\Big) \\ &s.t.\big(\xi_\omega\chi_\omega\big)^l=\big(\beta_\omega\big)^l,\big(\xi_\omega\chi_\omega\big)^c=\big(\beta_\omega\big)^c,\big(\xi_\omega\chi_\omega\big)^u=\big(\beta_\omega\big)^u \qquad \forall\omega, \\ &\big(\chi_\omega\big)^u-\big(\chi_\omega\big)^c\geq 0,\big(\chi_\omega\big)^c-\big(\chi_\omega\big)^l\geq 0,\big(\chi_\omega\big)^l\geq 0 \qquad \forall\omega, \end{aligned} \tag{3.16}$$

Phase 2: The first objective function ($Max(Min)\sum_{\omega} \Phi_{\omega}\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{c}$) of Model (3.16) is solved with regard to the constraints. If an optimal solution is reached for $\tilde{\chi}_{\omega}^{*} = \left(\left(\chi_{\omega}^{*}\right)^{l}, \left(\chi_{\omega}^{*}\right)^{c}, \left(\chi_{\omega}^{*}\right)^{u}\right)$, then we stop; otherwise, Phase 3 must be implemented. $\tilde{\chi}_{\omega}^{*} = \left(\left(\chi_{\omega}^{*}\right)^{l}, \left(\chi_{\omega}^{*}\right)^{c}, \left(\chi_{\omega}^{*}\right)^{u}\right)$ is assumed an optimal solution, if:

(i) $\tilde{\chi}_{\omega}^{*} \in TF\,(\mathrm{R})^{+}$

(ii) $\xi_{\omega}\chi_{\omega}^{*} = \beta_{\omega}$,

(iii) $\forall\, \tilde{\chi}_{\omega} = ((\chi)^{l}, (\chi)^{c}, (\chi)^{u}) \in \tilde{S} = \{\tilde{\chi} \mid \tilde{\xi}\tilde{\chi} = \tilde{\beta},\ \tilde{\chi} = [\tilde{\chi}_{j}]_{\acute{n}*1}$ where $\tilde{\chi}_{j} \in TF\,(\mathrm{R})^{+}\}$, $\tilde{\rho}^{T}\chi \leq \tilde{\rho}^{T}\chi^{*}$ (in case of minimization $\tilde{\rho}^{T}\chi \geq \tilde{\rho}^{T}\chi^{*}$).

(iv) $\forall\, \tilde{\chi}_{\omega}^{*} = \left(\left(\chi_{\omega}^{*}\right)^{l}, \left(\chi_{\omega}^{*}\right)^{c}, \left(\chi_{\omega}^{*}\right)^{u}\right) \in \tilde{S} = \{\tilde{\chi}_{\omega} \mid \tilde{\xi}_{\omega}\tilde{\chi}_{\omega} = \tilde{\beta}_{\omega}$, where $\tilde{\chi}_{\omega} \in TF\,(\mathrm{R})^{+}\}$, $\tilde{\rho}_{\omega}^{T}\chi_{\omega} \leq \tilde{\rho}_{\omega}^{T}\chi_{\omega}^{*}$ (in case of minimization $\tilde{\rho}_{\omega}^{T}\chi_{\omega} \geq \tilde{\rho}_{\omega}^{T}\chi_{\omega}^{*}$).

Phase 3: The second objective function ($\sum_{\omega} \Phi_{\omega}\left(\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{u} - \left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{l}\right)$) is solved with regard to the constraints and the solution ($\sum_{\omega} \Phi_{\omega}\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{c} = ḅ^{*}$) computed in Phase 2. If an optimal solution is reached for $\tilde{\chi}_{\omega}^{*} = \left(\left(\chi_{\omega}^{*}\right)^{l}, \left(\chi_{\omega}^{*}\right)^{c}, \left(\chi_{\omega}^{*}\right)^{u}\right)$, then we stop, otherwise, Phase 4 must be followed.

Phase 4: The third objective function ($\sum_{\omega} \Phi_{\omega}\left(\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{l} + \left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{u}\right)$) is solved with regard to the constraints and the solutions ($\sum_{\omega} \Phi_{\omega}\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{c} = ḅ^{*}$ and $\sum_{\omega} \Phi_{\omega}\left(\left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{u} - \left(\rho_{\omega}{}^{T}\chi_{\omega}\right)^{l}\right) = ḍ^{*}$) computed in Phases 2 and 3.

As described by the integrated algorithm, the pessimistic, realistic, and optimistic values of the objective function are required to be identified at the first step. According to the fuzzy arithmetic operation, the difference between two TFNs of $\tilde{ṇ}$ = (ị, ḳ, ḷ) and $\tilde{ụ}$ = (ṛ, ṣ, ṭ) complies with the following rule, if $\tilde{ụ} \geq \tilde{ṇ}$ (Kauffman and Gupta, 1991):

ų̃ - ņ̃ = (ŗ - ļ, ş - ķ, ţ - į), (3.17)

The objective function includes two portions; the first portion is related to the income obtained from selling LAB, while the second portion is associated with all types of fixed and variable costs. Then, the optimistic value of the objective is occurred when the parameters ($\tilde{L}_j$, $\tilde{O}_n$), and the decision variables ($\tilde{R}_{pmj\omega t}$, $\tilde{X}_{bpn\omega t}$) contributing to reaching the revenue have their highest values, and the rest of the parameters and decision variables causing incurred cost have their lowest values. The pessimistic value of the objective function can be achieved through the reverse approach. Therefore, the proposed FFSP model for the LAB CLSC network is defined as follows:

$$Max \;\; z_1^l = \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega L_j^l R_{pmj\omega t}^l - $$

$$\left(\begin{array}{l} \sum_s \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(K_{sn}^u + D_n^u Z_{sp} \right) W_{spn\omega t}^u + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega C_j^u Y_{pj\omega t}^u + \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega A_j^u Z_{pm} R_{pmj\omega t}^u \\ + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega h_j^u I_{pj\omega t}^u + \sum_m \sum_b \sum_j \sum_\omega \sum_t \Phi_\omega E_j^u Z_{mb} U_{mbj\omega t}^u + \sum_b \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(-O_n^l + F_n^u Z_{bp} \right) X_{bpn\omega t}^l \\ + \sum_b \sum_n \sum_\omega \sum_t \Phi_\omega \left(\theta_n^u + G_n^u Z_l \right) \lambda_{bn\omega t}^u + \sum_s \delta_s^u q_s + \sum_p H_p^u c_p + \sum_b Q_b^u e_b \end{array} \right)$$

$$Max \;\; z_1^c = \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega L_j^c R_{pmj\omega t}^c - $$

$$\left(\begin{array}{l} \sum_s \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(K_{sn}^c + D_n^c Z_{sp} \right) W_{spn\omega t}^c + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega C_j^c Y_{pj\omega t}^c + \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega A_j^c Z_{pm} R_{pmj\omega t}^c \\ + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega h_j^c I_{pj\omega t}^c + \sum_m \sum_b \sum_j \sum_\omega \sum_t \Phi_\omega E_j^c Z_{mb} U_{mbj\omega t}^c + \sum_b \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(-O_n^c + F_n^c Z_{bp} \right) X_{bpn\omega t}^c \\ + \sum_b \sum_n \sum_\omega \sum_t \Phi_\omega \left(\theta_n^c + G_n^c Z_l \right) \lambda_{bn\omega t}^c + \sum_s \delta_s^c q_s + \sum_p H_p^c c_p + \sum_b Q_b^c e_b \end{array} \right)$$

$$Max \;\; z_1^u = \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega L_j^u R_{pmj\omega t}^u - $$

$$\left(\begin{array}{l} \sum_s \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(K_{sn}^l + D_n^l Z_{sp} \right) W_{spn\omega t}^l + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega C_j^l Y_{pj\omega t}^l + \sum_p \sum_m \sum_j \sum_\omega \sum_t \Phi_\omega A_j^l Z_{pm} R_{pmj\omega t}^l \\ + \sum_p \sum_j \sum_\omega \sum_t \Phi_\omega h_j^l I_{pj\omega t}^l + \sum_m \sum_b \sum_j \sum_\omega \sum_t \Phi_\omega E_j^l Z_{mb} U_{mbj\omega t}^l + \sum_b \sum_p \sum_n \sum_\omega \sum_t \Phi_\omega \left(-O_n^u + F_n^l Z_{bp} \right) X_{bpn\omega t}^u \\ + \sum_b \sum_n \sum_\omega \sum_t \Phi_\omega \left(\theta_n^l + G_n^l Z_l \right) \lambda_{bn\omega t}^l + \sum_s \delta_s^l q_s + \sum_p H_p^l c_p + \sum_b Q_b^l e_b \end{array} \right)$$

s.t.

$$I^{l}_{pj\omega t} = I^{l}_{pj\omega(t\text{-}1)} - \sum_{m} R^{l}_{pmj\omega t} + Y^{l}_{pj\omega t} \qquad \forall p, j, \omega, t \qquad (3.18)$$

$$I^{c}_{pj\omega t} = I^{c}_{pj\omega(t\text{-}1)} - \sum_{m} R^{c}_{pmj\omega t} + Y^{c}_{pj\omega t} \qquad \forall p, j, \omega, t \qquad (3.19)$$

$$I^{u}_{pj\omega t} = I^{u}_{pj\omega(t\text{-}1)} - \sum_{m} R^{u}_{pmj\omega t} + Y^{u}_{pj\omega t} \qquad \forall p, j, \omega, t \qquad (3.20)$$

$$Y^{l}_{pj\omega t} + I^{l}_{pj\omega t} \geq \sum_{m} R^{l}_{pmj\omega t} \qquad \forall p, j, \omega, t \qquad (3.21)$$

$$Y^{c}_{pj\omega t} + I^{c}_{pj\omega t} \geq \sum_{m} R^{c}_{pmj\omega t} \qquad \forall p, j, \omega, t \qquad (3.22)$$

$$Y^{u}_{pj\omega t} + I^{u}_{pj\omega t} \geq \sum_{m} R^{u}_{pmj\omega t} \qquad \forall p, j, \omega, t \qquad (3.23)$$

$$\sum_{b} X^{l}_{bpn\omega t} + \sum_{s} W^{l}_{spn\omega t} = \sum_{j} \left(Y^{l}_{pj\omega t}\right) V_{jn} \qquad \forall p, n, \omega, t \qquad (3.24)$$

$$\sum_{b} X^{c}_{bpn\omega t} + \sum_{s} W^{c}_{spn\omega t} = \sum_{j} \left(Y^{c}_{pj\omega t}\right) V_{jn} \qquad \forall p, n, \omega, t \qquad (3.25)$$

$$\sum_{b} X^{u}_{bpn\omega t} + \sum_{s} W^{u}_{spn\omega t} = \sum_{j} \left(Y^{u}_{pj\omega t}\right) V_{jn} \qquad \forall p, n, \omega, t \qquad (3.26)$$

$$\sum_{p} R^{l}_{pmj\omega t} \leq d^{l}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.27)$$

$$\sum_{p} R^{c}_{pmj\omega t} \leq d^{c}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.28)$$

$$\sum_{p} R^{u}_{pmj\omega t} \leq d^{u}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.29)$$

$$\sum_{p} R^{l}_{pmj\omega t} \geq \sum_{b} U^{l}_{mbj\omega t} \qquad \forall m, j, \omega, t \qquad (3.30)$$

$$\sum_{p} R^{c}_{pmj\omega t} \geq \sum_{b} U^{c}_{mbj\omega t} \qquad \forall m, j, \omega, t \qquad (3.31)$$

$$\sum_{p} R^{u}_{pmj\omega t} \geq \sum_{b} U^{u}_{mbj\omega t} \qquad \forall m, j, \omega, t \qquad (3.32)$$

$$\sum_{b} U^{l}_{mbj\omega t} = r^{l}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.33)$$

$$\sum_{b} U^{c}_{mbj\omega t} = r^{c}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.34)$$

$$\sum_{b} U^{u}_{mbj\omega t} = r^{u}_{mjt} \qquad \forall m, j, \omega, t \qquad (3.35)$$

$$\alpha_{n\omega} \sum_{m} \sum_{j} \left(U^{l}_{mbj\omega t} \right) V_{jn} \le \lambda^{l}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.36)$$

$$\alpha_{n\omega} \sum_{m} \sum_{j} \left(U^{c}_{mbj\omega t} \right) V_{jn} \le \lambda^{c}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.37)$$

$$\alpha_{n\omega} \sum_{m} \sum_{j} \left(U^{u}_{mbj\omega t} \right) V_{jn} \le \lambda^{u}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.38)$$

$$\sum_{m} \sum_{j} \left(U^{l}_{mbj\omega t} \right) V_{jn} = \sum_{p} X^{l}_{bpn\omega t} + \lambda^{l}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.39)$$

$$\sum_{m} \sum_{j} \left(U^{c}_{mbj\omega t} \right) V_{jn} = \sum_{p} X^{c}_{bpn\omega t} + \lambda^{c}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.40)$$

$$\sum_{m} \sum_{j} \left(U^{u}_{mbj\omega t} \right) V_{jn} = \sum_{p} X^{u}_{bpn\omega t} + \lambda^{u}_{bn\omega t} \qquad \forall b, n, \omega, t \qquad (3.41)$$

$$\sum_{s} \sum_{n} W^{l}_{spn\omega t} + \sum_{b} \sum_{n} X^{l}_{bpn\omega t} \le c_{p} \sum_{n} g^{l}_{pn} \qquad \forall p, \omega, t \qquad (3.42)$$

$$\sum_{s} \sum_{n} W^{c}_{spn\omega t} + \sum_{b} \sum_{n} X^{c}_{bpn\omega t} \le c_{p} \sum_{n} g^{c}_{pn} \qquad \forall p, \omega, t \qquad (3.43)$$

$$\sum_{s} \sum_{n} W^{u}_{spn\omega t} + \sum_{b} \sum_{n} X^{u}_{bpn\omega t} \le c_{p} \sum_{n} g^{u}_{pn} \qquad \forall p, \omega, t \qquad (3.44)$$

$$\sum_{m} \sum_{j} U^{l}_{mbj\omega t} \le e_{b} \sum_{j} l^{l}_{bj} \qquad \forall b, \omega, t \qquad (3.45)$$

$$\sum_{m} \sum_{j} U^{c}_{mbj\omega t} \le e_{b} \sum_{j} l^{c}_{bj} \qquad \forall b, \omega, t \qquad (3.46)$$

$$\sum_{m} \sum_{j} U^{u}_{mbj\omega t} \le e_{b} \sum_{j} l^{u}_{bj} \qquad \forall b, \omega, t \qquad (3.47)$$

$$\sum_{p} \sum_{n} W^{l}_{spn\omega t} \le q_{s} \sum_{n} k^{l}_{sn} \qquad \forall s, \omega, t \qquad (3.48)$$

$$\sum_p \sum_n W^c_{spn\omega t} \leq q_s \sum_n k^c_{sn} \qquad \forall s,\omega,t \qquad (3.49)$$

$$\sum_p \sum_n W^u_{spn\omega t} \leq q_s \sum_n k^u_{sn} \qquad \forall s,\omega,t \qquad (3.50)$$

$$W^u_{spn\omega t} - W^c_{spn\omega t} \geq 0 \qquad \forall s,p,n,\omega,t \qquad (3.51)$$

$$W^c_{spn\omega t} - W^l_{spn\omega t} \geq 0 \qquad \forall s,p,n,\omega,t \qquad (3.52)$$

$$U^u_{mbj\omega t} - U^c_{mbj\omega t} \geq 0 \qquad \forall m,b,j,\omega,t \qquad (3.53)$$

$$U^c_{mbj\omega t} - U^l_{mbj\omega t} \geq 0 \qquad \forall m,b,j,\omega,t \qquad (3.54)$$

$$X^u_{bpn\omega t} - X^c_{bpn\omega t} \geq 0 \qquad \forall b,p,n,\omega,t \qquad (3.55)$$

$$X^c_{bpn\omega t} - X^l_{bpn\omega t} \geq 0 \qquad \forall b,p,n,\omega,t \qquad (3.56)$$

$$\lambda^u_{bn\omega t} - \lambda^c_{bn\omega t} \geq 0 \qquad \forall b,n,\omega,t \qquad (3.57)$$

$$\lambda^c_{bn\omega t} - \lambda^l_{bn\omega t} \geq 0 \qquad \forall b,n,\omega,t \qquad (3.58)$$

$$Y^u_{pj\omega t} - Y^c_{pj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.59)$$

$$Y^c_{pj\omega t} - Y^l_{pj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.60)$$

$$I^u_{pj\omega t} - I^c_{pj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.61)$$

$$I^c_{pj\omega t} - I^l_{pj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.62)$$

$$R^u_{pmj\omega t} - R^c_{pmj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.63)$$

$$R^c_{pmj\omega t} - R^l_{pmj\omega t} \geq 0 \qquad \forall p,j,\omega,t \qquad (3.64)$$

$$q_s, c_p, e_b \in \{0,1\} \qquad \forall s,p,b \tag{3.65}$$

$$W_{spn\omega t}, R_{pmj\omega t}, Y_{pj\omega t}, X_{bpn\omega t}, U_{mbj\omega t}, \lambda_{bn\omega t}, I_{pj\omega t} \geq 0 \qquad \forall s,p,n,\omega,t,j,m,b \tag{3.66}$$

3.3.2. Presentation of the environmental FFSP model

The overall framework to approach the environmental FFSP problem is provided in Fig. 3.4. In the 1st Step, FFP is utilized to formulate the optimization model in which all parameters and decision variables are supposed to be uncertain. In the 2nd Step, different scenarios are defined for the disposal fraction rate of components in LAB recovery centers. In the 3rd Step, the bi-objective model is proposed to consider the environmental compliance of third parties.

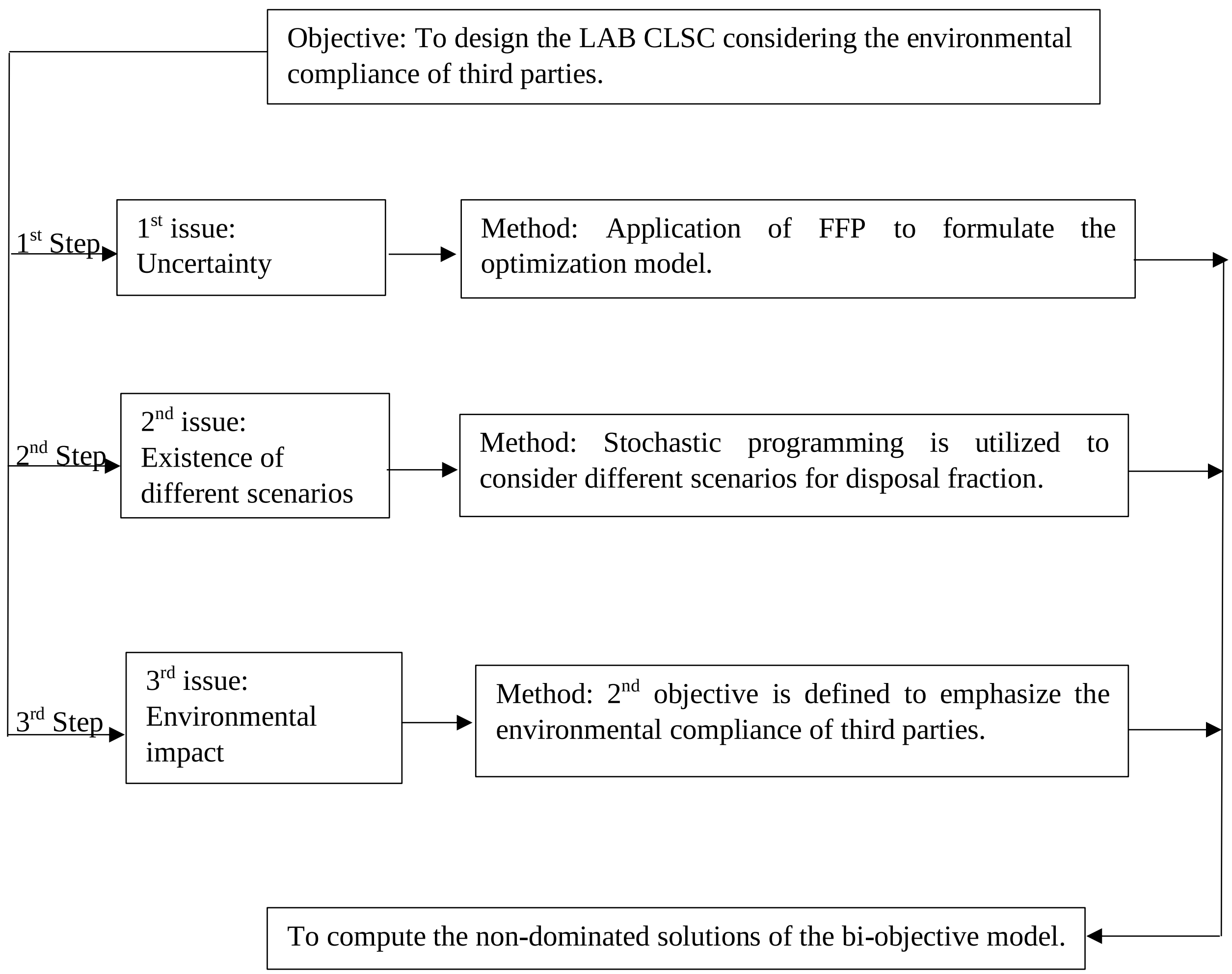

Fig. 3.4. The overall outline to approach the multi-objective fuzzy stochastic problem

In the 1st Step, TFNs are used to define imprecise parameters. For instance, the middle values for the demand of LAB related to municipality area m in period t ($\tilde{d}_{mj1t}$) are computed as one percent of the population in such a region in accordance with the 2011 census of Canada. Accordingly, the middle values of returned LAB related to municipality area m in period t ($\tilde{r}_{mj1t}$) are calculated as ten percent of demand in a market located in area m. The lower and upper values of demand and return are assumed as 25 percent less and higher than their middle values, respectively.

In the 2nd Step, stochastic programming (scenario-based) is employed to consider different scenarios for disposal fraction, since the quality of the returned LAB varies. Therefore, ω scenarios are defined to represent different rates of disposal fractions with the probability of Φ_ω.

To maximize the environmental compliance of third parties in a LAB CLSC, the 2nd objective is defined in Section 3.4. The solutions related to the multi-objective model is provided in Section 3.5. Table 3.2 contains the values of the of TFNs utilized in the FFSP problem. In this study, we applied the symmetric TFNs, since they are intuitive and flexible to estimate. Interested readers can refer to Klir and Yuan, 1995 for more information about TFNs.

Table 3.2
The parameters' value applied in the FFSP model

$J = 2$	$\tilde{\delta}_s$ = (9,000, 10,000, 11,000)	$\tilde{h}_j$ = (10, 15, 20)
$N = 3$	$\tilde{H}_p$= (35,000, 40,000, 45,000)	$\tilde{O}_n$ = (9, 10, 11)
$S = 5$	$\tilde{Q}_b$= (15,000, 20,000, 25,000)	$\tilde{k}_{sn}$ = (3,000, 3,100, 3,200)
$P = 6$	$\tilde{C}_j$ = (9, 10, 11)	$\tilde{g}_{pn}$ = (5,000, 5,500, 6,000)
$M = 15$	$\tilde{L}_j$ = (145, 150, 155)	$\tilde{l}_{bj}$ = (1,000, 1,500, 2,000)
$B = 4$	$\tilde{A}_j$= $\tilde{E}_j$= (0.087, 0.097, 0.107)	$\tilde{K}_{sn}$ = (4, 5, 6)
$T = 2$	$\tilde{D}_n$=$\tilde{F}_n$=$\tilde{G}_n$= (0.0174, 0.0194, 0.0214)	$\alpha_{1\omega}$= (0.01, 0.02, 0.03)
$\Omega = 3$	Φ_ω= (0.15, 0.70, 0.15)	$\alpha_{2\omega}$= (0.05, 0.10, 0.15)
$\tilde{\theta}_n$ = (1, 1.5, 2)	S'_{sn} = (0.46, 0.64, 0.58, 0.54, 0.48)	$\alpha_{3\omega}$= (0.01, 0.03, 0.05)
	P'_{pn} = (0.60, 0.56, 0.64, 0.61, 0.67, 0.63)	B'_{bn} = (0.64, 0.55, 0.62, 0.69)

IBM ILOG CPLEX 12.8.0 has been utilized to solve the FFSP model. In the final step, the model comprised of 9,061 constraints, 9,077 non-negative variables, 15 binary variables, and 75,670 non-zero coefficients. The solution time was 12 seconds. The results of the FFSP model are provided in Table 3.3. The optimal solutions show lower, middle, and upper values of the total profit for the LAB CLSC. Therefore, decision-makers can predict a certain range of network's profit by application of the proposed model in uncertain situations.

Table 3.3
Solutions for the scenario-based robust possibilistic model

Objective value			Supplier	Plant	Batter recovery center
z_1^l = 1,095,072	z_1^c = 1,727,693	z_1^u = 1,892,738	q_5 : St. James-Brooklands	c_2 : Fort Rouge-East Fort Garry	e_3 : Point Douglas

As illustrated in Fig. 3.5, the FFSP model has been developed to optimize the LAB CLSC network in Winnipeg. We apply Google Maps to compute the real driving distances and transportation costs between the potential locations. Fig. 3.6 shows the routes among the selected facilities.

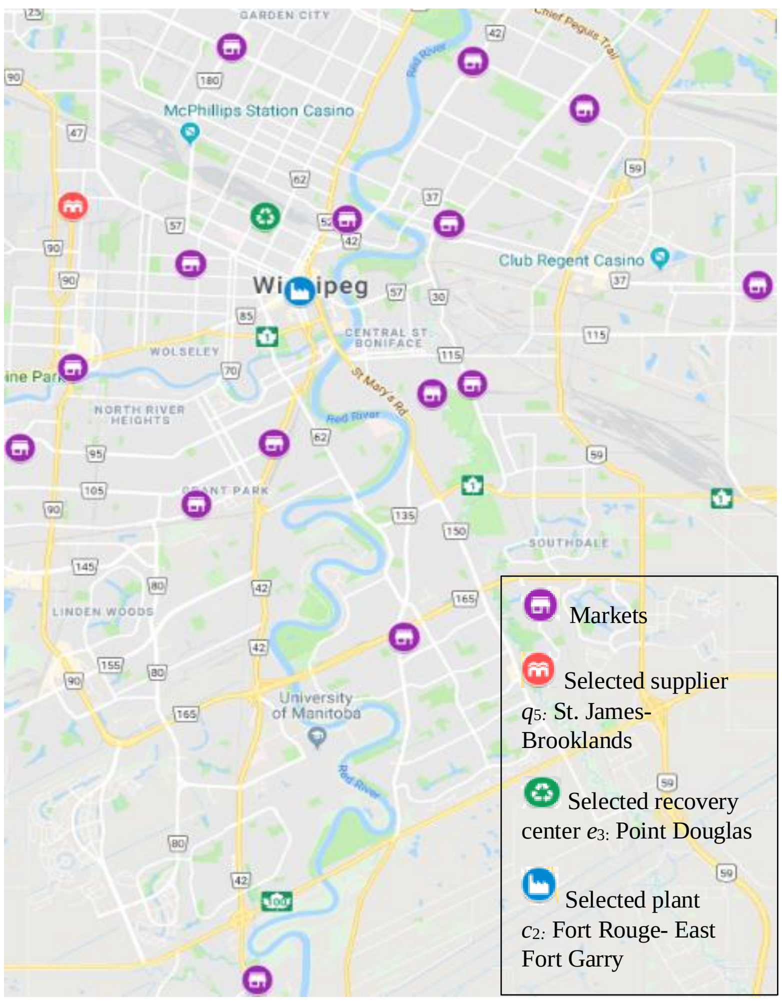

Fig. 3.5. The selected facility locations in the LAB CLSC network

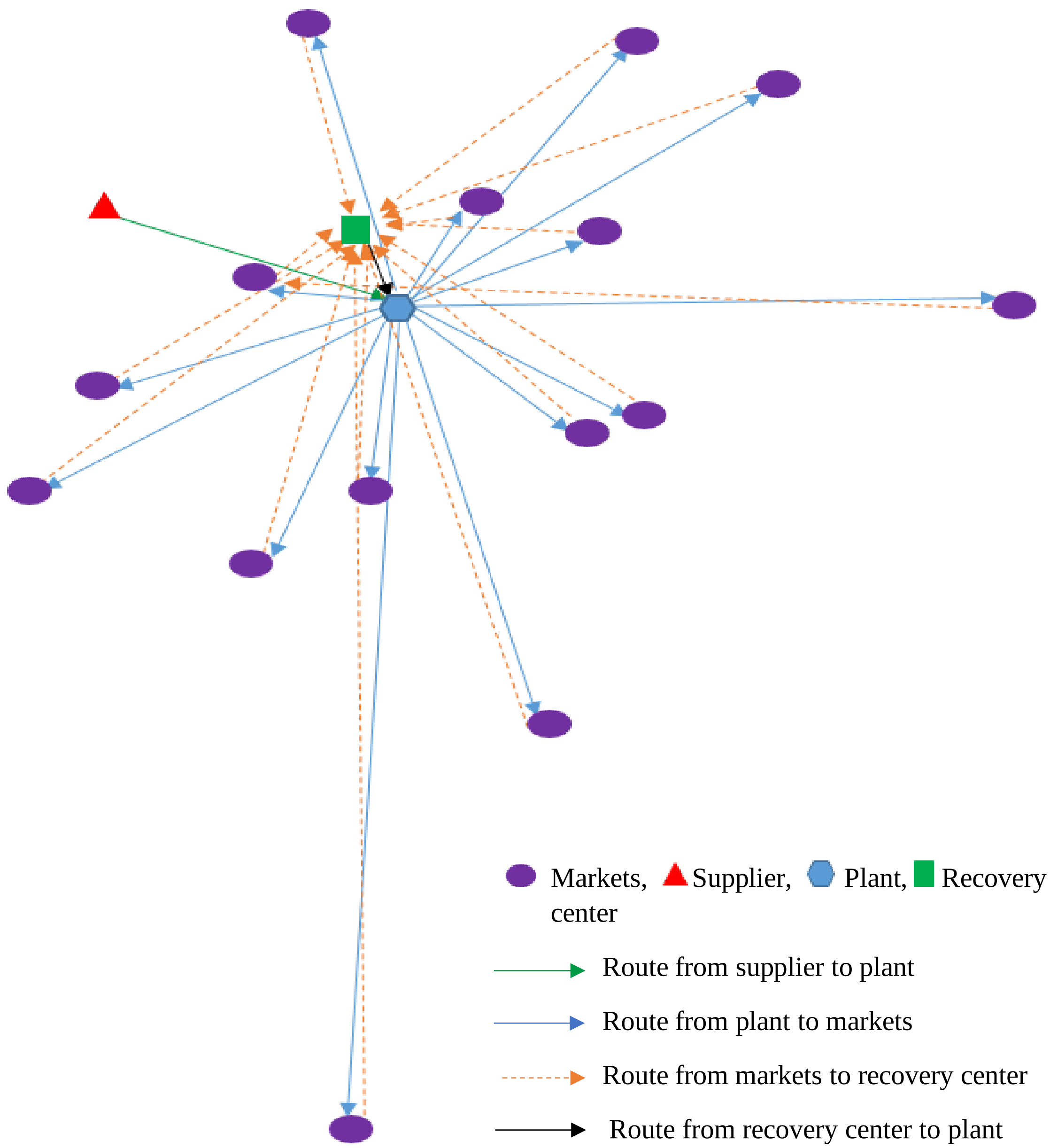

Fig. 3.6. The optimal routes associated with the LAB CLSC network

As mentioned before, the proposed FFSP is the unique approach considering lower, middle, and upper levels of decision variables in optimization, while the different ranges of decision variables are ignored in the other methods. To evaluate the performance of the proposed model, we compare the FFSP with a possibilistic approach based on the middle value of the objective function (z_1^c). In this regard, we apply the combinatorial possibilistic and scenario-based approach based on Parra et al. (2005) and Snyder (2006). Accordingly, Constraints (3.4) and (3.6) are defuzzified and converted to Constraints (3.67), (3.68), and (3.69). To handle other imprecise parameters, the lateral margins of TFNs are taken into account based on the approach introduced by Peidro et al. (2009).

$$\sum_{p} R_{pmj\omega t} \leq (1-\alpha)\left(\frac{d_{mjt}^{c}+d_{mjt}^{u}}{2}\right)+(\alpha)\left(\frac{d_{mjt}^{l}+d_{mjt}^{c}}{2}\right) \qquad \forall m, j, \omega, t \qquad (3.67)$$

$$\sum_{b} U_{mbj\omega t} \geq \left(1-\frac{\alpha}{2}\right)\left(\frac{r_{mjt}^{l}+r_{mjt}^{c}}{2}\right)+\left(\frac{\alpha}{2}\right)\left(\frac{r_{mjt}^{c}+r_{mjt}^{u}}{2}\right) \qquad \forall m, j, \omega, t \qquad (3.68)$$

$$\sum_{b} U_{mbj\omega t} \leq \left(1-\frac{\alpha}{2}\right)\left(\frac{r_{mjt}^{c}+r_{mjt}^{u}}{2}\right)+\left(\frac{\alpha}{2}\right)\left(\frac{r_{mjt}^{l}+r_{mjt}^{c}}{2}\right) \qquad \forall m, j, \omega, t \qquad (3.69)$$

In this approach, the value of objective varies based on different levels of α-cut. Hence, decision-makers decide about the value of feasibility degree (α) with respect to the type of uncertain parameters. As illustrated in Table 3.4, as α increases, z (total profit) decreases due to less amount of upward deviation for demand and return. The average value of four α-cuts shows the negligible difference between FFSP and possibilistic approach. However, FFSP is capable to find the lower and upper values for the decision variables and the objective function.

Table 3.4
The optimal solutions based on different levels of α-cut

α = 0.25	α = 0.50	α = 0.75	α = 1	Average	Selected facilities
1,898,132.27	1,785,571.59	1,673,010.92	1,560,450.24	1,729,291.26	q_5 - c_2 - e_3

To consider the effects of unpredictable changes in demand and return, sensitivity analysis is undertaken. Table 3.5 indicates the lower, middle, and upper ranges of the total profit associated with 8 scenarios of unpredictable changes in demand and return. The scenarios are compared with the original solutions (provided in Table 3.3) based on the middle value. It can be observed that the solutions of LAB CLSC are very sensitive to such changes. This analysis proves the necessity of the proposed model since the FFSP model is capable of computing pessimistic, realistic, and optimistic values for the objective function and the decision variables in uncertain situations.

Table 3.5
Sensitivity analysis

Scenarios	Objective value	Change %
1. 10% increase in demand and return	z_1^l = 1,206,515 z_1^c = 1,903,608 z_1^u = 2,086,350	z_1^l =10.18 z_1^c =10.18 z_1^u = 10.23
2. 10% increase in demand and 10% decrease in return	z_1^l = 1,197,479 z_1^c = 1,893,113 z_1^u = 2,076,329	z_1^l =9.35 z_1^c = 9.57 z_1^u = 9.70
3. 10% decrease in demand and 10% increase in return	z_1^l = 984,630 z_1^c = 1,557,198 z_1^u = 1,707,068	z_1^l = -10.09 z_1^c = -9.87 z_1^u = -9.81
4. 10% decrease in demand and return	z_1^l = 977,513 z_1^c = 1,547,933 z_1^u = 1,697,581	z_1^l = -10.74 z_1^c = -10.40 z_1^u = -10.31
5. 10% increase in demand, while return is not changed	z_1^l = 1,201,936 z_1^c = 1,898,270 z_1^u = 2,081,239	z_1^l = 9.76 z_1^c = 9.87 z_1^u = 9.96
6. 10% decrease in demand, while return is not changed	z_1^l = 981,028 z_1^c = 1,552,486 z_1^u = 1,702,223	z_1^l = -10.41 z_1^c = -10.14 z_1^u = -10.07
7. 10% increase in return, while demand is not changed	z_1^l = 1,098,673 z_1^c = 1,732,405 z_1^u = 1,897,583	z_1^l = 0.33 z_1^c = 0.27 z_1^u = 0.26
8. 10% decrease in return, while demand is not changed	z_1^l = 1,091,553 z_1^c = 1,723,140 z_1^u = 1,888,082	z_1^l = -0.32 z_1^c = -0.26 z_1^u = -0.25

Table 3.6 demonstrates the impact of disposal fraction rate on the profitability of the LAB CLSC network. Each column represents 3 scenarios for disposal fraction rate related to component *n*. By increasing the rate of disposal fraction, the total profit of the CLSC decreases. It is noticeable that the saving cost of LAB recovery (i.e., purchasing raw materials from suppliers) is superior to the cost of the recovery process. Therefore, the existence of an efficient recovery plan can increase the total profit in addition to reducing the negative environmental impact of the discarded end of life LAB.

Table 3.6
The total expected profits associated with different disposal fraction

$\alpha_{1\omega}$= (0.11, 0.12, 0.13) $\alpha_{2\omega}$= (0.15, 0.20, 0.25) $\alpha_{3\omega}$= (0.11, 0.13, 0.15)	$\alpha_{1\omega}$= (0.21, 0.22, 0.23) $\alpha_{2\omega}$= (0.25, 0.30, 0.35) $\alpha_{3\omega}$= (0.21, 0.23, 0.25)	$\alpha_{1\omega}$= (0.31, 0.32, 0.33) $\alpha_{2\omega}$= (0.35, 0.40, 0.45) $\alpha_{3\omega}$= (0.31, 0.33, 0.35)	$\alpha_{1\omega}$= (0.41, 0.42, 0.43) $\alpha_{2\omega}$= (0.45, 0.50, 0.55) $\alpha_{3\omega}$= (0.41, 0.43, 0.45)
z_1^l = 1,089,943	z_1^l = 1,084,815	z_1^l = 1,079,394	z_1^l = 1,073,276
z_1^c = 1,720,845	z_1^c = 1,716,279	z_1^c = 1,710,381	z_1^c = 1,704,044
z_1^u = 1,887,338	z_1^u = 1,881,949	z_1^u = 1,876,434	z_1^u = 1,870,763

3.4. Introducing the 2nd objective to consider the environmental compliance of third parties

In order to reduce environmental issues associated with the LAB CLSC network, green practices of third parties are taken into account. Hence, three qualitative parameters are employed including $S'_{sn}, P'_{pn}, B'_{bn}$ as the indicators of the green performance associated with suppliers, plants, and LAB recovery centers. Fuzzy TOPSIS can be applied to prioritize related facilities based on their green practices (Junior et al., 2014). S'_{sn} represents the green performance of supplier *s* to provide raw materials required for the production of *n* components. P'_{pn} is the indicator of green practices implemented by plant *p* to produce LAB comprising *n* components. B'_{bn} represents the green practices of LAB recovery center *b* to recover returned LAB including *n* components. The 2nd objective function is shown in Eq. (3.70).

$$
\begin{aligned}
Max\ \ z_2 = & \sum_{s}\sum_{n} S'_{sn}\left(\sum_{p}\sum_{\omega}\sum_{t}\tilde{W}_{spn\omega t}\right)+ \\
& \sum_{p}\sum_{n} P'_{pn}\left(\sum_{s}\sum_{\omega}\sum_{t}\tilde{W}_{spn\omega t}+\sum_{b}\sum_{\omega}\sum_{t}\tilde{X}_{bpn\omega t}+\sum_{j}\sum_{\omega}\sum_{t}\left(\tilde{Y}_{pj\omega t}\right)V_{jn}+\sum_{m}\sum_{j}\sum_{\omega}\sum_{t}\left(\tilde{R}_{pmj\omega t}\right)V_{jn}\right) \\
& +\sum_{b}\sum_{n} B'_{bn}\left(\sum_{m}\sum_{j}\sum_{\omega}\sum_{t}\left(\tilde{U}_{mbj\omega t}\right)V_{jn}+\sum_{p}\sum_{\omega}\sum_{t}\tilde{X}_{bpn\omega t}+\sum_{\omega}\sum_{t}\tilde{\lambda}_{bn\omega t}\right)
\end{aligned}
\tag{3.70}
$$

3.5. Distance method and the solutions

Solutions of multi-objective problems are called non-dominated solutions. In this paper, the distance method is employed for the bi-objective fuzzy stochastic CLSC network to calculate non-dominated solutions. Eq. (3.71) indicates the distance formula in which w_i is defined as the distance metric for objective *i*. * represents an ideal solution. The ideal solutions are the optimal values reached for each objective irrespective of the other objective functions (Branke et al., 2008; Mirzapour Al-E-Hashem et al., 2011). Eq. (3.72) represents the objective function for the bi-objective model. In this study, it is aimed to maximize this bi-objective model consisting of the total expected profit of the LAB CLSC and the environmental compliance of third parties.

$$z = \left(\sum_i w_i^{\tau} \left(\frac{z_i - z_i^*}{z_i^*} \right)^{\tau} \right)^{\frac{1}{\tau}} \qquad \forall\ i = 1, 2, \ldots, \infty \tag{3.71}$$

$$Max\ z = \left(w_1^{\tau} \left(\frac{z_1 - z_1^*}{z_1^*} \right)^{\tau} + w_2^{\tau} \left(\frac{z_2 - z_2^*}{z_2^*} \right)^{\tau} \right)^{\frac{1}{\tau}} \tag{3.72}$$

s.t. *Eqs.* (3.18) – (3.66)

First, the FFSP model described in Section 3.1 is used to compute the ideal solutions. Table 3.7 includes the results of each objective separately. To reach the non-dominated solutions, the distance method is utilized for the bi-objective environmental model.

Table 3.7
Optimal solutions of the 1st and 2nd objectives

	Pessimistic value	Realistic value	Optimistic value
Total profit	1,095,072	1,727,693	1,892,738
Environmental compliance	163,050	188,848	190,230

In order to find enough efficient solutions for the two mentioned objective functions, various pairs of w_i (i = 1, 2) are examined ($\sum_i w_i = 1$). The efficient solutions for the lower range of the bi-objective model are 1,095,072 (z_1^l) and 48,297 (z_2^l), respectively. Furthermore, the non-dominated solutions for the upper range can be computed (1,892,738 and 49,674). Table 3.8 contains the solutions associated with the middle values of the total profit and environmental compliance. The locations and the numbers of the selected third parties change as the weight factors associated with the objectives change.

Table 3.8
The non-dominated solutions for the middle values of the 1st and 2nd objectives

w_1	0 to 0.4	0.5	0.6	0.7	0.8	0.9	1
Total profit	805,230	1,433,700	1,575,700	1,651,300	1,653,900	1,725,400	1,727,772
Environmental compliance	188,848	125,440	107,360	88,261	87,113	53,849	48,297
Selected third parties	c_3, c_5, c_6, e_4, q_1 to q_5	c_3, c_5, e_4, q_2, q_3, q_4	c_3, c_5, e_4, q_2, q_3	c_5, e_4, q_2, q_3	c_5, e_4, q_2, q_5	c_5, e_4, q_4	c_2, e_3, q_5

According to the efficient solutions of the bi-objective model (maximization), the value of the environmental compliance of the third parties cannot be increased, unless the total expected profit is decreased. The trade-off surface of the LAB CLSC network is indicated in Fig. 3.7.

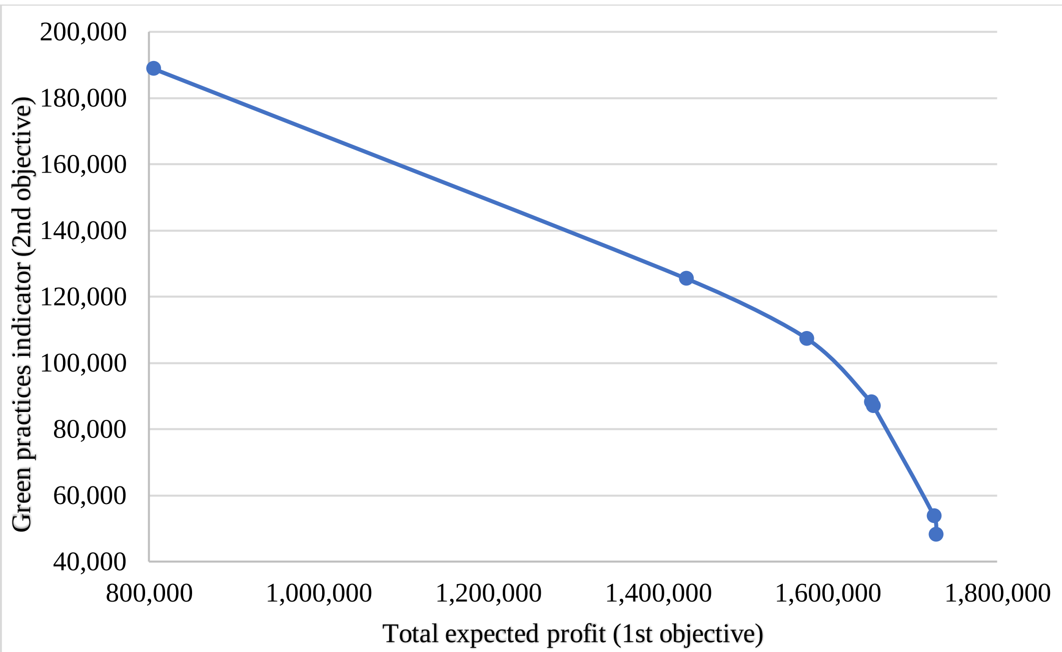

Fig. 3.7. The trade-off surface of the LAB CLSC network

Value path analysis (VPA) is utilized to display the non-dominated solutions in multi-objective problems (Schilling et al., 1983, Wadhwa and Ravinsdran, 2007; Tosarkani and Amin, 2018b). The normalized scales of the efficient solutions are computed as the ratio of the objective's value divided by its minimum value. The results are written in Table 3.9. As illustrated in Fig. 3.8, none of the efficient solutions are dominated because their value paths intersect.

Table 3.9
Normalized scales of non-dominated solutions

w_1	0 to 0.4	0.5	0.6	0.7	0.8	0.9	1
Total profit	1	1.7805	1.9568	2.0507	2.0539	2.1427	2.1457
Environmental compliance	3.9101	2.5973	2.2229	1.8275	1.8037	1.1150	1

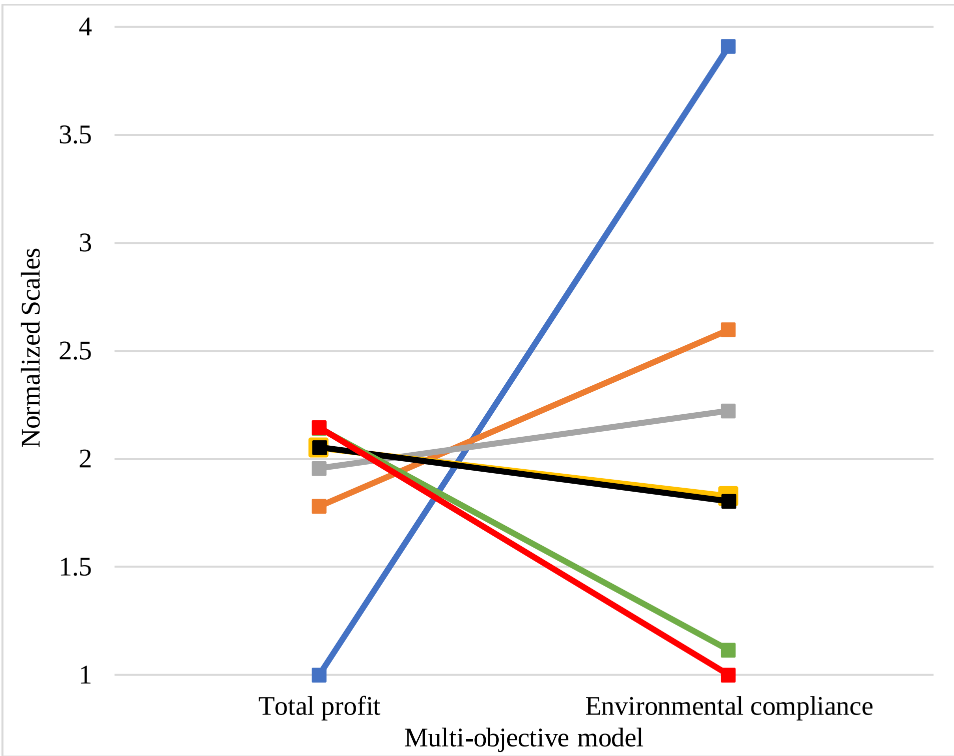

Fig. 3.8. The value path analysis

3.6. Conclusions

In this study, a fully fuzzy stochastic programming has been developed and applied for a LAB CLSC network with respect to an uncertain situation. Managing this network is a challenging task because it involves many parties. The multi-echelon network includes supplier(s), plant(s), demand markets, and LAB recovery center(s). To continue the LAB recovery, the profitability of CLSC should be taken into account. Most of the parameters contributing to the profit of CLSC networks are imprecise. Therefore, the impact of uncertain parameters should be considered and discussed.

In order to deal with uncertain factors, stochastic programming has been integrated with fully fuzzy programming as an innovative approach to consider different scenarios. The main advantage of the fully fuzzy optimization model is determining the relevant values of decision variables associated with imprecise parameters. The existence of fuzzy decision variables has led to have acceptable flexibility for making strategic decisions. The obtained solution in this paper includes the optimal pessimistic, realistic, and optimistic values of the objective and the decision variables in multiple periods.

We have analyzed and discussed the results of the mathematical model. Sensitivity analysis has been applied for the disposal fraction. The results have indicated that the total profit decreases as the disposal fraction increases. Therefore, the efficiency in recovery of the returned LAB can enhance both profit and environmental compliance simultaneously. To evaluate the performance of the FFSP approach, we have compared the solutions computed by our proposed model and the possibilistic approach. Thereafter, the optimization model has been extended to a bi-objective model to include green performances of suppliers, plants, and LAB recovery centers. To find the trade-off surface and the solutions of the bi-objective environmental model, distance method has been utilized. This research is the first study that applies the integration of fully fuzzy programming and stochastic programming for a bi-objective LAB CLSC network.

There are some future investigations for this study. Delivery plans have a significant impact on the network's profitability and carbon emissions. Therefore, the roles of transportation strategies can be considered in the optimization model. In this paper, an integrated approach including fuzzy and stochastic programming has been utilized. To deal with imprecise information, other useful methods such as robust optimization can be combined with our proposed model. Furthermore, it is valuable to develop game theoretic models to examine the effects of collaboration and competition between different players in the CLSC network. Finally, it is helpful to examine this research as a part of an integrated supply chain that includes several elements and features such as grid computing.

Chapter 4. A scenario-based robust possibilistic model for a multi-objective electronic reverse logistics network

4.1. Introduction

Reverse logistics (RL) is defined as the backward flow of products, specifically products that are returned for recycling. A reverse stream includes several entities, such as regional collection depots, remanufacturing plants, and recovery and disposal centers. In the contemporary competitive market, the reliability and competency of all entities involved in RL are integral to the process functioning as a whole. The reliability of an entity refers to the fulfillment of market demands on-time, while the competency indicates how well the entity is able to operate with minimum environmental impact and disposal fraction (Amin et al., 2017; Kumar et al., 2017). These characteristics are largely dependant on the entity's network configuration. The locations of facilities are decided upon strategically which makes the locations impossible to change in the short-term (e.g., opening or closing the recovery center) (Krumwiede and Sheu, 2002; Min et al., 2006; Kannan and Sasi Kumar, 2009; Paksoy et al., 2011; Ramos et al., 2014; Zolfagharinia et al., 2014; Mohajeri and Fallah, 2016; Zhalechian et al., 2016; Ramezanian and Behboodi, 2017, Amin et al., 2018).

A good example of an RL network can be observed in the electronics industry in Ontario, Canada. Ontario Electronic Stewardship (OES) is a not-for-profit organization focusing on electronics recycling in Ontario. As a result of OES activities, 507,619 metric tonnes of unwanted electronic appliances have been turned away from landfills since 2009, when the program began. Measured public awareness indicates that 66% of Ontario's population is familiar with OES. Additionally, more than 900 third parties, such as manufacturers and retailers, participate in this program. In terms of accessibility to OES, over 99% of Ontario's population live less than 25 km away from the regional collection centers (OES annual report, 2017). In recent publications, some mathematical methods have been applied to design RL networks. However, the application of deterministic optimization models has not been sufficient in configuring electronic RL networks due to various sources of uncertainty (i.e., imprecise parameters) and complexity. This study considers some of the sources of uncertainty in order to design and optimize an electronic RL network.

4.1.1. Literature review

One of the main difficulties of designing RL networks is uncertainty due to the lack of precise information. A real RL is supposed to operate in a dynamic environment that includes uncertainty. This is because remanufacturing plants are regularly required to deal with unpredictable factors that arise (Govindan et al., 2012; John et al., 2018). Deterministic methods cannot support decision-makers in predicting possible outcomes (Amin and Zhang, 2013a). To deal with such unpredictable circumstances, there are some approaches that can be used, such as stochastic programming (Nickel et al., 2012; Cardoso et al., 2013; Garrido et al., 2015; Sahling and Kayser, 2016), robust optimization (Pishvaee et al., 2011; Chen et al., 2014; Lorca and Sun, 2015), and fuzzy programming (Zarandi et al., 2011; Zhang et al., 2014; Wan et al., 2015). Stochastic programming is applied when parameters fluctuate with distributional information. Robust optimization is a modeling methodology which attempts to estimate feasible solutions for all circumstances that could arise due to uncertain parameters (Ben-Tal et al., 2009). In fuzzy programming, the mathematical model may include fuzzy parameters which are applied as the coefficient of decision variables in either objective function and constraints, or the right-hand side of constraints (Zimmermann, 1978; Chanas, 1983; Delgado et al., 1989; Bit et al., 1992). Since our focus is to address uncertainty and risky situations in designing RL networks, some applied methodologies in the fields of RL and closed-loop supply chain (CLSC) are reviewed in this section.

4.1.1.1. Application of stochastic programming in facility location design

The most relevant studies that have utilized stochastic programming to configure facility locations are reviewed in this subsection. El-Sayed et al. (2010) developed a multi-echelon forward and RL network in multiple periods with stochastic demand. Kara and Onut (2010) utilized a two-stage stochastic model to specify the long-term strategy for designing optimal facility locations for a paper recycling network. The results show that stochastic models result in more economical solutions in comparison with deterministic models.

Alumur et al. (2012) expressed that designing an RL is a complex problem. They mentioned that locations and capacities of third parties (i.e., collection centers, and remanufacturing plants) have a significant impact on the configuration of the optimal network. They applied a scenario-based optimization model to maximize the potential profit of a household appliance RL network in Germany. Ramezani et al. (2013) proposed a multi-objective stochastic model to design a forward and RL network under uncertainty. The multi-objective model included the optimization of profit, quality, and customer responsiveness. Roghanian and Pazhoheshfar (2014) introduced a probabilistic model to configure an RL network. The priority-based genetic algorithm was employed to minimize the total cost of the proposed model under uncertainty.

Ayvaz et al. (2015) examined a generic RL network with transportation costs and an uncertain return. The two-stage stochastic programming was considered to maximize the total profit of the network. Soleimani et al. (2016) investigated a multi-period, multi-product CLSC with stochastic demand and price. The authors applied a scenario-based approach to compute optimal solutions. Sawik (2016) used multi-objective stochastic programming to configure a multi-echelon supply chain while considering the local disruption risk. Different shipping scenarios were taken into consideration in order to optimize the trade-off associated with the total cost and service level in the network.

Ahmadi and Amin (2019) developed a chance-constrained stochastic model to design a CLSC network for the purpose of recycling unwanted mobile phones. They considered different types of product returns such as commercial, end-of-use, and end-of-life returns. Baptista et al. (2019) applied a two-stage stochastic mixed-integer bilinear model to design a multi-product CLSC network in multiple periods. The performance of their proposed approach was assessed by a real-life glass supply chain network under uncertainty of demand, production cost, and return.

4.1.1.2. Application of fuzzy programming in facility location design

There are a variety of studies that have used the fuzzy programming method to design optimal networks. Torabi and Hassini (2008) introduced a multi-objective possibilistic model to deal with imprecise information related to the market demand, cost, time, and capacity for designing a supply chain. Peidro et al. (2009) applied a fuzzy mathematical programming model to consider the uncertainty of supply and demand for supply chain planning.

Pishvaee and Razmi (2012) proposed a multi-objective fuzzy model to configure a supply chain network structure. They applied an interactive fuzzy solution method to handle the proposed model. Amin and Zhang (2013b) introduced a three-stage model for CLSC configuration. In the first stage, quality function development (QFD) and fuzzy sets theory were applied to evaluate the suppliers and the remanufacturing centers. Thereafter, a scenario-based mixed-integer non-linear programming model was employed to design the CLSC network with stochastic demand. In the last part, a multi-objective model was developed to identify the non-dominated solutions for the total cost, the importance of facilities, defect rate, and on-time delivery. Zare and Lotfi (2015) formulated a possibilistic mixed-integer linear programming method (MILP) to design a CLSC. To show the responsiveness of the proposed network, it was assumed that the products must be shipped within the expected delivery time.

Sherfati and Bashiri (2016) considered fuzzy tactical decision variables to formulate a mathematical model for a CLSC network. Tosarkani and Amin (2018a) developed a fully fuzzy programming method to design a battery CLSC network. Ghahremani-Nahr et al. (2019) applied a mixed-integer nonlinear programming (MINLP) model to design a multi-echelon CLSC under uncertainty. They applied a robust fuzzy programming method to deal with uncertain parameters such as demand, return, and some variable costs. Kuşakcı et al. (2019) discussed that recovery choices are required to avoid the rapid depletion of natural resources. They applied a fuzzy MILP model to design an RL network for end-of-life vehicles (ELVs). Khishtandar (2019) developed a fuzzy chance-constrained programming model to configure a biogas supply chain network under uncertainty of available workforce, biomass demand, and biomass price.

4.1.1.3. Application of robust optimization in facility location design

Robust optimization is a relatively new technique that is utilized for its computational flexibility. Contrary to stochastic programming, the probability of possible outcomes is unknown when using the robust optimization method. Therefore, several relevant research studies have applied robust optimization techniques. For instance, Bohle et al. (2010) studied an agricultural planning optimization problem regarding the uncertainty of labour productivity during harvesting. An alternative robust optimization method was developed to reach feasible solutions. Vahdani et al. (2012) integrated a robust optimization method with fuzzy multi-objective programming to design a reliable forward and RL network.

Hasani et al. (2015) examined a global supply chain by considering exchange rates, tariffs, taxes, and regulations on global trade. A robust optimization method was applied to maximize the profits of a medical device network under uncertainty. Babazadeh et al. (2015) used robust optimization and scenario-based stochastic programming to find optimal solutions for their proposed network. According to their findings, robust and stochastic approaches can effectively deal with uncertainty in quality and quantity of product returns, while deterministic models fail to handle the imprecise parameters in the same cases. Aras and Bilge (2018) used a robust MILP model to minimize the total cost of the supply chain network in the snack market. They extended their proposed deterministic model to a minimax regret model to tackle the uncertain demand.

Kim et al. (2018) discussed that production planning is affected by the uncertainty of customers' demand and product return in RL flow. They developed a robust optimization model to maximize the total profit in a multi-echelon CLSC network. Haddadsisakht and Ryan (2018) also examined the configuration of a CLSC network under uncertainty. They applied hybrid robust stochastic programming to deal with uncertain demand, return, and carbon tax rates. Recently, Ouhimmou et al. (2019) designed a distribution network in the pulp and paper industry. They utilized a robust optimization model to address the uncertain changes in demand over time.

4.1.1.4. Application of multi-objective approaches to consider environmental factors

Traditionally, the profitability of the RL network has been the primary concern. However, in recent years, due to the rise in environmental awareness and the development of new regulations, significant attention has been directed at configuring facility locations with environmental considerations. Govindan et al. (2015b) proposed a robust hybrid multi-objective model to design a multi-echelon supply chain. The multi-objective model includes the minimization of total cost and environmental impact considering stochastic demand. Alhaj et al. (2016) configured a multi-echelon green supply chain with stochastic demand. They considered some environmental factors and combined them with a joint location inventory model.

Fazli-Khalaf et al. (2017) designed a bi-objective green CLSC in response to environmental regulations and a shortage of natural resources. They proposed a robust fuzzy stochastic programming model to minimize the overall cost and the hazardous gas emissions associated with the network. Rezaee et al. (2017) investigated a green supply chain design through the application of a two-stage stochastic programming model. The optimal material flow was determined considering uncertain demand and carbon price.

Tosarkani and Amin (2018b) employed a multi-objective MILP to maximize the total profit, green practices, and on-time delivery of an RL network, while minimizing the defect rate. Liao (2018) mentioned that designing of RL has become a prominent strategy due to environmental concerns. He developed an MINLP to maximize the total profit of a multi-echelon RL network including regional and centralized collection centers, repairing and remanufacturing plants, disposal sites, distribution centers, processing, and recycling facilities.

Rahimi and Ghezavati (2018) proposed a multi-objective model to optimize the total profit, the social effects, and the environmental impact of a multi-period RL network under uncertainty. They developed a risk-averse two-stage stochastic programming to deal with the uncertainty in their proposed model. Xiao et al. (2019) configured a multi-echelon RL network with regard to the measurement of carbon emissions. They discussed that there is a significant gap between the growth rate of carbon ownership with a recovery rate of ELVs in China. They applied a MILP model to minimize the total cost of improper management of ELVs in the automotive industry. Lastly, Zhen et al. (2019) presented a bi-objective optimization model to optimize the total cost and sustainability in a CLSC network.

By considering the literature, we can observe that most studies have utilized one type of solution approach (e.g., either stochastic programming or possibilistic programming) to design facility location models under uncertainty. However, several types of uncertainty exist in practice based on the type of parameters (e.g., fuzzy or random parameters). Therefore, we aim to develop a holistic solution approach to address different types of uncertainty simultaneously. Table 4.1 includes a summary of the relevant literature.

Table 4.1
Some mathematical approaches to deal with uncertainties

Authors	Uncertainty	Multi-product	Type of products	Multi-period	Multi-objective	Mathematical approach *, Solution methodology	Real locations
Torabi and Hassini (2008)	Demand, variable costs, and capacity	✓		✓	✓	FP, Interactive fuzzy approach	
Peidro et al. (2009)	Supply, demand, and capacity	✓	Automobile industry	✓		FP, Fuzzy numbers ranking method	✓
El-sayed et al. (2010)	Demand			✓		SMILP	
Pishvaee and Razmi (2012)	Demand, return, and capacity		Medical needle and syringe		✓	FP, Interactive fuzzy approach	✓
Alumur et al. (2012)		✓	Household appliances	✓		MILP	✓
Ramezani et al. (2013)	Demand and variable costs	✓			✓	SMILP, ε-constraint method	
Roghanian and Pazhoheshfar (2014)	Demand	✓				SMILP, Genetic algorithm	
Govindan et al. (2015b)	Demand				✓	SMILP and RO, Metaheuristic algorithm	
Hasani et al. (2015)	Purchasing cost, demand, product returns, and recovery	✓	Medical device industry	✓		RO, Heuristic approach (memetic algorithm)	✓
Sawik (2016)	Disruption risks	✓	Electronics	✓	✓	SMILP, Weighted-sum aggregation	✓
Haddadsisakht and Ryan (2018)	Demand, return, carbon tax rate					SMILP and RO, Benders cuts using the dual solutions	✓
Baptista et al. (2019)	Demand, production cost, and return	✓	Glass industry	✓		SMIBM, Fix-and-relax decomposition algorithm	✓
Kuşakcı et al. (2019)	Returned product	✓	Automobile industry			FP	✓
The Proposed Model	Fixed and variable costs, demand and return, capacity of plant(s), disposal fraction rate	✓	Electronics	✓	✓	Scenario-based robust possibilistic, Two-phase fuzzy compromise approach	✓

* Stochastic mixed-integer linear programming (SMILP), Fuzzy programming (FP), Robust optimization (RO), Stochastic mixed-integer bilinear model (SMIBM).

4.1.2. Research contributions and objectives

With the passage of Bill 151 and the development of circular economy strategies in Ontario, greater attention has been directed towards electronics recycling (OES annual report, 2017). Accordingly, the presence of an efficient, effective, and optimal electronic RL network is essential. This research is inspired by an electronic RL network in the Greater Toronto Area (GTA). The RL network includes customers (who return the used products), recovery center(s), a disposal center, remanufacturing plant(s), and retailer(s). In this respect, there are several uncertain factors interfering with the configuration of the optimal RL. The most important parameters include fixed and variable costs (related to transportation, production, agreement with facilities, purchasing raw materials), volatility in the market's demand, and the quality and quantity of the returns (Jayaraman et al., 1999; Fleischmann et al., 2001; Kim et al., 2006; Achillas et al., 2010; Amin and Baki, 2017). This paper's proposed model considers an environmental robust structure for an electronic RL which includes several sources of uncertainty simultaneously. In this paper, a bi-objective model consisting of the total profit and green practices of the third parties that are associated with the network is considered and solved.

In RL network design, many studies have focused on the operational aspects, such as the recovery process, production scheduling, and inventory policy (Gou et al., 2008; Zeballos et al., 2014; Bazan et al., 2016; Tosarkani and Amin, 2019). Due to operational needs, there are adequate reasons to investigate the impact of uncertain parameters on RL network design (Govindan and Soleimani, 2017; Islam and Huda, 2018). Uncertainties stem from either external or internal factors in RL, such as supply, demand, return, or the recycling process. Such factors have a significant impact on the economic and environmental aspects of the network in the long term. In addition to the above-mentioned uncertain parameters, the quality of returned products should be considered, which can affect the recovery rate of the remanufacturing process. This underscores the significant need to capture several uncertainty sources when designing an RL network.

We develop a scenario-based approach to consider different types of returned products based on their quality. In addition, a robust possibilistic approach is utilized to reach feasible solutions with uncertain parameters. The impact of fuel prices is taken into account through the application of real distances between the facilities in the GTA. As indicated in Table 4.1, the contributions of this work can be summarized as follows:

- To configure an electronic RL network in the GTA based on realistic scenarios occurring in the OES. Furthermore, Google Maps is employed to consider real distances in the proposed multi-echelon RL. Transportation costs can be considered as functions of fuel prices and distances between potential locations. The historical data on Canadian fuel prices indicates unpredictable volatilities in fuel prices (refer to Fig. 4.A.1. in Appendix 4.A). In this regard, the fuzzy sets theory is utilized to address such uncertainties.
- To propose a scenario-based robust possibilistic model. To the best of our knowledge, such a hybrid method is new to RL literature. Furthermore, the effects of various sources of uncertainty on the RL network can be incorporated simultaneously. This method enables us to deal with different types of imprecise parameters.
- To consider the environmental compliance of third parties through a bi-objective model. Some criteria are identified according to the literature (Yücenur et al., 2011; Bhattacharya et al., 2014; Sharma et al., 2017; Tosarkani and Amin, 2018b). These criteria are determined based on the responsibility and character of partners.
- To compute the non-dominated solutions for the bi-objective model by utilizing the two-phase fuzzy compromise approach.

This study is organized as follows: In Section 4.2, the problem statement is discussed. In Section 4.3, the optimization model, and the solution approach for the scenario-based robust possibilistic model are presented, and the computational results are discussed. In Section 4.4, a Monte-Carlo simulation is conducted to evaluate the performance of the proposed model. Thereafter, green practices are introduced as the second objective in Section 4.5. The fuzzy compromise method is introduced and applied to generate efficient solutions in Section 4.6. The managerial implications are discussed in Section 4.7. Finally, Section 4.8 is devoted to conclusions and future research avenues.

4.2. Problem statement

There is a growing concern to keep used-electronics out of landfills. In Ontario, OES has collected and recycled about 52,712 tonnes of unwanted electronic appliances, which is almost equal to 3.92 kg/capita in 2017. Electronics collected by OES include display devices, non-cellular telephones, desktop computers, portable computers, computer accessories, printers, portable and home audio/video systems, photocopiers, and cellular devices. OES has mostly focused on the recoverable modules inside the end-of-life electronics. Several questions arise in accordance with the efficiency of RL networks. It is worthwhile to note that the profitability of such sustainable plans should be taken into account, as well as the green practices of the third parties. Accordingly, program efficiency has a significant impact on the reduction of the cost associated with electronic RL networks (OES annual report, 2017).

The application of our proposed model is examined using a remanufacturing plant involved in the OES. This company has been operating as a producer and remanufacturer in the electronics industry, with the GTA being one of its main markets. According to regulatory and environmental compliance to reduce noise pollution, and hazardous and industrial waste, there are limited options for selecting third parties in urban areas. Hence, the company has been challenged to increase both its green practices and profitability. Fig. 4.1 illustrates municipal districts in the GTA.

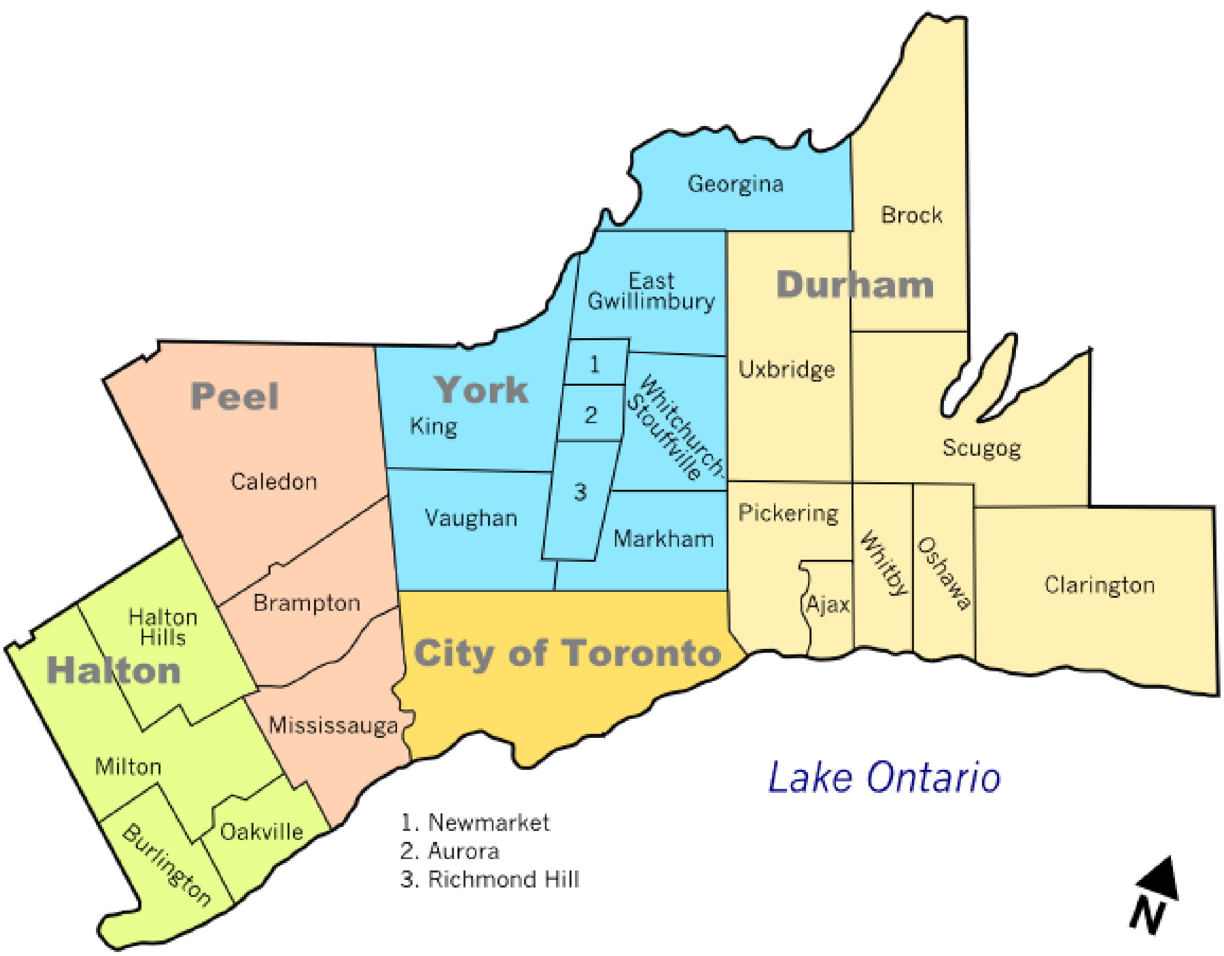

Fig. 4.1. The Greater Toronto Area (GTA), (GTA, 2018)

Fig. 4.2 illustrates a multi-echelon, multi-product, multi-component, multi-period electronic RL network. The unwanted electronics (e.g., desktop computers) are received by regional collection centers from the consumers. After sorting, the returned products are transported to the recovery centers. Product recovery services are provided for every product which is assumed to have five main modules (e.g., desktop computers include monitor, keyboard, motherboard, case, and CPU air cooler). Since the quality of returned products varies, five scenarios are considered to analyze different quality types of unrecoverable products. For example, if one module is unrecyclable, the disposal fraction becomes 20%. Disposal fractions of 40%, 60%, 80%, and 100% can be interpreted similarly.

Customers may return products to the RL for different reasons (commercial, end of use, end of life, repair, and warranty returns). It is noteworthy that some parts of the returned products can be used again after the product recovery process. The recovered products are transferred to the retailer(s), while the unrecoverable products (end of life returns) are sent to the disposal center. Some products contain both recoverable and unrecoverable modules. The unrecoverable modules are separated and sent to the disposal center, and the recoverable modules are shipped to the remanufacturing plant(s). The supplier(s) then provide(s) complementary modules to be assembled with the recovered ones. The remanufactured products are shipped to the retailer(s). In this study, we assume that the remanufacturing plant(s) are part of the main plant(s). Hence, plant(s) are responsible for fulfilling demand either by reassembling the recovered modules or producing the new products. Accordingly, the cost of purchasing raw materials from suppliers can be decreased as the usage of recovered modules is increased. For instance, Canon collects, refurbishes, and remanufactures devices which consist of multiple modules, such as floor-standing photocopiers. The remanufactured products are guaranteed to have the same quality and reliability as a new product (Remanufacturing, Recycling of Used Products, 2018). Therefore, efficiency in the recovery center(s) increases the profitability of the entire network due to the reduction of disposal fraction. The green practices of the third parties involved in the electronic RL network should be taken into account because of the environmental concerns. The objective of this study is to answer the following research questions:

I. Which location(s) should be considered for supplier(s), remanufacturing plant(s), regional collection center(s), recovery center(s), and retailer(s)?

II. How many components should be purchased from the available supplier(s)?

III. How many products should be offered to the market to maximize the total profits by considering the uncertain rate of disposal fraction, demand, return, and fixed and variable costs associated with an electronic RL network?

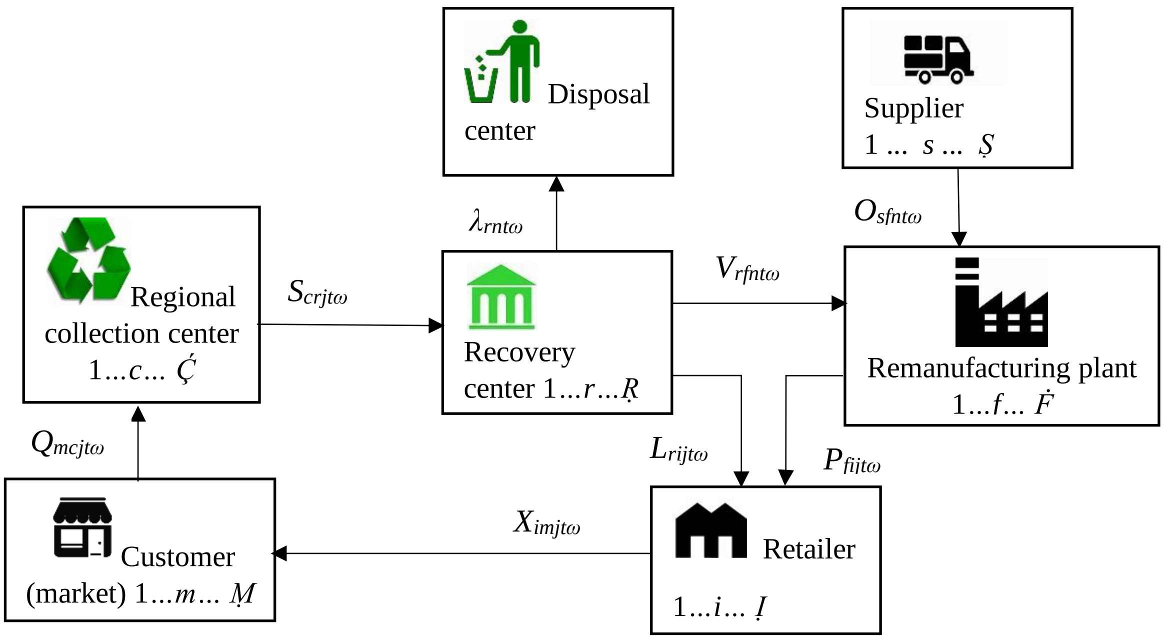

Fig. 4.2. The proposed electronic RL network

4.3. Optimization model

There is a growing consensus that extreme environmental issues and climate change are universal problems which all countries are facing. However, there is no single plan and general agreement on how to tackle this issue. For example, there are different views on how to address environmental issues in Canada. While one of the political parties believes that a minimum carbon tax can be a successful policy to stop major emitters, the other party is fundamentally against the carbon tax policy and suggests focusing on green technology instead (Tasker, 2019). Therefore, we first consider the total expected profit as the main objective, which is traditionally the most important goal in RL networks. We then introduce the impact of environmental policies on designing the electronic RL network as the second objective. This objective is introduced to address the environmental compliance of third parties in the proposed optimization model.

A scenario-based robust possibilistic mathematical model is developed to configure the facility location model under uncertainty. In this study, triangular fuzzy numbers (TFNs) are applied to deal with imprecise parameters. The fuzzy sets theory is employed to deal with uncertainty in different fields of operation research, decision-making processes, engineering, management science, and statistics (Zimmermann, 2012; Zadeh et al., 2014; Peng et al., 2016; Wei et al., 2017; Faizi et al., 2018). In the real world, different parameters contributing to the optimization model cannot be addressed by a single value. Therefore, imprecise parameters can be replaced by TFNs due to their computational flexibility (Gani and Assarudeen, 2012). Tables 4.2, 4.3, 4.4 illustrate sets, parameters, and decision variables (i.e., non-negatives, and binary variables) applied to formulate the mathematical model.

Table 4.2
All the sets of the proposed model

$\underset{.}{S}$ = set of suppliers ($s \in \underset{.}{S}$)
$\dot{F}$ = set of locations related to remanufacturing plants ($f \in \dot{F}$)
J = set of products ($j \in J$)
$\underset{.}{M}$ = set of demand markets ($m \in \underset{.}{M}$)
$\underset{.}{R}$ = set of locations related to electronic recovery centers ($r \in \underset{.}{R}$)
$\acute{Ç}$ = set of locations related to regional collection centers ($c \in \acute{Ç}$)
$\underset{.}{N}$ = set of components ($n \in \underset{.}{N}$)
$\underset{.}{I}$ = set of retailers ($i \in \underset{.}{I}$)
Ŧ = set of time periods ($t \in$ Ŧ)
Ω = set of scenarios ($\omega \in \Omega$)

Table 4.3
The parameters of the proposed model

Φ_ω = probability of scenario ω
$\widetilde{A}_s$ = triangular fuzzy number related to fixed-cost of agreement with supplier s
$\widetilde{B}_c$ = triangular fuzzy number related to fixed-cost of agreement with regional collection center c
$\widetilde{C}_i$ = triangular fuzzy number related to fixed-cost of agreement with retailer i
$\widetilde{Y}_r$ = triangular fuzzy number related to fixed-cost of agreement with recovery center r
$\widetilde{D}_f$ = triangular fuzzy number related to fixed-cost of agreement with remanufacturing plant f
$\widetilde{E}_{sn}$ = triangular fuzzy number related to purchasing cost of components n from supplier s
$\widetilde{F}_j$ = triangular fuzzy number related to cost of product recovery related to product j
$\widetilde{R}_j$ = triangular fuzzy number related to selling price of product j
$\widetilde{G}_j$ = triangular fuzzy number related to cost of remanufacturing related to product j
$\widetilde{T}_n$ = triangular fuzzy number related to disposal cost related to component n
$\tilde{o}_n$ = triangular fuzzy number related to unit cost of transportation per Km associated with component n from supplier(s) to remanufacturing plant(s)
$\tilde{p}_j$ = triangular fuzzy number related to unit cost of transportation per Km associated with product j from markets to regional collection center(s)
$\tilde{h}_j$ = triangular fuzzy number related to unit cost of transportation per Km associated with product j from regional collection center(s) to recovery center(s)

$\tilde{e}_n$ = triangular fuzzy number related to unit cost of transportation per Km associated with component n from recovery center(s) to disposal center
$\tilde{g}_j$ = triangular fuzzy number related to unit cost of transportation per Km associated with product j from recovery center(s) to retailer(s)
$\tilde{k}_n$ = triangular fuzzy number related to unit cost of transportation per Km associated with component n from recovery center(s) to remanufacturing plant(s)
$\tilde{l}_j$ = triangular fuzzy number related to unit cost of transportation per Km associated with product j from remanufacturing plant(s) to retailer(s)
$\tilde{a}_j$ = triangular fuzzy number related to unit cost of transportation per Km associated with product j from retailer(s) to markets
u_{mc} = the distance between location m and c
u_r = the distance between recovery center r and disposal center
$\tilde{d}_{mjt}$ = triangular fuzzy number related to demand of customer (market) m for product j related to period t
$\tilde{v}_{mjt}$ = triangular fuzzy number related to return of market m for product j related to period t
υ_j = recovery rate of product j
$\varepsilon_{n\omega}$ = disposal fraction of component n in scenario ω
$\tilde{H}_{fn}$ = triangular fuzzy number related to number of capacity of remanufacturing center f for component n
U_{cj} = capacity of regional collection center c for product j
W_{rj} = capacity of recovery center r for product j
Γ_{sn} = capacity of supplier s for component n
Λ_{ij} = capacity of retailer i for product j
I_{jn} = number of component n in product j
K_{sn} = environmental compliance of supplier s, while providing n components
M_{fn} = environmental compliance of remanufacturing plant f, while assembling n components
N_{rn} = environmental compliance of recovery center r, while recycling n components via product recovery

Table 4.4
The decision variables of the proposed model

$O_{sfnt\omega}$ = number of component n shipped to remanufacturing plant f by supplier s related to period t in scenario ω
$P_{fijt\omega}$ = number of product j produced by remanufacturing plant f for retailer i related to period t in scenario ω
$Q_{mcjt\omega}$ = number of returned product j from customer m to regional collection center c related to period t in scenario ω
$S_{crjt\omega}$ = number of product j shipped by regional collection center c to recovery center r related to period t in scenario ω
$\lambda_{rnt\omega}$ = number of component n (unrecoverable modules) shipped to disposal center from recovery center r related to period t in scenario ω
$V_{rfnt\omega}$ = number of component n (recoverable modules) shipped to remanufacturing plant f from recovery center r related to period t in scenario ω
$L_{rijt\omega}$ = number of product j shipped to retailer i from recovery center r related to period t in scenario ω
$X_{imjt\omega}$ = number of product j shipped to customer m from retailer i related to period t in scenario ω
q_c = 1, if the regional collection center located in site c is utilized to collect the products, 0, otherwise.
w_r = 1, if the recovery center located in site r is utilized to recycle the used products, 0, otherwise.
x_f = 1, if the remanufacturing plant is selected at potential site f, 0, otherwise.
y_s = 1, if supplier s is selected, 0, otherwise.
z_i = 1, if retailer i is selected, 0, otherwise.

$$
\begin{aligned}
Max\ Z_1 = & \sum_i \sum_m \sum_j \sum_t \sum_\omega \Phi_\omega \left(\tilde{R}_j - \tilde{a}_j u_{im} \right) X_{imjt\omega} - \left(\sum_f \sum_i \sum_j \sum_t \sum_\omega \Phi_\omega \left(\tilde{G}_j + \tilde{l}_j u_{fi} \right) P_{fijt\omega} \right) - \\
& \left(\sum_s \sum_f \sum_n \sum_t \sum_\omega \Phi_\omega \left(\tilde{E}_{sn} + \tilde{o}_n u_{sf} \right) O_{sfnt\omega} \right) - \left(\sum_m \sum_c \sum_j \sum_t \sum_\omega \Phi_\omega \left(\tilde{p}_j u_{mc} \right) Q_{mcjt\omega} \right) - \\
& \left(\sum_c \sum_r \sum_j \sum_t \sum_\omega \Phi_\omega \left(\tilde{F}_j + \tilde{h}_j u_{cr} \right) S_{crjt\omega} \right) - \left(\sum_r \sum_n \sum_t \sum_\omega \Phi_\omega \left(\tilde{T}_n + \tilde{e}_n u_r \right) \lambda_{rnt\omega} \right) - \\
& \left(\sum_r \sum_f \sum_n \sum_t \sum_\omega \Phi_\omega \left(\tilde{k}_n u_{rf} \right) V_{rfnt\omega} \right) - \left(\sum_r \sum_i \sum_j \sum_t \sum_\omega \Phi_\omega \left(\tilde{g}_j u_{ri} \right) L_{rijt\omega} \right) - \\
& \left(\sum_s \tilde{A}_s y_s \right) - \left(\sum_c \tilde{B}_c q_c \right) - \left(\sum_r \tilde{Y}_r w_r \right) - \left(\sum_f \tilde{D}_f x_f \right) - \left(\sum_i \tilde{C}_i z_i \right)
\end{aligned}
$$

s.t.

$$\sum_r V_{rfnt\omega} + \sum_s O_{sfnt\omega} = \sum_i \sum_j \left(P_{fijt\omega} \right) I_{jn} \qquad \forall f, n, t, \omega \qquad (4.1)$$

$$\sum_f P_{fijt\omega} + \sum_r L_{rijt\omega} = \sum_m X_{imjt\omega} \qquad \forall i, j, t, \omega \qquad (4.2)$$

$$\sum_i X_{imjt\omega} \mathrel{\tilde{\leq}} \tilde{d}_{mjt} \qquad \forall m, j, t, \omega \qquad (4.3)$$

$$\sum_c Q_{mcjt\omega} = \tilde{v}_{mjt} \qquad \forall m, j, t, \omega \qquad (4.4)$$

$$\sum_r S_{crjt\omega} = \sum_m Q_{mcjt\omega} \qquad \forall c, j, t, \omega \qquad (4.5)$$

$$\sum_i L_{rijt\omega} \leq \sum_c \left(S_{crjt\omega} \right) \upsilon_j \qquad \forall r, j, t, \omega \qquad (4.6)$$

$$\sum_c \sum_j \left(\left(S_{crjt\omega} \right) \left(1 - \upsilon_j \right) I_{jn} \right) \varepsilon_{n\omega} \leq \lambda_{rnt\omega} \qquad \forall r, n, t, \omega \qquad (4.7)$$

$$\sum_f V_{rfnt\omega} + \lambda_{rnt\omega} + \sum_i \sum_j \left(L_{rijt\omega} \right) I_{jn} = \sum_c \sum_j \left(S_{crjt\omega} \right) I_{jn} \qquad \forall r, n, t, \omega \qquad (4.8)$$

$$\sum_r \sum_n V_{rfnt\omega} + \sum_s \sum_n O_{sfnt\omega} \mathrel{\tilde{\leq}} x_f \sum_n \tilde{H}_{fn} \qquad \forall f, t, \omega \qquad (4.9)$$

$$\sum_m \sum_j Q_{mcjt\omega} \leq q_c \sum_j U_{cj} \qquad \forall c, t, \omega \qquad (4.10)$$

$$\sum_{c}\sum_{j} S_{crjt\omega} \le w_r \sum_{j} W_{rj} \qquad \forall r,t,\omega \qquad (4.11)$$

$$\sum_{f}\sum_{n} O_{sfnt\omega} \le y_s \sum_{n} \Gamma_{sn} \qquad \forall s,t,\omega \qquad (4.12)$$

$$\sum_{f}\sum_{j} P_{fijt\omega} + \sum_{r}\sum_{j} L_{rijt\omega} \le z_i \sum_{j} \Lambda_{ij} \qquad \forall i,t,\omega \qquad (4.13)$$

$$q_c, w_r, x_f, y_s, z_i \in \{0,1\} \qquad \forall c,r,f,s,i \qquad (4.14)$$

$$O_{sfnt\omega}, P_{fijt\omega}, Q_{mcjt\omega}, S_{crjt\omega}, \lambda_{rnt\omega}, V_{rfnt\omega}, L_{rijt\omega}, X_{imjt\omega} > 0 \qquad \forall s,f,j,m,r,c,n,t,\omega \qquad (4.15)$$

The objective function maximizes the total expected profit in the electronic RL network. To find the expected profit, the summation of variable costs (provision of raw materials, remanufacturing, transportation, recovery, and disposal costs) and fixed costs are subtracted from the revenue earned by selling products to customers. Hence, the first term computes the gross revenue of the RL network (where the transportation cost between the retailer(s) and markets is deducted from the selling price). The second term shows the costs of remanufacturing and shipping from remanufacturing plant(s) to the retailers. The third term represents the purchasing and transportation costs of raw materials from the supplier(s) to the remanufacturing plant(s). The next term denotes the cost of shipment related to the returned products from markets to regional collection center(s). The returned products are overhauled in the recovery center(s). The recovered products are shipped to the retailers, and unrecoverable products are disassembled to their operational and unusable modules. To this aim, the cost of product recovery, disposal, and shipment between recovery center(s), the disposal center, remanufacturing plant(s), and retailer(s) are considered. Furthermore, the total fixed costs associated with supplier(s), regional collection center(s), recovery center(s), remanufacturing plant(s), and retailer(s) are defined, respectively.

Constraint (4.1) ensures that the summation of modules provided by suppliers and recovery center(s) is equal to the number of modules that are remanufactured or produced by plants. Constraint (4.2) obligates retailer(s) to sell all products received from the recovery center(s) and remanufacturing plant(s) to the markets. Constraint (4.3) indicates that the number of products shipped to the markets by the retailer(s) should be less than customer demand. Constraints (4.4) and (4.5) determine that the total returned products received by regional collection center(s) from markets are required to be transferred to the recovery center(s). Constraints (4.6) and (4.7) imply the recovery rates and disposal fraction in the recovery center(s). Constraint (4.8) states that the summation of recyclable modules ($V_{rfnt\omega}$), disposable modules ($\lambda_{rnt\omega}$), and the components of recovered products ($L_{rijt\omega} \times I_{jn}$) are required to be equal to the components of all products received from the regional collection center(s) ($S_{crjt\omega} \times I_{jn}$). Constraints (4.9), (4.10), (4.11), (4.12), and (4.13) are the capacity constraints associated with remanufacturing plant(s), regional collection center(s), recovery center(s), supplier(s), and retailer(s), respectively. Finally, Constraints (4.14) and (4.15) present binary and non-negative variables.

4.3.1. Solution approach

We develop a novel scenario-based robust possibilistic model building on the methods proposed by Cadenas and Verdegay (1997), Snyder (2006), Jiménez et al. (2007), Al-Othman et al. (2008), Amin and Zhang (2013a), and Pishvaee and Fazeli Khalaf (2016). As suggested by the literature, imprecise parameters should be addressed according to their natures (i.e., stochastic and fuzzy). Our proposed approach enables decision-makers to deal with different uncertain parameters simultaneously. We also consider the affected constraints consisting of uncertain parameters (i.e., demand, return, and the capacity of the remanufacturing plants):

- Constraint (4.3): $\sum_i X_{imjt\omega} \tilde{\leq} \tilde{d}_{mjt}$
- Constraint (4.4): $\sum_c Q_{mcjt\omega} = \tilde{v}_{mjt}$
- Constraint (4.9): $\sum_r \sum_n V_{rfnt\omega} + \sum_s \sum_n O_{sfnt\omega} \tilde{\leq} x_f \sum_n \tilde{H}_{fn}$

As mentioned in Section 4.3, we define ω scenarios representing different rates of disposal fractions with the probability of Φ_ω to consider the various types of quality in returns. It is also assumed that all parameters in the optimization model are uncertain (e.g., selling price, fixed costs, variable costs, demand, and return).

The mathematical symbol $\tilde{\leq}$ is the fuzzy version of $\leq$. It means that the left-hand side is less than or equal to the right-hand side of the constraint (Peidro et al., 2009). The demand and production capacity can be estimated approximately, while they have a significant impact on the profitability of the network. Listeş and Dekker (2005), and Amin and Zhang (2013a) indicated that optimal solutions are very sensitive to demand in the facility location design. Furthermore, Paraskevopoulos et al. (1991), Van Mieghem (2003), Geng et al. (2009) examined uncertainty in manufacturing capacities since they believed that deterministic approaches could not address dynamic changes in the real world. Therefore, we choose ($\tilde{\leq}$) for two constraints associated with the demand and capacity of the remanufacturing plant(s). The fuzzy version of (≤) indicates that decision-makers would like to have the left-hand side of the constraint become less than or equal to the right-hand side, “if possible”. To cope with a violation of such constraints, two triangular fuzzy numbers $\tilde{\varsigma}, \tilde{\tau}$ are applied. Eqs. (4.3) and (4.9) are rewritten by Eqs. (4.16), (4.17), and (4.18).

$$
\begin{aligned}
& Max\, Z_2^r = Z_1 - \gamma\left(\tilde{\varsigma}\left(1-\alpha\right)\right) - \sigma\left(\tilde{\tau}\left(1-\beta\right)x_f\right) \\
& s.t. \\
& \sum_i X_{imjt\omega} \leq \tilde{d}_{mjt} + \tilde{\varsigma}\left(1-\alpha\right), \qquad \forall m, j, t, \omega \qquad (4.16) \\
& \sum_r \sum_n V_{rfnt\omega} + \sum_s \sum_n O_{sfnt\omega} \leq x_f \sum_n \tilde{H}_{fn} + \tilde{\tau}\left(1-\beta\right)x_f \qquad \forall f, t, \omega \qquad (4.17) \\
& 0 \leq \alpha, \beta \leq 1 \qquad (4.18)
\end{aligned}
$$

α and β are the minimum satisfaction levels applied as the variables. In addition, γ and σ are defined as the parameters of penalty costs associated with possible violations in the soft constraints. These penalty costs are utilized to optimize the minimum values of satisfaction levels in the soft constraints. Since $\tilde{\varsigma} = \left(\varsigma^l, \varsigma^c, \varsigma^u\right), \tilde{\tau} = \left(\tau^l, \tau^c, \tau^u\right)$ are assumed as TFNs, they are defuzzified and represented by $\varsigma^c + \frac{\left(\varsigma^u - \varsigma^c\right) - \left(\varsigma^c - \varsigma^l\right)}{3}$ and $\tau^c + \frac{\left(\tau^u - \tau^c\right) - \left(\tau^c - \tau^l\right)}{3}$ based on the fuzzy ranking method developed by Yager (1981).

A combinatorial approach developed by Parra et al. (2005) and Jiménez et al. (2007) is utilized to defuzzify the imprecise parameters, including demand, return, and remanufacturing plant(s) capacity. The expected interval and the value of TFN $\tilde{d} = (d^l, d^c, d^u)$ are presented by Eqs. (4.19) and (4.20).

$$EI\left(\tilde{d}\right)=\left[E_1^d,E_2^d\right]=\left[\frac{1}{2}\left(d^l+d^c\right),\frac{1}{2}\left(d^c+d^u\right)\right] \tag{4.19}$$

$$EA\left(\tilde{d}\right)=\frac{E_1^d+E_2^d}{2}=\frac{\left(d^l+2*d^c+d^u\right)}{4} \tag{4.20}$$

According to the fuzzy ranking method proposed by Jiménez et al. (2007), the degree in which $\tilde{d}$ is greater than $\tilde{\xi}$ can be indicated by Eq. (4.21).

$$\mu_M\left(\tilde{d},\tilde{\xi}\right)=\begin{cases}0, & if\ E_2^d-E_1^\xi<0\\ \dfrac{E_2^d-E_1^\xi}{E_2^d-E_1^\xi-\left(E_1^d-E_2^\xi\right)}, & if\ 0\in\left[E_1^d-E_2^\xi,E_2^d-E_1^\xi\right]\\ 1, & if\ E_1^d-E_2^\xi>0\end{cases} \tag{4.21}$$

If $\mu_M\left(\tilde{d},\tilde{\xi}\right)\geq\delta$, $\tilde{d}$ is greater than or equal to $\tilde{\xi}$ at least with the degree of δ. This point can be shown by $\tilde{d}\geq_\delta\tilde{\xi}$. In the case of equality, it can be said that $\tilde{v}$ is indifferent to $\tilde{\imath}$ in degree of θ, if we have $\tilde{v}\geq_{\theta/2}\tilde{\imath}$ and $\tilde{v}\leq_{\theta/2}\tilde{\imath}$ (Parra et al., 2005). Therefore, the equality relation of $\tilde{v}\approx_\theta\tilde{\imath}$ can be rewritten by Eq. (4.22).

$$\frac{\theta}{2}\leq\mu_M\left(\tilde{v},\tilde{\imath}\right)\leq1-\frac{\theta}{2} \tag{4.22}$$

Then, in the constraint of $\sum_i\tilde{\xi}_{mjt}X_{imjt\omega}\leq\tilde{d}_{mjt},\forall m,j,t,\omega$ the decision variable $X_{imjt\omega}$ is feasible with degree δ, if min $\{\mu_M\left(\tilde{d}_{mjt},\sum_i\tilde{\xi}_{mjt}X_{imjt\omega}\right)\}=\delta$. Accordingly, $\sum_i\tilde{\xi}_{mjt}X_{imjt\omega}\leq\tilde{d}_{mjt}$ and $\sum_c\tilde{\imath}_{mjt}Q_{mcjt\omega}=\tilde{v}_{mjt}$ can be written by Eqs. (4.23) and (4.24).

$$\frac{E_2^{d_{mjt}}-E_1^{\xi_{mjt}\sum_i X_{imjt\omega}}}{E_2^{d_{mjt}}-E_1^{\xi_{mjt}\sum_i X_{imjt\omega}}-\left(E_1^{d_{mjt}}-E_2^{\xi_{mjt}\sum_i X_{imjt\omega}}\right)}\geq\delta,\qquad\forall m,j,t,\omega \tag{4.23}$$

$$\frac{\theta}{2} \le \frac{E_2^{\nu_{mjt}} - E_1^{\iota_{mjt} \sum_c Q_{mcjt\omega}}}{E_2^{\nu_{mjt}} - E_1^{\iota_{mjt} \sum_c Q_{mcjt\omega}} - \left(E_1^{\nu_{mjt}} - E_2^{\iota_{mjt} \sum_c Q_{mcjt\omega}} \right)} \le 1 - \frac{\theta}{2} \qquad \forall m, j, t, \omega \tag{4.24}$$

Eqs. (4.23) and (4.24) can be simplified to Eqs. (4.25), (4.26), and (4.27).

$$\left[\delta E_2^{\xi_{mjt}} + (1-\delta) E_1^{\xi_{mjt}} \right] \sum_i X_{imjt\omega} \le \delta E_1^{d_{mjt}} + (1-\delta) E_2^{d_{mjt}} \qquad \forall m, j, t, \omega \tag{4.25}$$

$$\left[\left(1 - \frac{\theta}{2}\right) E_2^{\iota_{mjt}} + \frac{\theta}{2} E_1^{\iota_{mjt}} \right] \sum_c Q_{mcjt\omega} \ge \left(1 - \frac{\theta}{2}\right) E_1^{\nu_{mjt}} + \frac{\theta}{2} E_2^{\nu_{mjt}} \qquad \forall m, j, t, \omega \tag{4.26}$$

$$\left[\left(1 - \frac{\theta}{2}\right) E_1^{\iota_{mjt}} + \frac{\theta}{2} E_2^{\iota_{mjt}} \right] \sum_c Q_{mcjt\omega} \le \left(1 - \frac{\theta}{2}\right) E_2^{\nu_{mjt}} + \frac{\theta}{2} E_1^{\nu_{mjt}} \qquad \forall m, j, t, \omega \tag{4.27}$$

Constraints (4.4), (4.16), and (4.17) can be converted to the equivalent crisp versions (4.29), (4.30), (4.31), (4.32). The range of the associated confidence level is also defined by Constraint (4.33). To optimize the confidence level, the penalty costs are applied based on the method of Pishvaee and Fazeli Khalaf (2016), and are included in the objective function (Eq. (4.28)).

$$\begin{aligned}
Max\, Z_2^r = {} & E[Z_1] - \varphi\left(E[Z_1] - Z_1^l\right) - \eta \sum_m \sum_j \sum_t \left(\delta \left(\frac{d_{mjt}^l + d_{mjt}^c}{2} \right) + (1-\delta) \left(\frac{d_{mjt}^c + d_{mjt}^u}{2} \right) - d_{mjt}^l \right) \\
& -\pi_1 \sum_m \sum_j \sum_t \left(v_{mjt}^c - \left(1 - \frac{\theta}{2}\right) \left(\frac{v_{mjt}^l + v_{mjt}^c}{2} \right) - \left(\frac{\theta}{2}\right) \left(\frac{v_{mjt}^c + v_{mjt}^u}{2} \right) \right) \\
& -\pi_2 \sum_m \sum_j \sum_t \left(\left(1 - \frac{\theta}{2}\right) \left(\frac{v_{mjt}^c + v_{mjt}^u}{2} \right) + \left(\frac{\theta}{2}\right) \left(\frac{v_{mjt}^l + v_{mjt}^c}{2} \right) - v_{mjt}^l \right) \\
& -\Delta \sum_f \sum_n \left(\rho \left(\frac{H_{fn}{}^l + H_{fn}{}^c}{2} \right) + (1-\rho) \left(\frac{H_{fn}{}^c + H_{fn}{}^u}{2} \right) - H_{fn}{}^l \right) x_f \\
& -\gamma \left(\left(\varsigma^c + \frac{\left(\varsigma^u - \varsigma^c\right) - \left(\varsigma^c - \varsigma^l\right)}{3} \right) (1-\alpha) \right) - \sigma \sum_f \left(\left(\tau^c + \frac{\left(\tau^u - \tau^c\right) - \left(\tau^c - \tau^l\right)}{3} \right) (1-\beta)\, x_f \right)
\end{aligned} \tag{4.28}$$

s.t.

Constraints (4.1), (4.2), (4.5 to 4.8), (4.10 to 4.15)

$$\sum_i X_{imjt\omega} \le \delta\left(\frac{d^l_{mjt}+d^c_{mjt}}{2}\right)+(1-\delta)\left(\frac{d^c_{mjt}+d^u_{mjt}}{2}\right)$$
$$+\left(\varsigma^c+\frac{(\varsigma^u-\varsigma^c)-(\varsigma^c-\varsigma^l)}{3}\right)(1-\alpha), \qquad \forall m,j,t,\omega \qquad (4.29)$$

$$\sum_c Q_{mcjt\omega} \ge \left(1-\frac{\theta}{2}\right)\left(\frac{v^l_{mjt}+v^c_{mjt}}{2}\right)+\left(\frac{\theta}{2}\right)\left(\frac{v^c_{mjt}+v^u_{mjt}}{2}\right), \qquad \forall m,j,t,\omega \qquad (4.30)$$

$$\sum_c Q_{mcjt\omega} \le \left(1-\frac{\theta}{2}\right)\left(\frac{v^c_{mjt}+v^u_{mjt}}{2}\right)+\left(\frac{\theta}{2}\right)\left(\frac{v^l_{mjt}+v^c_{mjt}}{2}\right), \qquad \forall m,j,t,\omega \qquad (4.31)$$

$$\sum_r\sum_n V_{rfnt\omega}+\sum_s\sum_n O_{sfnt\omega} \le x_f\sum_n \rho\left(\frac{{H_{fn}}^l+{H_{fn}}^c}{2}\right)+(1-\rho)\left(\frac{{H_{fn}}^c+{H_{fn}}^u}{2}\right)$$
$$+\left(\tau^c+\frac{(\tau^u-\tau^c)-(\tau^c-\tau^l)}{3}\right)(1-\beta)x_f \qquad \forall f,t,\omega \qquad (4.32)$$

$$0\le \alpha,\beta \le 1,\ 0.5 \le \delta,\rho,\theta \le 1 \qquad (4.33)$$

Where φ is applied to minimize the worst deviation from the expected value of the objective. To calculate the worst possible outcome for the first objective function (Z_1^l), the highest value of the fixed and variable costs is subtracted from the lowest value of the revenue (Eq. (4.34)). Furthermore, the expected value of the first objective function ($E[Z_1]$) can be estimated by the arithmetic average of triangular parameters. The parameters of η, π_1, π_2, and Δ are defined as the penalty cost to control the feasibility robustness related to uncertain parameters. While γ, and σ are associated with feasibility robustness in terms of flexibility of constraint (i.e., possible violation in soft constraints).

$$Z_1^l = \sum_i \sum_m \sum_j \sum_t \sum_\omega \Phi_\omega R_j^l X_{imjt\omega} - \left(\sum_i \sum_m \sum_j \sum_t \sum_\omega \Phi_\omega \left(G_j^u + l_j^u u_{fi} \right) P_{fijt\omega} \right) -$$

$$\left(\sum_s \sum_f \sum_n \sum_t \sum_\omega \Phi_\omega \left(E_{sn}^u + o_n^u u_{sf} \right) O_{sfnt\omega} \right) - \left(\sum_m \sum_c \sum_j \sum_t \sum_\omega \Phi_\omega \left(p_j^u u_{mc} \right) Q_{mcjt\omega} \right) -$$

$$\left(\sum_c \sum_r \sum_j \sum_t \sum_\omega \Phi_\omega \left(F_j^u + h_j^u u_{cr} \right) S_{crjt\omega} \right) - \left(\sum_r \sum_n \sum_t \sum_\omega \Phi_\omega \left(T_n^u + e_n^u u_r \right) \lambda_{rnt\omega} \right) -$$

$$\left(\sum_r \sum_f \sum_n \sum_t \sum_\omega \Phi_\omega \left(k_n^u u_{rf} \right) V_{rfnt\omega} \right) - \left(\sum_r \sum_i \sum_j \sum_t \sum_\omega \Phi_\omega \left(g_j^u u_{ri} \right) L_{rijt\omega} \right) - \left(\sum_s A_s^u y_s \right) -$$

$$\left(\sum_c B_c^u q_c \right) - \left(\sum_r Y_r^u w_r \right) - \left(\sum_f D_f^u x_f \right) - \left(\sum_i C_i^u z_i \right) \tag{4.34}$$

Multiplication of x_f by ρ and β in Eqs. (4.28) and (4.32) causes non-linearity and leads to difficulty in optimization. To overcome this issue, two non-negative auxiliary variables, $\iota_f = \beta x_f$, $\chi_f = \rho x_f$ are introduced based on the method of Pishvaee and Fazeli Khalaf (2016). Then, Eq. (4.28) and Constraint (4.32) are replaced by Eq. (4.35) and Constraint (4.36). As indicated by Eqs. (4.37) to (4.40) and Eqs. (4.41) to (4.44), if $x_f = 0$, the auxiliary variables become zero. Otherwise, ι_f and χ_f are equal to β and ρ, respectively.

$$Max\, Z_2^r = E[Z_1] - \varphi\left(E[Z_1] - Z_1^l \right) - \eta \sum_m \sum_j \sum_t \left(\delta \left(\frac{d_{mjt}^l + d_{mjt}^c}{2} \right) + (1-\delta) \left(\frac{d_{mjt}^c + d_{mjt}^u}{2} \right) - d_{mjt}^l \right)$$

$$-\pi_1 \sum_m \sum_j \sum_t \left(v_{mjt}^c - \left(1 - \frac{\theta}{2} \right) \left(\frac{v_{mjt}^l + v_{mjt}^c}{2} \right) - \left(\frac{\theta}{2} \right) \left(\frac{v_{mjt}^c + v_{mjt}^u}{2} \right) \right)$$

$$-\pi_2 \sum_m \sum_j \sum_t \left(\left(1 - \frac{\theta}{2} \right) \left(\frac{v_{mjt}^c + v_{mjt}^u}{2} \right) + \left(\frac{\theta}{2} \right) \left(\frac{v_{mjt}^l + v_{mjt}^c}{2} \right) - v_{mjt}^l \right)$$

$$-\Delta \sum_f \sum_n \left(\chi_f \left(\frac{H_{fn}{}^l + H_{fn}{}^c}{2} \right) + \left(x_f - \chi_f \right) \left(\frac{H_{fn}{}^c + H_{fn}{}^u}{2} \right) - H_{fn}{}^l x_f \right) \tag{4.35}$$

$$-\gamma \left(\left(\varsigma^c + \frac{\left(\varsigma^u - \varsigma^c \right) - \left(\varsigma^c - \varsigma^l \right)}{3} \right) (1-\alpha) \right) - \sigma \sum_f \left(\left(\tau^c + \frac{\left(\tau^u - \tau^c \right) - \left(\tau^c - \tau^l \right)}{3} \right) \left(x_f - \iota_f \right) \right)$$

s.t.

$$\sum_{r}\sum_{n}V_{rfnt\omega}+\sum_{s}\sum_{n}O_{sfnt\omega}\leq\sum_{n}\chi_{f}\left(\frac{H_{fn}{}^{l}+H_{fn}{}^{c}}{2}\right)+\left(x_{f}-\chi_{f}\right)\left(\frac{H_{fn}{}^{c}+H_{fn}{}^{u}}{2}\right)$$

$$+\left(\frac{\tau^{l}+\tau^{c}+\tau^{u}}{3}\right)\left(x_{f}-\iota_{f}\right)\qquad\forall f,t,\omega\qquad(4.36)$$

$$\iota_{f}\leq M\,x_{f},\qquad\forall f\qquad(4.37)$$

$$\iota_{f}\geq M\left(x_{f}-1\right)+\beta,\qquad\forall f\qquad(4.38)$$

$$\iota_{f}\leq\beta,\qquad\forall f\qquad(4.39)$$

$$\iota_{f}\geq 0,\qquad\forall f\qquad(4.40)$$

$$\chi_{f}\leq M\,x_{f},\qquad\forall f\qquad(4.41)$$

$$\chi_{f}\geq M\left(x_{f}-1\right)+\rho,\qquad\forall f\qquad(4.42)$$

$$\chi_{f}\leq\rho,\qquad\forall f\qquad(4.43)$$

$$\chi_{f}\geq 0,\qquad\forall f\qquad(4.44)$$

Constraints (4.1), (4.2), (4.5 to 4.8), (4.10 to 4.15), (4.29 to 4.31), and (4.33).

4.3.2. Values of the parameters and the solutions

In this section, the application of the proposed model is examined using information related to the GTA. 25 major GTA areas are selected as the markets. The middle values of the demand in market *m* associated with product *j* related to period *t* (d_{mjt}) are supposed as one percent of the population of the region in accordance with the 2016 census of Canada. This assumption is consistent with the literature (see, e.g., Fleischmann et al., 2001; Amin and Baki, 2017). Accordingly, the middle values of return in market *m* associated with product *j* related to period *t* (v_{mjt}) are assumed as ten percent of d_{mjt}. The upper and lower values of d_{mjt} and v_{mjt} are computed as a 10 percent increase and decrease of their middle values, respectively. The values of other parameters used in the mathematical model are illustrated in Table 4.B.1 in Appendix 4.B. The values of these parameters are set according to the observed GTA case.

The proposed mathematical model has been programmed and solved using IBM ILOG CPLEX 12.8.0. The optimization problem includes 5,321 constraints, 32,108 decision variables, 47 binary variables, and 264,521 non-zero coefficients. The CPU time required to solve the proposed model was 29 seconds. The solutions of the proposed model, including the value of the objective function, the selected collection centers, recovery center, suppliers, remanufacturing plants, and retailers, along with the positive values of variables for products and components, are provided in Table 4.5.

Table 4.5
Solutions for the scenario-based robust possibilistic model

Objective value ($E[Z_1]$)	Selected collection centers	Selected recovery center	Selected suppliers	Selected remanufacturing plants	Selected retailers
19,260,584	q_2 : Mississauga q_3 : Brampton q_{10} : Toronto q_{14} : Richmond Hill	w_5 : Mississauga	y_1 : Toronto y_2 : Toronto y_5 : Mississauga	x_3: Mississauga x_4 : Toronto	z_1 : Toronto z_3 : Brampton z_7 : Markham

For all n = 1 to 5; t = 1, 2; ω = 1 to 5; j = 1 to 3:
$O_{1\,4nt\omega}$ = 2,500,000, $O_{2\,4nt\omega}$ = 375,000, $O_{5\,3nt\omega}$ = 1,432,455.
$P_{3\,3jt\omega}$ = 315,371, $P_{4\,1jt\omega}$ = 439,610, $P_{4\,7jt\omega}$ = 135,390.
$X_{1\,1jt\omega}$ = 389,250, $X_{1\,9jt\omega}$ = 13,080, $X_{1\,10jt\omega}$ = 17,055, $X_{1\,11jt\omega}$ = 22,725, $X_{1\,18jt\omega}$ = 3,495, $X_{1\,21jt\omega}$ = 1,658, $X_{1\,22jt\omega}$ = 13,110, $X_{3\,2jt\omega}$ = 102,825, $X_{3\,3jt\omega}$ = 84,592, $X_{3\,4jt\omega}$ = 9,480, $X_{3\,5jt\omega}$ = 27,615, $X_{3\,6jt\omega}$ = 26,123, $X_{3\,7jt\omega}$ = 15,690, $X_{3\,8jt\omega}$ = 8,715, $X_{3\,12jt\omega}$ = 43,635, $X_{7\,13jt\omega}$ = 46,883, $X_{7\,14jt\omega}$ = 27,787, $X_{7\,15jt\omega}$ = 6,533, $X_{7\,16jt\omega}$ = 7,897, $X_{7\,17jt\omega}$ = 12,000, $X_{7\,19jt\omega}$ = 3,420, $X_{7\,20jt\omega}$ = 6,472, $X_{7\,23jt\omega}$ = 3,083, $X_{7\,24jt\omega}$ = 3,022, $X_{7\,25jt\omega}$ = 18,293.
$Q_{2\,2jt\omega}$ = 10,826, $Q_{5\,2jt\omega}$ = 2,906, $Q_{6\,2jt\omega}$ = 2,749, $Q_{18\,2jt\omega}$ = 372, $Q_{1\,3jt\omega}$ = 12,776, $Q_{3\,3jt\omega}$ = 8,906, $Q_{4\,3jt\omega}$ = 1,001, $Q_{7\,3jt\omega}$ = 1,650, $Q_{8\,3jt\omega}$ = 915, $Q_{9\,3jt\omega}$ = 126, $Q_{11\,3jt\omega}$ = 32, $Q_{12\,3jt\omega}$ = 4,594, $Q_{1\,10jt\omega}$ = 28,200, $Q_{10\,10jt\omega}$ = 1,800, $Q_{9\,14jt\omega}$ = 1,254, $Q_{11\,14jt\omega}$ = 2,357, $Q_{13\,14jt\omega}$ = 4,935, $Q_{14\,14jt\omega}$ = 2,929, $Q_{15\,14jt\omega}$ = 686, $Q_{16\,14jt\omega}$ = 829, $Q_{17\,14jt\omega}$ = 1,264, $Q_{19\,14jt\omega}$ = 360, $Q_{20\,14jt\omega}$ = 679, $Q_{21\,14jt\omega}$ = 176, $Q_{22\,14jt\omega}$ = 1,380, $Q_{23\,14jt\omega}$ = 326, $Q_{24\,14jt\omega}$ = 315, $Q_{25\,14jt\omega}$ = 1,924.
$S_{2\,5jt\omega}$ = 16,853, $S_{3\,5jt\omega}$ = 30,000, $S_{10\,5jt\omega}$ = 30,000, $S_{14\,5jt\omega}$ = 19,414.
$L_{5\,1jt\omega}$ = 20,763, $L_{5\,3jt\omega}$ = 3,304.
$V_{5\,3nt\omega}$ = 144,399.
$\lambda_{5nt\omega}$ = 216,599.

As shown in Table 4.5, the obtained solution provides several recommendations to maximize the total profit. These recommendations include the selected locations of the network, the components that should be purchased from suppliers, the products to be offered to markets, and the number of products to be shipped between RL echelons. For example, the number of products shipped to retailer 1 from recovery center 5 (i.e., $L_{5\,1jt\omega}$ = 20,763) and the remanufacturing plant 4 (i.e., $P_{4\,1jt\omega}$ = 439,610) are equal to the number of products shipped from retailer 1 to the markets (i.e., $X_{1\,1jt\omega} + X_{1\,9jt\omega} + X_{1\,10jt\omega} + X_{1\,11jt\omega} + X_{1\,18jt\omega} + X_{1\,21jt\omega} + X_{1\,22jt\omega}$ = 460,373). In this regard, the electronic RL network will be more profitable if the recovery center operates efficiently and fulfills bigger portions of the market demand. The sensitivity analyses associated with the impact of recovery rate and disposal fraction on the total profit are discussed in the next section.

As illustrated in Fig. 4.3, the model has been applied to optimize an electronic RL network in the GTA, using Google Maps to estimate the real driving distances and transportation costs between potential locations. The optimal network includes 4 locations for collection centers, 1 recovery center site, 3 suppliers, 2 remanufacturing plant locations, and 3 retailers.

Fig. 4.3. The selected facility locations in the electronic RL network

If both feasibility robustness and optimality robustness are reached, the obtained solution is called robust. Feasibility robustness is reached when the solutions are feasible for all possible changes in uncertain parameters or degrees of flexible constraints. The optimality robustness is achieved when there is less deviation between all possible changes with the optimal value (Ben-Tal and Nemirovski, 2000). Robust optimization models are able to deal with uncertain parameters by reaching optimal solutions in the bounded uncertainty sets. In this study, the possibilistic approach and scenario-based programming are utilized to define the deviation of uncertain parameters from their nominal values. In most cases, decision-makers decide about δ, θ, ρ, α, and β parameters. To reach a better value of the objective function, the confidence level of the constraint needs to be decreased. In this situation, the decision-makers are faced with two contradictory objectives: to obtain more satisfactory objective values, or to improve the confidence level of constraints. Penalty costs have been employed to optimize the satisfaction levels of constraints. In this respect, some sensitivity analyses are conducted for various values of penalty costs to show the robustness of the proposed model. Table 4.6 indicates the feasibility and optimality robustness while the associated parameters are changed.

Table 4.6
Sensitivity analyses of φ, η, γ, π_1, π_2, Δ, σ

Results of the optimization problem		Remark
$E[Z_1]$	19,260,585	1. The objective value had no deviation, while we changed φ from 0.15 to 0.90 (other penalty costs were fixed).
$\delta = \alpha = \beta = \rho = \theta$	1	2. The objective value had no deviation, while we changed η and γ from 100 to 350 (other penalty costs were fixed).
Collection centers	q_2 , q_3 , q_{10} , q_{14}	
Recovery center	w_5	3. The objective value had no deviation, while we changed π_1 and π_2 from 100 to 350 (other penalty costs were fixed).
Suppliers	y_1, y_2 , y_5	
Remanufacturing plants	x_3, x_4	4. The objective value had no deviation, while we changed Δ and σ from 100 to 350 (other penalty costs were fixed).
Retailers	z_1 , z_3 , z_7	

In the proposed method, fulfilling the confidence level of constraints (i.e., $\delta = \alpha = \beta = \rho = \theta = 1$) is the first priority. According to the type of problem and the associated risk level, the upper range of the confidence level is determined by decision-makers. As indicated in Table 4.7, the value of the objective function is increased while the degrees of feasibility are decreased from 1 to 0.5. It is worth noting that the minimum confidence levels must be greater than 0.5 to make sure that the constraints are not violated.

Table 4.7
Changing the degree of feasibility while the other parameters are fixed

Confidence levels	$\delta = \alpha = \beta = \rho = \theta \leq 1$	$\delta = \alpha = \beta = \rho = \theta \leq 0.9$	$\delta = \alpha = \beta = \rho = \theta \leq 0.8$	$\delta = \alpha = \beta = \rho = \theta \leq 0.7$	$\delta = \alpha = \beta = \rho = \theta \leq 0.6$	$\delta = \alpha = \beta = \rho = \theta \leq 0.5$
$E[Z_1]$	19,260,584	20,119,814	20,986,374	21,852,649	22,718,925	23,585,201
$\delta = \alpha = \beta = \rho = \theta$	1	0.9	0.8	0.7	0.6	0.5

4.3.3. Sensitivity analyses

Table 4.8 summarizes the impact of the recovery rate and disposal fraction on the total expected profit ($E[Z_1]$) of the electronic RL network. As mentioned previously, 5 scenarios have been considered for disposal fraction, which are demonstrated separately in each column. The last column is associated with the solutions of the scenario-based robust possibilistic model that includes all scenarios simultaneously. As disposal fraction ($\varepsilon_{n\omega}$) increases, the profit of the RL decreases. In addition, by increasing the recovery rate of the returned products, the profit of the RL increases. Therefore, the quality of the returned products, along with the efficiency in the product recovery, play prominent roles in the profitability of the RL network.

Table 4.8
The total expected profits associated with different recovery rates and disposal fraction

$\varepsilon_{n\omega}$ / υ_j	$\varepsilon_{n0.2}$	$\varepsilon_{n0.4}$	$\varepsilon_{n0.6}$	$\varepsilon_{n0.8}$	ε_{n1}	Proposed model
0.15	19,632,858	19,364,299	19,096,592	18,828,886	18,567,341	19,096,592
0.35	19,833,470	19,628,754	19,424,037	19,219,320	19,015,178	19,424,037
0.55	20,037,568	19,894,343	19,751,118	19,610,289	19,467,489	19,751,118
0.75	20,249,391	20,169,822	20,090,253	20,010,684	19,931,116	20,090,257

Table 4.9 includes the sensitivity analyses of the solutions with regard to the variation of the demand and return. The total profit of each case is compared against the original optimal value (e.g., (21,273,427 - 19,260,584)/19,260,584 = 10.45%). It is evident that the total profit becomes greater as the demand increases since more products can be sold to the market. Furthermore, there will be more cost-saving opportunities associated with a higher return rate. This is because the remanufacturing plants can utilize more recoverable parts from returned products instead of purchasing new components from suppliers.

Table 4.9
Sensitivity analyses on demand and return

Cases	Objective value	Change %
1. 10% increase in demand and return	$E[Z_1]$ = 21,273,427	10.45%
2. 10% increase in demand and 10% decrease in return	$E[Z_1]$ = 21,264,125	10.40%
3. 10% decrease in demand and 10% increase in return	$E[Z_1]$ = 17,262,654	-10.37%
4. 10% decrease in demand and return	$E[Z_1]$ = 17,253,791	-10.42%
5. 10% increase in demand, while return is not changed	$E[Z_1]$ = 21,265,370	10.41%
6. 10% decrease in demand, while return is not changed	$E[Z_1]$ = 17,254,817	-10.41%
7. 10% increase in return, while demand is not changed	$E[Z_1]$ = 19,269,059	0.04%
8. 10% decrease in return, while demand is not changed	$E[Z_1]$ = 19,259,558	-0.01%

Table 4.10 shows that the number of selected facilities may vary by changing the demand and return. As seen in this table, unsurprisingly, more facilities are required to fulfill the market demand when the demand and return increase. The results of the sensitivity analyses on the capacity of facilities are intuitive, as illustrated in Table 4.11. As results suggest, there is a need for fewer facilities by increasing the capacity levels. However, it should be noted that increasing the capacity of facilities does not automatically translate into higher profits. We discuss this point further, as an important managerial implication, in Section 4.7.

Table 4.10
Variation of the selected facilities by changing demand and return

Cases	Objective value	Change %	Selected facilities *
1. 50% decrease in demand and return	$E[Z_1]$ = 9,521,952	-50.56%	CC: q_3 , q_{10} – RC: w_5 – S: y_1 – RP: x_4 – R: z_1
2. 35% decrease in demand and return	$E[Z_1]$ = 12,451,310	-35.35%	CC: q_2 , q_3 , q_{10} – RC: w_5 – S: y_1, y_2 – RP: x_4 – R: z_1, z_7
3. 20% decrease in demand and return	$E[Z_1]$ = 15,228,379	-20.94%	CC: q_2 , q_3 , q_{10} – RC: w_5 – S: y_1, y_5 – RP: x_3, x_4 – R: z_1 , z_3 , z_7
4. 5% decrease in demand and return	$E[Z_1]$ = 18,255,086	-5.22%	CC: q_2 , q_3 , q_{10} , q_{14} – RC: w_5 – S: y_1, y_2 , y_5 – RP: x_3, x_4 – R: z_1 , z_3 , z_7
5. 5% increase in demand and return	$E[Z_1]$ = 20,263,626	5.21%	CC: q_2 , q_3 , q_{10} , q_{14} – RC: w_5 – S: y_1, y_2 , y_5 – RP: x_3, x_4 – R: z_1 , z_2 , z_3 , z_7
6. 20% increase in demand and return	$E[Z_1]$ = 23,291,872	20.93%	CC: q_2 , q_3 , q_{10} , q_{14} – RC: w_5 – S: y_1, y_2 , y_5 – RP: x_3, x_4 – R: z_1 , z_2 , z_3 , z_7
7. 35% increase in demand and return	$E[Z_1]$ = 25,217,529	30.93%	CC: q_2 , q_3 , q_{10} , q_{14}, , q_{18} – RC: w_5 – S: y_1, y_2 , y_5 – RP: x_3, x_4 – R: z_1 , z_2 , z_3 , z_7
8. 50% increase in demand and return	$E[Z_1]$ = 29,053,855	50.85%	CC: q_2 , q_3 , q_{10} , q_{14}, , q_{18} – RC: w_5 – S: y_1, y_2 , y_5 – RP: x_1, x_3, x_4 – R: z_1 , z_2 , z_3 , z_7

* Collection centers (CC), recovery centers (RC), suppliers (S), remanufacturing plants (RP), retailers (R)

Table 4.11
Sensitivity analyses on capacity of facilities

Cases	Objective value	Change %	Selected facilities *
1. 50% decrease in capacity of facilities	$E[Z_1]$ = 18,213,113	-5.44%	CC: q_1, q_2, q_3, q_4, q_{10}, q_{18}, q_{21} – RC: w_5 – S: y_1, y_2, y_5, y_6 – RP: x_1, x_3, x_4 – R: z_1, z_3, z_7
2. 35% decrease in capacity of facilities	$E[Z_1]$ = 18,868,785	-2.03%	CC: q_1, q_2, q_3, q_{10}, q_{14} – RC: w_5 – S: y_1, y_2, y_5 – RP: x_1, x_3, x_4 – R: z_1, z_3, z_7
3. 20% decrease in capacity of facilities	$E[Z_1]$ = 19,216,406	-0.23%	CC: q_2, q_3, q_{10}, q_{14}, q_{18} – RC: w_5 – S: y_1, y_2, y_5 – RP: x_3, x_4 – R: z_1, z_2, z_3
4. 5% decrease in capacity of facilities	$E[Z_1]$ = 19,244,435	-0.08%	CC: q_2, q_3, q_{10}, q_{14} – RC: w_5 – S: y_1, y_2, y_5 – RP: x_3, x_4 – R: z_1, z_2, z_3, z_7
5. 5% increase in capacity of facilities	$E[Z_1]$ = 19,272,764	0.06%	CC: q_2, q_3, q_{10}, q_{14} – RC: w_5 – S: y_1, y_2, y_5 – RP: x_3, x_4 – R: z_1, z_3, z_7
6. 20% increase in capacity of facilities	$E[Z_1]$ = 19,294,625	0.18%	CC: q_2, q_3, q_{10} – RC: w_5 – S: y_1, y_2, y_5 – RP: x_3, x_4 – R: z_1, z_3, z_7
7. 35% increase in capacity of facilities	$E[Z_1]$ = 19,308,582	0.25%	CC: q_2, q_3, q_{10} – RC: w_5 – S: y_1, y_5 – RP: x_3, x_4 – R: z_1, z_3, z_7
8. 50% increase in capacity of facilities	$E[Z_1]$ = 19,025,149	-1.22%	CC: q_2, q_3, q_{10} – RC: w_5 – S: y_1, y_2 – RP: x_4 – R: z_1, z_7

* Collection centers (CC), recovery centers (RC), suppliers (S), remanufacturing plants (RP), retailers (R)

4.4. Evaluating the proposed solution approach

As discussed previously, the main feature of the proposed scenario-based robust possibilistic (SRP) model is to assist with strategic decisions under uncertainty of various input parameters. To verify the performance of the proposed SRP model, we conducted a Monte Carlo simulation and generated a series of numerical experiments (e.g., Jato-Espino et al., 2014). Then, we employed an ANOVA test to compare the means of the SRP and simulated deterministic (SD) models. As mentioned in Subsection 4.3.1, the solution approach has been introduced to address uncertain parameters, such as demand, return, and remanufacturing plant capacities. In the SRP model, TFNs have been incorporated to deal with uncertainty. In this regard, Beta distribution is utilized to simulate TFNs due to its similarity to triangular distribution (Johnson, 1997). The beta distribution is defined in terms of α and β which are two parameters (Walck, 1996). Eqs. (4.45) and (4.46) are applied to estimate the mean and the variance of Beta distribution in the interval [V^l, V^u].

$$\mu = V^l + \left(V^u - V^l\right)\left(\frac{\alpha}{\alpha+\beta}\right) \tag{4.45}$$

$$\sigma^2 = \left(\frac{\alpha}{\alpha+\beta}\right)\left(\frac{\beta}{\alpha+\beta}\right)\left(\frac{\left(V^u - V^l\right)^2}{\alpha+\beta+1}\right) \tag{4.46}$$

α and β related to TFN (V^l minimum, V^m average, V^u maximum) can be obtained through Eqs. (4.47) and (4.48). For further information, interested readers can refer to Davis (2008).

$$\alpha = \left(\frac{2\left(V^u + 4\left(V^m\right) - 5\left(V^l\right)\right)}{3\left(V^u - V^l\right)}\right)\left(1 + 4\left(\frac{\left(V^m - V^l\right)\left(V^u - V^m\right)}{\left(V^u - V^l\right)^2}\right)\right) \tag{4.47}$$

$$\beta = \left(\frac{2\left(5\left(V^u\right) - 4\left(V^m\right) - V^l\right)}{3\left(V^u - V^l\right)}\right)\left(1 + 4\left(\frac{\left(V^m - V^l\right)\left(V^u - V^m\right)}{\left(V^u - V^l\right)^2}\right)\right) \tag{4.48}$$

To apply the simulation, random values for uncertain parameters are generated in Microsoft Excel by application of BETAINV (RAND (), α, β, V^l, V^u) function. The computed BETAINV function associated with each TFN is replicated 1,000 times. Then, minimums, averages, and maximums of the simulated numbers are estimated for TFNs (i.e., category of demand, return, and remanufacturing capacity). Table 4.12 represents the optimal values, means, and standard deviations of ten numerical experiments for the SD and SRP models.

Table 4.12
Comparison between the simulated deterministic model and the scenario-based robust possibilistic model

Experiment	SD model	SD computational time (seconds)	SRP model	SRP computational time (seconds)
1	19,412,288	7.26	19,412,528	29.85
2	19,408,218	6.01	19,411,241	28.95
3	19,378,087	7.00	19,379,200	12.02
4	19,374,360	6.87	19,374,771	43.76
5	19,374,779	14.45	19,377,532	23.22
6	19,424,030	7.47	19,423,650	27.80
7	19,407,858	16.01	19,409,704	27.06
8	19,404,934	6.92	19,403,529	23.02
9	19,422,846	9.16	19,423,293	29.21
10	19,419,652	8.33	19,420,489	47.35
Mean	19,402,705		19,403,594	
Std. Deviation	19,694		19,312	

Table 4.13 indicates the results of the ANOVA test. There is not a significant difference between the means of the SD and the SRP models, since the P-value is equal to 0.920. We verified that the SRP model performs similarly to the SD model with 1,000 replications. Therefore, it is worthy to note that the SRP approach enables decision-makers to reach optimal solutions in uncertain situations without time-consuming mathematical simulations.

Table 4.13
Summary of the ANOVA test computed by IBM SPSS Statistics (V24)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3,947,161.250	1	3,947,161.250	0.010	0.920
Within Groups	6,847,136,108	18	380,396,450.4		
Total	6,851,083,269	19			

4.5. An extension to the multi-objective model

Eq. (4.49) is utilized to optimize the environmental compliance of third parties. To this aim, three qualitative parameters are considered including K_{sn}, M_{fn}, and N_{rn} as the indicators of the green performances of suppliers, remanufacturing plant(s), and electronic recovery center(s), respectively. K_{sn} represents the green practices employed by Supplier s to provide the supplementary module n required for remanufacturing. M_{fn} displays the green practices used by the potential plant f to remanufacture electronics by assembling n components. N_{rn} indicates the green practices of the recovery center r to recover the returned products and recycle n components via disassembling the unrecoverable products. In this study, a fuzzy TOPSIS method is adopted to prioritize the facilities based on their green practices. This type of multiple-criteria decision-making (MCDM) analysis is suitable for conducting a systematic comparison between different alternatives while uncertainty may interfere with an expert's judgment (Kannan et al., 2014). The related calculations to determine K_{sn}, M_{fn}, and N_{rn} are provided in Appendix 4.C.

$$
\begin{aligned}
& Max\ Z_3 = \sum_s \sum_n K_{sn} \left(\sum_f \sum_t \sum_\omega O_{sfntw} \right) + \\
& \sum_f \sum_n M_{fn} \left(\sum_s \sum_t \sum_w O_{sfntw} + \sum_r \sum_t \sum_\omega V_{rfnt\omega} + \sum_i \sum_j \sum_t \sum_\omega \left(P_{fijt\omega} \right) I_{jn} \right) \qquad (4.49) \\
& + \sum_r \sum_n N_{rn} \left(\left(\sum_c \sum_j \sum_t \sum_\omega S_{crjt\omega} + \sum_i \sum_j \sum_t \sum_\omega L_{rijt\omega} \right) I_{jn} + \sum_f \sum_t \sum_\omega V_{rfnt\omega} + \sum_t \sum_\omega \lambda_{rntw} \right)
\end{aligned}
$$

4.6. Two-phase fuzzy compromise approach and the solutions

A multi-objective approach should be utilized when there is no single solution that can optimize all the existing objectives simultaneously. The optimal decisions are made based on a trade-off between different objectives. In this regard, the solutions of the multi-objective problems are known as efficient or non-dominated solutions. The main feature of non-dominated solutions is that the value of each objective function cannot be improved without sacrificing at least another objective function value (Branke et al., 2008; Mirzapour Al-E-Hashem et al., 2011). In this paper, the two-phase fuzzy compromise approach, based on the method of Li et al. (2006) is employed to solve the multi-objective problem. This method is the enhanced version of the max-min approach, and it leads to more precise non-dominated solutions than the max-min approach. To comply with the two-phase fuzzy compromise approach, the following steps are taken:

- In the first step, the maximum (Z_k^{max}) and the minimum (Z_k^{min}) values of each objective are calculated.
- In the second step, the minimum value of each objective is replaced as the initial solution (O_k) in Eq. (4.50), and Model (4.M_1) is solved to achieve an optimal solution x^o with Z^0_k. Then, the membership function of each objective $u_k(x^o)$ from Eq. (4.50) is recalculated.

$$u_k(x) = \begin{cases} 1, & Z_k(x) > Z_k^{max}, \\ 1 - \dfrac{Z_k^{max} - Z_k(x)}{Z_k^{max} - O_k} & O_k < Z_k(x) \le Z_k^{max}, \qquad k = 2,3. \\ 0, & Z_k(x) \le O_k, \end{cases} \tag{4.50}$$

$$\begin{aligned} & Max\ \lambda \\ & s.t. \\ & \lambda \le u_k(x), \\ & 0 \le \lambda \le 1, \end{aligned} \tag{4.M_1}$$

Constraints (4.1), (4.2), (4.5 to 4.8), (4.10 to 4.15), (4.29 to 4.31), (4.33), (4.36 to 4.44).

Finally, it is assumed that $\lambda^l_k = u_k(x^o)$, and Model (4.M_2) are solved to generate the efficient solution x^*.

$$
\begin{aligned}
&Max \sum_{k=1}^{N} w_k \lambda_k \\
&s.t. \\
&\lambda_k^l \le \lambda_k \le u_k(x), \\
&0 \le \lambda_k \le 1, \\
&\sum_{k=1}^{N} w_k = 1, \quad 0 < w_k, \qquad (4.M_2)
\end{aligned}
$$

Constraints (4.1), (4.2), (4.5 to 4.8), (4.10 to 4.15), (4.29 to 4.31), (4.33), (4.36 to 4.44).

As shown in Table 4.14, the maximum and the minimum of each objective are calculated separately. By solving Model (4.M_1), λ = 0.78, $Z^0{}_2$ = 9,891,800, $Z^0{}_3$ = 9,995,400, and $u_2(x^o) = u_3(x^o)$ = 0.78. Furthermore, the maximum and minimum values of total expected profit (Z_1) are 19,260,585 and 3,804,657, respectively while $\delta = \alpha = \beta = \rho = \theta = 1$.

Table 4.14
The maximum and the minimum of each objective

Objective function	Z^{max}	Z^{min}
Z_2^r	12,671,470	0
Z_3	12,389,439	1,475,624

As evidenced by Table 4.15, Model (4.M_2) is computed with different combinations of w_k. Then, two efficient solutions are obtained for Z_2^r and Z_3. The obtained total expected profit (Z_1) is 21,074,000 for w_1 = 0.3, w_2 = 0.7, 21,375,000 and for w_1 = 0.8, w_2 = 0.2.

Table 4.15
Efficient solutions associated with different combinations of w_k

Objective function	w_1 = 0.3, w_2 = 0.7	w_1 = 0.8, w_2 = 0.2
Z_2^r	9,883,700	10,191,000
Z_3	10,118,000	9,988,400
Degree of feasibility	δ = 0.5, α = 0.773, $\beta = \rho = \theta = 1$	δ = 0.5, α = 0.821, $\beta = \rho = \theta = 1$

Fig. 4.4 illustrates the impact of robustness price on non-dominated solutions of the bi-objective model. The application of the robust approach imposes a cost called the “robustness price” (Talaei et al., 2016). This type of cost is allocated to the system for the purpose of facing the uncertainties. Therefore, the solutions obtained in deterministic modes incur less cost in comparison with robust modes.

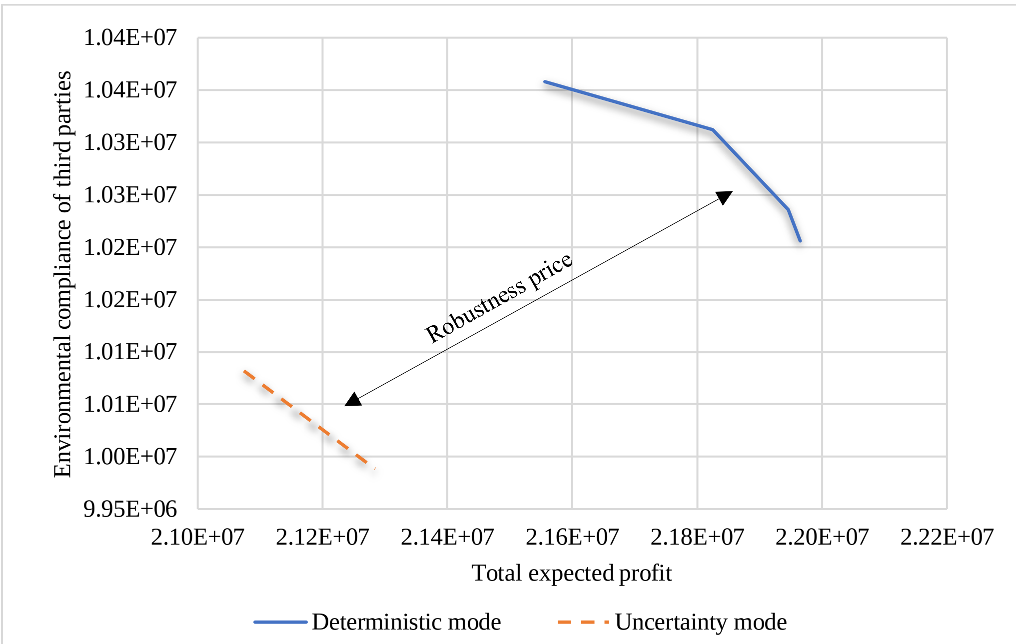

Fig. 4.4. Impact of robustness price on the non-dominated solutions of bi-objective model

4.7. Managerial implications

Nowadays, electronic stewardship programs are experiencing growing attention for two reasons. First, several companies have attempted to contribute to recovery activities by delivering a green image of their products (Alumur et al., 2012; John et al., 2018). Second, government policies and environmental regulations have urged producers to design eco-friendly business frameworks (Hafezi and Zolfagharinia, 2018). This study offers valuable insights for managers. As demonstrated in Section 4.3.1, there are a variety of parameters (e.g., fixed and variable costs, demand, return, capacities of facilities and quality of the returned products) involved in an electronic RL network which can be uncertain in the real world. Some of those parameters are interrelated (e.g., uncertainty in demand, return, and the capacities of facilities), and are difficult to address with deterministic models. Therefore, managers can apply the proposed method to configure RL networks considering uncertainty for several parameters simultaneously.

In Section 4.3.3, we provided the results of the sensitivity analyses on the capacity of facilities (see Table 4.11). Based on the obtained results, the capacities of facilities have a direct impact on the RL network. As the capacity increases, fewer facilities are required to fulfill the market demand. For example, the total selected facilities drop from 18 to 9 when moving from Case 1 to Case 8. In this regard, the distances between facilities increase, and consequently, the transportation costs will elevate.

To illustrate this behaviour, we compared the distances between 3 tiers (i.e., retailers, markets, and collection centers) of the multi-echelon network for different capacity levels. Fig. 4.5 and Fig. 4.6 depict the optimal networks and distances between the selected echelons for Case 8 of Table 4.11 and the original solutions (Table 4.5). As shown in Fig. 4.5, the selected retailers decreased from 3 (in the original case) to 2 (in Case 8 of Table 4.11) by increasing the capacity levels of facilities. As a result, the fixed-cost associated with open facilities decreased while the transportation cost grew due to the distance increase. The red dotted lines demonstrate how distances between the locations are extended by reducing the number of retailers. For example, the distance between the retailer in Brampton (z_3) to the market m^* is less than the distance between the retailer in Toronto (z_1) to m^*. Fig. 4.6 illustrates the same concept between the market m^{**} and the q_3 and q_{14} collection centers in the reverse flow. Therefore, an increase in the capacity of facilities does not necessarily lead to a higher total profit in the RL network. In this regard, decision-makers should apply the proposed model before deciding to increase the capacities of facilities.

In this paper, the bi-objective model is solved with different pairs of distance metrics (w_k). As mentioned previously, the value of one objective function cannot be improved without sacrificing the value of another objective function in the non-dominated solutions of bi-objective models. For example, it has been indicated in Table 4.15 that the value of environmental compliance from the third parties decreased from 10,118,000 to 9,988,400, while the value of the proposed SRP model increased from 9,883,700 to 10,191,000 by changing the distance metric. This provides managers with an opportunity to decide how to compromise between the two objectives based on their supply chain strategies. In addition, the minimum satisfaction level (i.e., α) of the possible violation for the soft constraint of demand has been increased from 0.77 to 0.82. As mentioned before, higher minimum satisfaction levels are more desirable when decision-makers are conservative and not interested in the violation of soft constraints.

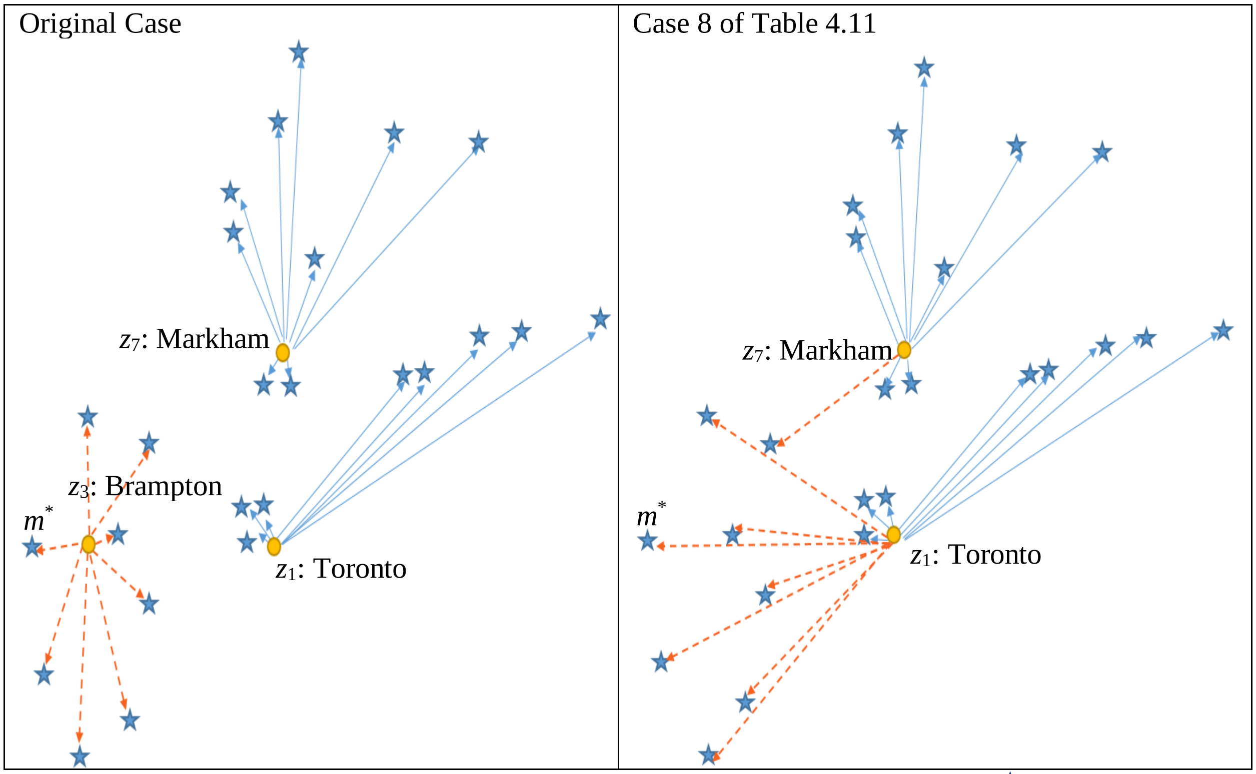

Fig. 4.5. The distances between the locations of retailers and locations of markets based on the real scale.

The connections that stay the same by moving from the original case to Case 8 of Table 4.11

The connections that change by moving from the original case to Case 8 of Table 4.11

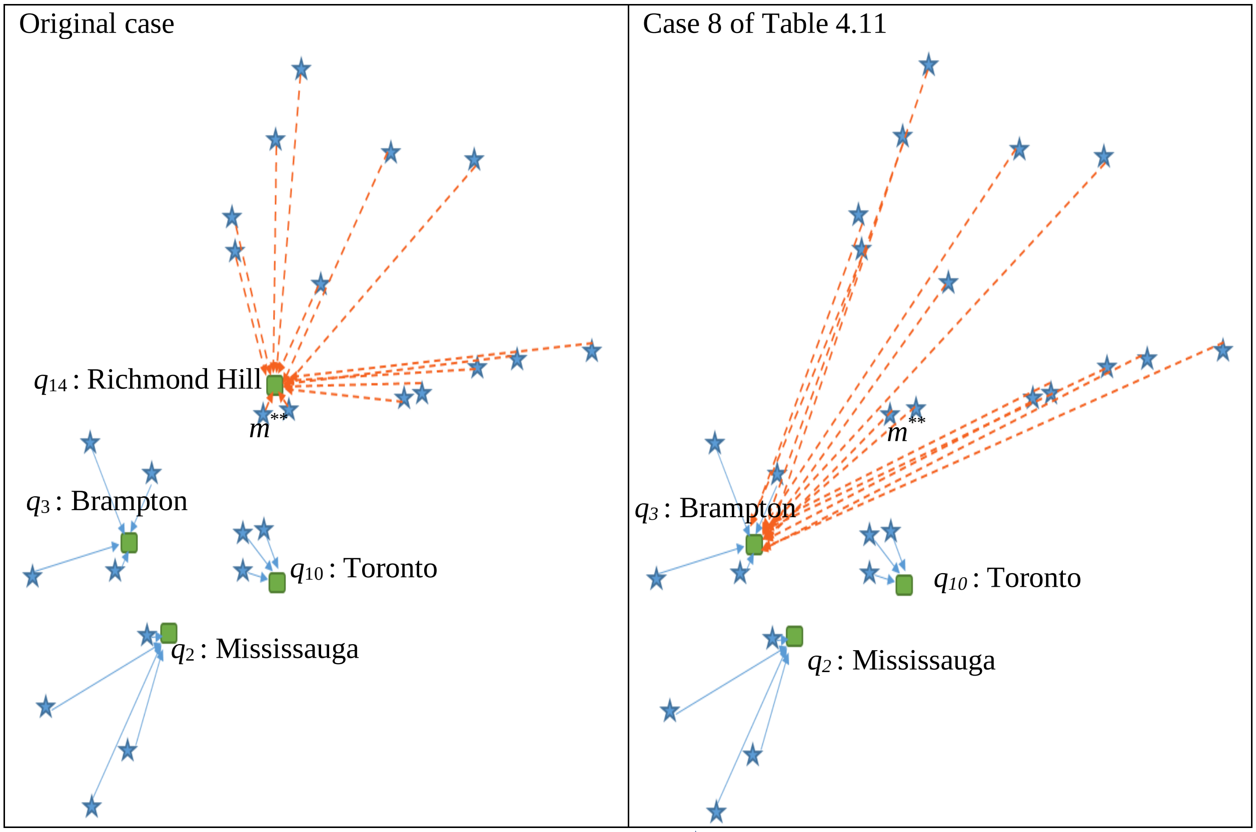

Fig. 4.6. The distances between the locations of markets and locations of collection centers based on the real scale.

The connections that stay the same by moving from the original case to Case 8 of Table 4.11

The connections that change by moving from the original case to Case 8 of Table 4.11

4.8. Conclusions

In this study, a scenario-based robust possibilistic optimization model has been developed and applied to an electronic RL network under uncertainty. The network includes multiple echelons, components, products, and periods. In the proposed mathematical model, each parameter has been defined based on triangular fuzzy numbers to cover the possible ranges of values. The expected value has been applied to deal with the fuzzy objective function, while fuzzy lateral and expected interval have been utilized to convert the fuzzy constraints to the equivalent crisp versions. The scenario-based programming has been integrated with robust possibilistic optimization to consider the role of efficiency in product recovery. To control the feasibility robustness and optimality robustness related to uncertain parameters and flexible constraints, penalty costs have been defined. One of the main advantages of the proposed model, compared to other methods in the literature, is simultaneously considering the feasibility robustness and the optimality robustness for different scenarios. The solutions include the optimal ranges of the objective function and decision variables. The conducted sensitivity analyses have verified the robustness of the proposed model. It has been shown that the increase in the confidence level of constraints has led to a lower value of the objective function (total expected profit). This is intuitive because a large degree of feasibility emphasizes fulfilling the constraints instead of maximizing the objective value.

To handle resource shortages and economic volatility, reducing the defect rate should be taken into account. Therefore, sensitivity analysis has been conducted on disposal fraction for different ranges of recovery rates. According to the findings, the disposal fraction had a major negative impact on the total profit of the RL network. In other words, the efficiency in recycling returned electronics can enhance profitability and reduce environmental issues significantly.

A Monte Carlo simulation has been undertaken to evaluate the performance of our proposed model. Although uncertain parameters are used in the scenario-based robust possibilistic model, the ANOVA test has statistically verified our model. To consider the environmental compliance of the third parties, the optimization model has been extended to a bi-objective model. The two-phase fuzzy compromise approach has been utilized to calculate the efficient solutions for the multi-objective optimization model. Comparing the two non-dominated solutions illustrates that the degree of feasibility (α) deviates from 0.773 to 0.821 by changing the weight factors. In this type of multi-objective problem, choosing an appropriate solution depends on the managerial approach, optimal values, and feasibility robustness associated with the uncertain parameters.

The proposed scenario-based robust possibilistic model combined with the MCDM method offers a new approach for designing an electronic RL network. Some potential research directions emerge from this study. For instance, since one of the main strategies to reduce the environmental impact of RL networks is associated with the transportation sector, transportation strategies can be further considered and examined in this optimization model. Besides, the role of the carbon tax rate and its impact on CO_2 emission can also be investigated in the facility location design. In addition, possibilistic programming methods such as fully fuzzy programming can be utilized to solve the proposed model and compare the results. Other forms of robust optimization, such as ellipsoidal and box uncertainty sets, represent interesting potential methods to address imprecise parameters.

Chapter 5. An ecological multi-objective model to configure a sustainable beverage container reverse logistics network

5.1. Introduction

The business definition of RL is to create value over the entire life cycle of a product through the recovery of used products (Carter and Ellram, 1998; Srivastava, 2008; Dekker et al., 2013; Govindan and Soleimani, 2017; Amin et al., 2018). The RL network design has received great attention due to the economic impact, environmental compliance, and social responsibility (Pishvaee et al., 2010; Kannan et al., 2012; Alumur et al., 2012; Noman and Amin, 2017; Papen and Amin, 2019). On this matter, the optimal configuration of facility location networks provides benefits to the companies involved in reverse flow (i.e., optimizing the resource utilization), and also works in the favor of sustainability (i.e., usage of natural resources wisely and efficiently). The Beverage Container Stewardship Program Regulation (BCSPR) emphasizes on considering environmental factors in beverage container RL networks in Vancouver, Canada. As illustrated in Fig. 5.1, three aspects of economic, environmental, and social must be addressed to design a sustainable RL network. Furthermore, there is a variety of uncertain parameters affecting the configuration of facility location models (Guiffrida and Jaber, 2008; Cardoso et al., 2013; Trochu et al., 2018; Tosarkani and Amin, 2019). In this study, an integrated multi-objective model is developed to address multiple sources of uncertainty for a sustainable beverage container RL network.

Fig. 5.1. The interconnected pillars of sustainability

5.2. Literature review

This section reviews the literature related to facility location design in RL and closed-loop supply chain (CLSC). Jayaraman et al. (1999) applied a MILP model to design a multi-echelon, multi-product RL network. Fleischmann et al. (2001) configured a CLSC with regards to forward facility locations. They applied the copier remanufacturing case study to evaluate the accuracy of the proposed CLSC. Ko and Evans (2007) applied a MILP model for a multi-product, multi-period, two-echelon network. Demirel and Gökçen (2008) used a MILP model to develop a multi-echelon model for a CLSC consisting of manufacturers, distribution centers, customer zones, disassembly, and collection centers.

Gomes et al. (2011) used a generic MILP model to configure an electric and electronic equipment recovery network including private consumers, companies, public services, municipalities, original equipment manufacturer (OEM), private collection, and sorting centers, recycling facilities, and waste incineration. Özceylan and Paksoy (2013) applied a MILP model to design the facility location for a CLSC. Alshamsi and Diabat (2015) mentioned that designing the RL network has received attention on account of different aspects (e.g., economic, environment, and social values). They utilized a MILP model to optimize the total profit of a household RL network. Mohammad-Pajooh et al. (2018) applied a MILP model to configure a facility location model for the purpose of treating flowback water as the result of shale gas hydraulic fracturing.

The lack of precise information adds a level of complexity for the RL network design. Some researchers have addressed this by developing mathematical programming models that account for uncertainty in the parameters. Amin and Zhang (2012) presented a multi-echelon CLSC network consisting of supplier(s), manufacturer(s), distributor(s), retailer(s), customer(s), recycling, and disposal sites. They used a scenario-based MILP model to consider the impact of imprecise demand and return on the total cost.

Kilic et al. (2015) mentioned that the amount of waste has been increased considerably due to the growing consumption in recent years. They utilized a MILP model with different scenarios to handle electronic waste. Ayvaz et al. (2015) used two-stage stochastic programming to maximize the profit for an electronic RL network. Rezaee et al. (2017) employed two-stage stochastic programming to configure an environmental office furniture supply chain. Jin et al. (2018) applied fuzzy logic and non-dominated sorting genetic algorithm (NSGA-II) to consider a location-allocation problem for NdFeB magnet recovery under supply and demand uncertainties. Tosarkani and Amin (2018a) developed a fully fuzzy method to address uncertain fixed and variable costs in a battery CLSC network.

In some RL models, there are not necessarily linear relationships between the parameters and the decision variables. Therefore, finding a solution for the non-linear parts can be managed using mixed-integer non-linear programming (MINLP) models. Miranda and Garrido (2004) presented a multi-echelon network (i.e., plant, central and regional warehouses, retailers, or demand zones). They used an MINLP model to formulate the mathematical model. Kim et al. (2006) introduced a mathematical model for a CLSC to maximize the profit. Min et al. (2006) employed an MINLP model to configure a network including customers, initial collection points, and centralized return centers. Sasikumar et al. (2010) designed a multi-echelon RL network for a case study of a truck tire. They employed an MINLP model to maximize the profit of the proposed model.

In facility location problems, the economic aspect of networks has been conventionally considered as the main objective. However, various factors have an impact on the configuration of facility location models (e.g., environmental issues, social responsibility, and technological innovation of third parties). Pati et al. (2008) formulated a mixed-integer goal programming model for a paper recycling network including vendors, dealers, suppliers, and manufacturers. They proposed a MOM including the total cost of the RL, product quality, and environmental benefits of the recovery process. Bojarski et al. (2009) developed a MOM for a supply chain network. They aimed to optimize the net present value and damage impacts of the network.

Ramezani et al. (2013) formulated a stochastic MOM for designing the facility location for a forward and reverse logistics network. They aimed to maximize the total profit, customer service level, and minimize the defect rate. Bing et al. (2014) designed a MOM to minimize the transportation cost and environmental issues for a plastic waste RL network. Govindan et al. (2016) presented a fuzzy MOM to design a sustainable RL network under uncertainty. Yu and Solvang (2016) presented a MOM to minimize the cost, carbon emissions, resource utilization, and waste for an RL network.

Amin and Baki (2017) presented a multi-objective MILP model to configure a global CLSC with regard to uncertain demand. Amin et al. (2017) applied a decision tree approach to consider different transition probabilities to compute the total expected profit in a tire CLSC network. Tosarkani and Amin (2018b) proposed a multi-objective MILP model to optimize the total profit, on-time delivery, environmental compliance, and reliability of an electronic RL network. Jin et al.

(2019) proposed a bi-objective model consisting of the total profit and environmental benefits for the value recovery of neodymium-iron-boron magnets in the United States. Fakhrzad and Goodarzian (2019) developed a new fuzzy multi-objective programming approach for a production distribution model. The proposed multi-objective model included optimizing the total cost, gas emissions costs, and reliability of delivery demand. Karimi et al. (In Press) designed a multi-objective green closed-loop supply chain (GCLSC) under uncertainty. The objectives were to optimize the total profit, the fill rate of market demand, and the satisfaction of GCLSC stakeholders. Tosarkani et al. (2020) mentioned that the profitability of an RL cannot be sustained unless all the entities involved in the network consider both economic and environmental aspects. They proposed a bi-objective model for an electronic RL network under uncertainty. Table 5.1 includes an overview of some related mathematical models.

Table 5.1
Summary of some papers related to design and optimize CLSC and RL networks

Authors	Multi-product	Multi-period	Multi-objective	Uncertainty	Types of industry	Types of network	Solution approach	Real locations
Demirel and Gökçen (2008)	✓					RL	MILP	
Pati et al. (2008)	✓		✓		Paper recycling	RL	MILP, Goal programming	
Bojarski et al. (2009)	✓	✓	✓		Maleic anhydride	SC	MILP	✓
Sasikumar et al. (2010)		✓			Truck tire	RL	MINLP	✓
Gomes et al. (2011)	✓	✓			Electronic		MILP	✓
Özceylan and Paksoy (2013)	✓	✓				CLSC	MILP	
Bing et al. (2014)	✓		✓		Household plastic	RL	MILP	✓
Kilic et al. (2015)	✓				Electronic		MILP	✓
Govindan et al. (2016)		✓	✓	✓		RL	Fuzzy programming, Particle swarm	✓
Yu and Solvang (2016)			✓			RL	MILP	
Amin and Baki (2017)	✓	✓	✓	✓		CLSC	MILP, Fuzzy programming	✓
Tosarkani and Amin (2018a)	✓	✓	✓	✓	Battery	RL	MILP, Fuzzy programming	✓
Proposed model	✓	✓	✓	✓	Beverage container	RL	Multi-objective stochastic possibilistic programming	✓

According to the review of the related literature, designing and optimizing beverage container RL networks have not been considered in the other academic papers. Furthermore, most studies emphasize on economic and environmental aspects of facility location design. However, social responsibility and technological innovation of third parties may have a significant impact on designing RL networks. In this research, we develop a stochastic possibilistic MOM for a beverage container RL network. This hybrid model is developed for a multi-echelon (multiple suppliers, beverage companies, container recovery centers, markets, regional depots, and disposal center), and multi-product RL in multiple periods. The total cost, carbon emissions, social responsibility, and technological innovation of third parties in the RL network are addressed under uncertainty in different scenarios. In summary, the significant research features of this study are stated as follows:

- Designing and optimizing a new multi-echelon, multi-product, multi-period beverage container RL network taking into consideration several supplier(s), beverage companies, regional depot(s), and container recovery center(s).
- Developing a hybrid optimization model integrating the fuzzy programming approach with scenario-based programming method. The application of the proposed model is demonstrated using real locations in Vancouver, Canada.
- Extending the optimization model to consider multiple objectives. The distances between the facilities affect the transportation costs and CO_2 emissions. Furthermore, establishing a new facility has a significant social impact on the specific geographic region. Therefore, it is required to consider multiple quantitative (e.g., the total cost and CO_2 emissions) and qualitative (e.g., social responsibility and technological innovation) objectives to design a sustainable RL network.
- Computing the non-dominated solutions for the proposed hybrid MOM. The various objectives may have conflict and have different impact on the network. In this regard, first, we illustrate the selected facilities for the proposed MOM, and then two bi-objective models (i.e., total cost and CO_2 emissions, total cost, and social responsibility and technological innovation of third parties) are considered to investigate the impact of different objectives on selected facilities.

Fig. 5.2 illustrates the overall framework of developing the multi-objective scenario-based possibilistic model. In the 1st Step, a deterministic optimization model is introduced to design a beverage container RL network. In the 2nd Step, the deterministic mathematical model is advanced to the scenario-based possibilistic model to address uncertainty. In the 3rd Step, the non-dominated solutions of the MOM are computed to indicate the trade-off surface between the objectives.

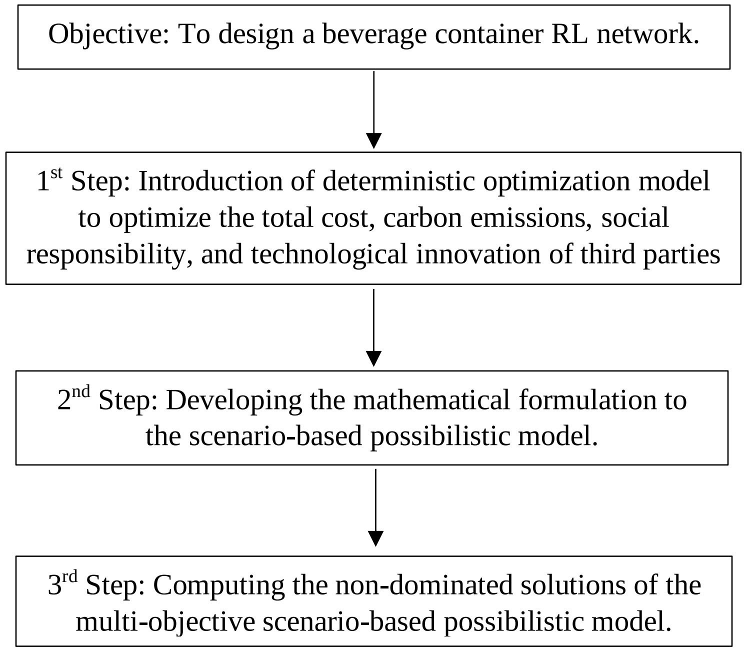

Fig. 5.2. The overall approach to develop the multi-objective scenario-based possibilistic model

The structure of this study is organized as follows: Section 5.3 is associated with the problem statement. In Section 5.4, solution methodologies (i.e., optimization model, sensitivity analyses, and the distance technique to reach the non-dominated solutions) are presented. Managerial implications are discussed in Section 5.5. Finally, Section 5.6 is devoted to the conclusions.

5.3. Problem statement

There is a great deal of concern related to the growing rate of the discarded beverage containers in the environment. Encorp Pacific (Canada) is the not-for-profit stewardship agency that supervises the recycling processes of beverage containers. With this respect, there are many third parties involving in the recovery plans across British Columbia (one of the provinces of Canada). As a result of Encorp's stewardship plan, 101.9 thousand tonnes of CO_2 emissions were reduced in 2016 (Encorp annual report, 2016). In British Columbia, 98.6% of the population has access to a regional return depot. The used aluminum cans collected by the regional depots are transported to a facility to be melted and converted to the sheets for producing new cans. The large portions of CO_2 emissions stem mostly from transportation. It is noticeable that different types of fixed and variable costs are associated with this recovery plan. In this regard, the program efficiency has a significant impact on the reduction of the total cost and CO_2 emissions. In this problem, we focus on Vancouver municipal areas as illustrated in Fig. 5.3.

Fig. 5.3. Municipal districts in Vancouver (Areas of the city, 2018)

Fig. 5.4 shows a multi-echelon, multi-period, multi-product beverage container RL network. The regional collection depot(s) collect the used beverage containers from the customers and send them to the container recovery center(s). The recovery process is provided for the used containers. As mentioned before, the used cans are converted into the aluminum sheets. There are different ratios of recovery rate due to the efficiency of the recovery center(s) and the quality of the used items. In this study, it is assumed that the recovery center(s) are parts of the plants that produce new cans. The aluminum cans produced by the recovery center(s) are shipped to the beverage companies, and the unrecoverable amounts are transferred to the disposal center. The beverage companies may send the order to the supplier(s) due to the shortage of containers provided by the recovery center(s). Finally, the beverage companies are responsible to fulfill the market demand. In this study, we aim to consider the total cost and environmental concerns (e.g., carbon emissions) social responsibility and technological innovation of third parties associated with this plan by answering the following questions:

- Which supplier(s), container recovery center(s), beverage companies, regional depot(s) must be selected?
- How many cans must be purchased by the beverage companies from the supplier(s) to fulfill the market demand (based on the capability of the recovery center(s) to recycle the beverage containers)?

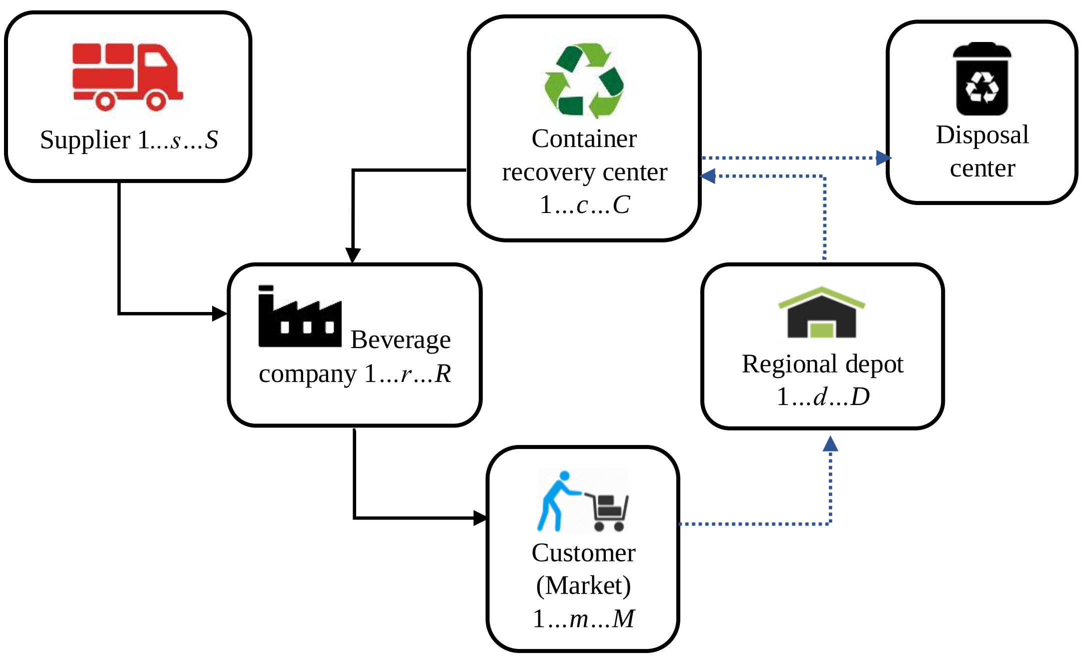

Fig. 5.4. The beverage container RL network

5.4. Optimization model

A mixed-integer linear programming model is defined to minimize the total cost and the carbon emissions of the proposed network. The required sets, parameters, and decision variables are employed as follows:

Sets

I = set of cans ($i \in I$)

S = set of suppliers ($s \in S$)

R = set of beverage companies ($r \in R$)

C = set of container recovery centers ($c \in C$)

M = set of customers (markets) ($m \in M$)

D = set of regional depots ($d \in D$)

T = set of periods ($t \in T$)

Parameters

A_c = cost of agreement (i.e., fixed-cost) with container recovery center c

B_r = cost of agreement (i.e., fixed-cost) with beverage company r

E_s = cost of agreement (i.e., fixed-cost) with supplier s

F_d = cost of agreement (i.e., fixed-cost) with regional depot d

G_i = purchasing cost of can i from suppliers

H_i = recovery cost related to can i

O_i = unit cost of transportation per Km associated with can i

L_{sr} = distance between locations s and r

L_c = distance between recovery center c and disposal center

J_i = cost saving of can i due to recovery process

K_i = disposal cost of can i

N_{mit} = demand of customer (market) m for can i associated with period t

e_i = disposal rate of can i

P_{mit} = return of can i related to customer (market) m associated with period t

f_{ci} = maximum capacity of container recovery center c for can i

k_{ri} = maximum capacity of beverage company r for can i

p_{si} = maximum capacity of supplier *s* for can *i*

l_{di} = maximum capacity of regional depot *d* for can *i*

g = truck capacity

u = truck CO_2 emissions per km

ζ_{si} = social responsibility and technological innovation of supplier *s* to provide can *i*

ξ_{ci} = social responsibility and technological innovation of container recovery center *c* to recover can *i*

Decision Variables

U_{srit} = number of can *i* shipped to beverage company *r* by supplier *s* associated with period *t*

V_{crit} = number of can *i* recovered by container recovery center *c* for beverage company *r* associated with period *t*

W_{rmit} = number of can *i* sent by beverage company *r* to market *m* associated with period *t*

X_{mdit} = number of can *i* returned from market *m* to regional depot *d* associated with period *t*

Y_{dcit}= number of used can *i* shipped to container recovery center *c* from regional depot *d* associated with period *t*

Z_{cit} = number of unrecoverable can *i* shipped to disposal center from container recovery center *c* associated with period *t*

w_r = 1, if the beverage company is located and set up at potential site *r*, 0, otherwise.

x_c = 1, if the container recovery center is located and set up at potential site *c*, 0, otherwise.

y_d = 1, if the regional depot is located and set up at potential site *d*, 0, otherwise.

v_s = 1, if the supplier *s* is selected, 0, otherwise.

$$
\begin{aligned}
Min\ z_1 = & \sum_d\sum_c\sum_i\sum_t (H_i + O_i L_{dc}) Y_{dcit} + \sum_c\sum_r\sum_i\sum_t (-J_i + O_i L_{cr}) V_{crit} + \sum_s\sum_r\sum_i\sum_t (G_i + O_i L_{sr}) U_{srit} \\
& + \sum_r\sum_m\sum_i\sum_t O_i L_{rm} W_{rmit} + \sum_m\sum_d\sum_i\sum_t O_i L_{md} X_{mdit} + \sum_c\sum_i\sum_t (K_i + O_i L_c) Z_{cit} \\
& + \sum_r B_r w_r + \sum_c A_c x_c + \sum_d F_d y_d + \sum_s E_s v_s
\end{aligned}
$$

$$
Min\ z_2 = u \left(\begin{aligned} & \sum_s\sum_r\sum_i\sum_t \left(\frac{U_{srit}}{g}\right) L_{sr} + \sum_r\sum_m\sum_i\sum_t \left(\frac{W_{rmit}}{g}\right) L_{rm} + \sum_m\sum_d\sum_i\sum_t \left(\frac{X_{mdit}}{g}\right) L_{md} \\ & + \sum_d\sum_c\sum_i\sum_t \left(\frac{Y_{dcit}}{g}\right) L_{dc} + \sum_c\sum_r\sum_i\sum_t \left(\frac{V_{crit}}{g}\right) L_{cr} + \sum_c\sum_i\sum_t \left(\frac{Z_{cit}}{g}\right) L_c \end{aligned} \right)
$$

$$Max\ z_3 = \sum_s \sum_i \zeta_{si} \left(\sum_r \sum_t U_{srit} \right) + \sum_c \sum_i \xi_{ci} \left(\sum_d \sum_t Y_{dcit} + \sum_r \sum_t V_{crit} + \sum_t Z_{cit} \right)$$

s.t.

$$\sum_m W_{rmit} = \sum_s U_{srit} + \sum_c V_{crit} \qquad \forall r,i,t \qquad (5.1)$$

$$\sum_r W_{rmit} \geq N_{mit} \qquad \forall m,i,t \qquad (5.2)$$

$$\sum_d X_{mdit} = P_{mit} \qquad \forall m,i,t \qquad (5.3)$$

$$\sum_c Y_{dcit} = \sum_m X_{mdit} \qquad \forall d,i,t \qquad (5.4)$$

$$e_i \sum_d Y_{dcit} \leq Z_{cit} \qquad \forall c,i,t \qquad (5.5)$$

$$\sum_d Y_{dcit} = \sum_r V_{crit} + Z_{cit} \qquad \forall c,i,t \qquad (5.6)$$

$$\sum_s \sum_i U_{srit} + \sum_c \sum_i V_{crit} \leq W_r \sum_i k_{ri} \qquad \forall r,t \qquad (5.7)$$

$$\sum_d \sum_i Y_{dcit} \leq x_c \sum_i f_{ci} \qquad \forall c,t \qquad (5.8)$$

$$\sum_r \sum_i U_{srit} \leq v_s \sum_i p_{si} \qquad \forall s,t \qquad (5.9)$$

$$\sum_m \sum_i X_{mdit} \leq Y_d \sum_i l_{di} \qquad \forall d,t \qquad (5.10)$$

$$w_r, x_c, y_d, v_s \in \{0,1\} \qquad \forall r,c,d,s \qquad (5.11)$$

$$U_{srit}, V_{crit}, W_{rmit}, X_{mdit}, Y_{dcit}, Z_{cit} \geq 0 \qquad \forall s,r,c,m,d,i,t \qquad (5.12)$$

The first objective function (z_1) is developed to minimize the total cost of the beverage container RL network. In this regard, variable costs (i.e., costs of recovery, transportation, purchasing new products, and disposal) along with fixed costs of agreement with supplier(s), recovery center(s), regional collection depot(s), and beverage company(s) are taken into account. The second objective (z_2) is implemented to minimize the carbon emissions of transportation in the RL network. The third objective function (z_3) is employed to maximize the social responsibility and technological innovation of suppliers (ζ_{si}) and container recovery centers (ξ_{ci}). The parameters of ζ_{si} and ξ_{ci} are qualitative indicators representing the values of suppliers and container recovery centers from consumer perspectives. As indicated by Fig. 5.5, an overall framework is proposed to measure the social responsibility and technological innovation of third parties based on the four criteria (e.g., Internet of Things (IoT) implementation) and ten sub-criteria (e.g., cloud-computing capabilities, digital connectivity requirements, and application of smart things such as smart machines and services). In this study, a multiple criteria decision-making (MCDM) technique (i.e., fuzzy analytic network process (FANP)) is utilized to convert such qualitative criteria to quantitative parameters (calculations are provided in Appendix 5.A).

Constraint (5.1) is required to balance the quantities of products sending to the market with the numbers of cans either reproduced by the container recovery center(s) or purchased from the supplier(s). Constraint (5.2) is applied to ensure that all market demands are fulfilled. Constraint (5.3) represents that the numbers of products shipped to the regional collection depots should be equal to the returns of used beverage containers. Constraint (5.4) balances the number of used cans returned by the markets with the ones shipped to the recovery center(s). Constraint (5.5) shows the disposal rate of used beverage containers. Constraint (5.6) is a trade-off between the quantities of returns, recovered and unrecovered containers. Constraint (5.7) indicates the maximum capacities of beverage companies for production. Constraints (5.8), (5.9), and (5.10) are associated with the capacities of recovery center(s), supplier(s), and regional collection depot(s), respectively. Constraint (5.11) illustrates the binary variables. Finally, non-negative decision variables are presented by Constraint (5.12).

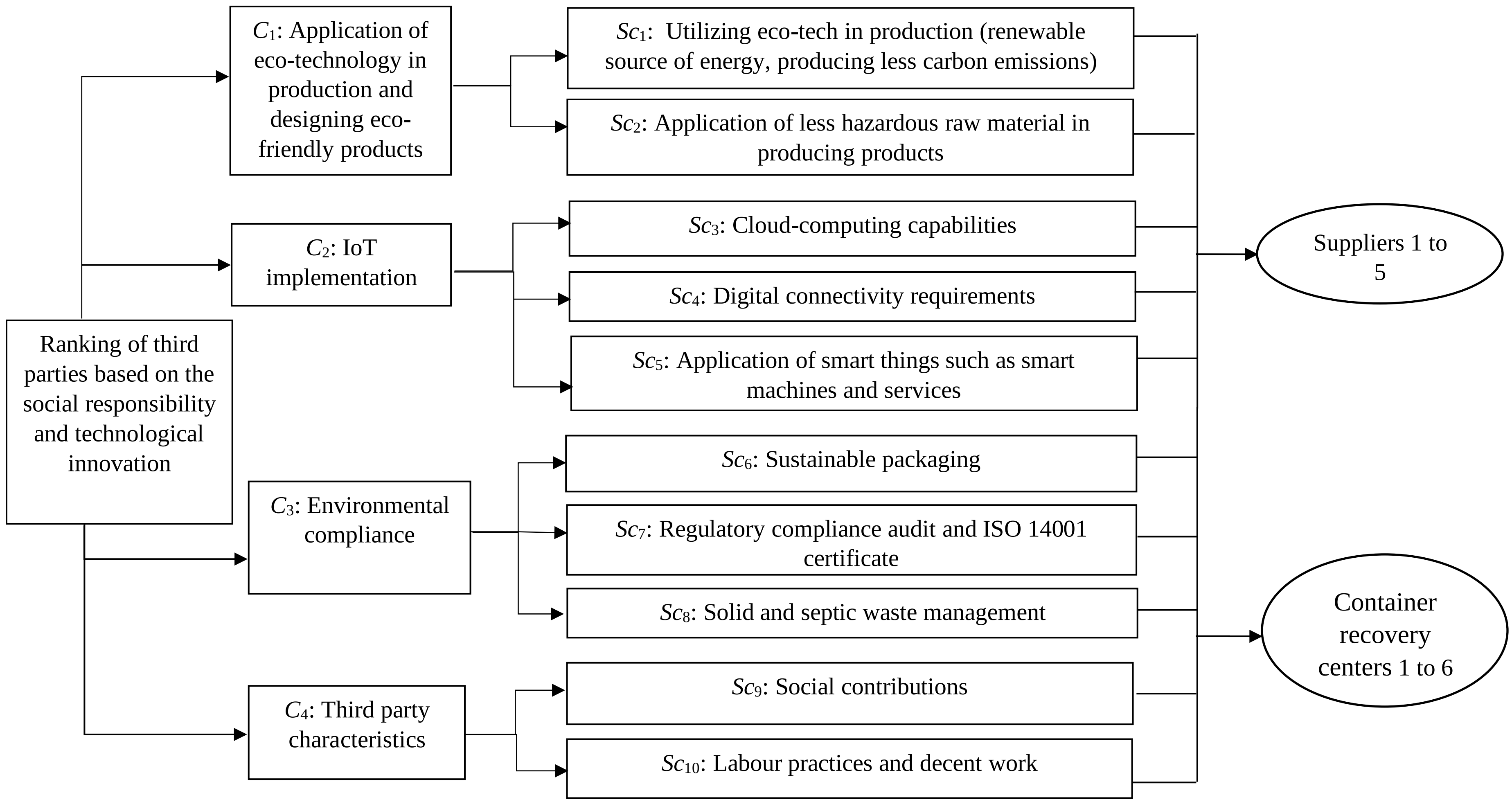

Fig. 5.5. The overall framework to prioritize suppliers and container recovery centers regarding the application of technological innovation and their influence on society (Sharma et al., 2017; Manavalan and Jayakrishna, 2019; Tosarkani et al., 2019)

5.4.1. Application of the optimization model

In this section, the optimization model is investigated using information related to Vancouver. As indicated in Fig. 5.3, there are 22 municipal areas that are considered as the regional markets. The values of the demands related to market *m* associated with product *i* in period *t* (N_{mjt}) are assumed as one percent of the population of the region based on the 2011 census of Canada. With this respect, the values of returns (P_{mjt}) are computed as ten percent of N_{mjt}.

Transportation costs can be considered as functions of fuel prices and distances between potential locations. In this regard, Google Maps is applied to calculate the driving distances that have a direct impact on transportation costs and carbon emissions. The disposal rate is estimated based on the recovery rate of aluminum containers (Encorp annual report, 2016). Since there are various types of aluminum cans containing different products, the disposal rate may vary. In this regard, different scenarios are considered for the disposal rate of containers that are discussed in Section 5.4.2. The parameter of *T* (i.e., number of periods) is equal to 2, since the model is investigated semi-annually. The other parameters' values are mentioned in Table 5.B.1 in Appendix 5.B. IBM ILOG CPLEX 12.8 is employed to solve the optimization model. There are 496 constraints, 3,104 single variables, 28 binary variables, and 14,996 non-zero coefficients. The 1st, 2nd, and 3rd objectives are solved independently with regard to Constraints (5.1) to (5.12). The minimum total cost, carbon emissions, technological innovation and social influence have been obtained as 3,768,800, 757,986, and 209,088 respectively. The selected facilities are mentioned in Table 5.2.

Table 5.2
Solution for the proposed beverage container RL

Objective value	Selected regional depots	Selected recovery centers	Selected suppliers	Selected beverage companies
Z_1: 3,768,800	y_3: Strathcona, y_4: Renfrew-Collingwood, y_5: Kitsilano	x_3: Kitsilano, x_5: Hastings Sunrise	v_1 and v_5: Downtown	w_1: Hastings Sunrise, w_4: Grandview Woodland, w_7: Downtown

Encorp is committed to monitoring consumer awareness, strategic planning, infrastructure development, and financial management. Therefore, it is logical that all operational activities delivered by supplier(s), recovery center(s), regional collection depot(s), and beverage companies should be implemented in an optimal RL network. Fig. 5.6 illustrates the optimal configuration of the beverage container RL network in Vancouver.

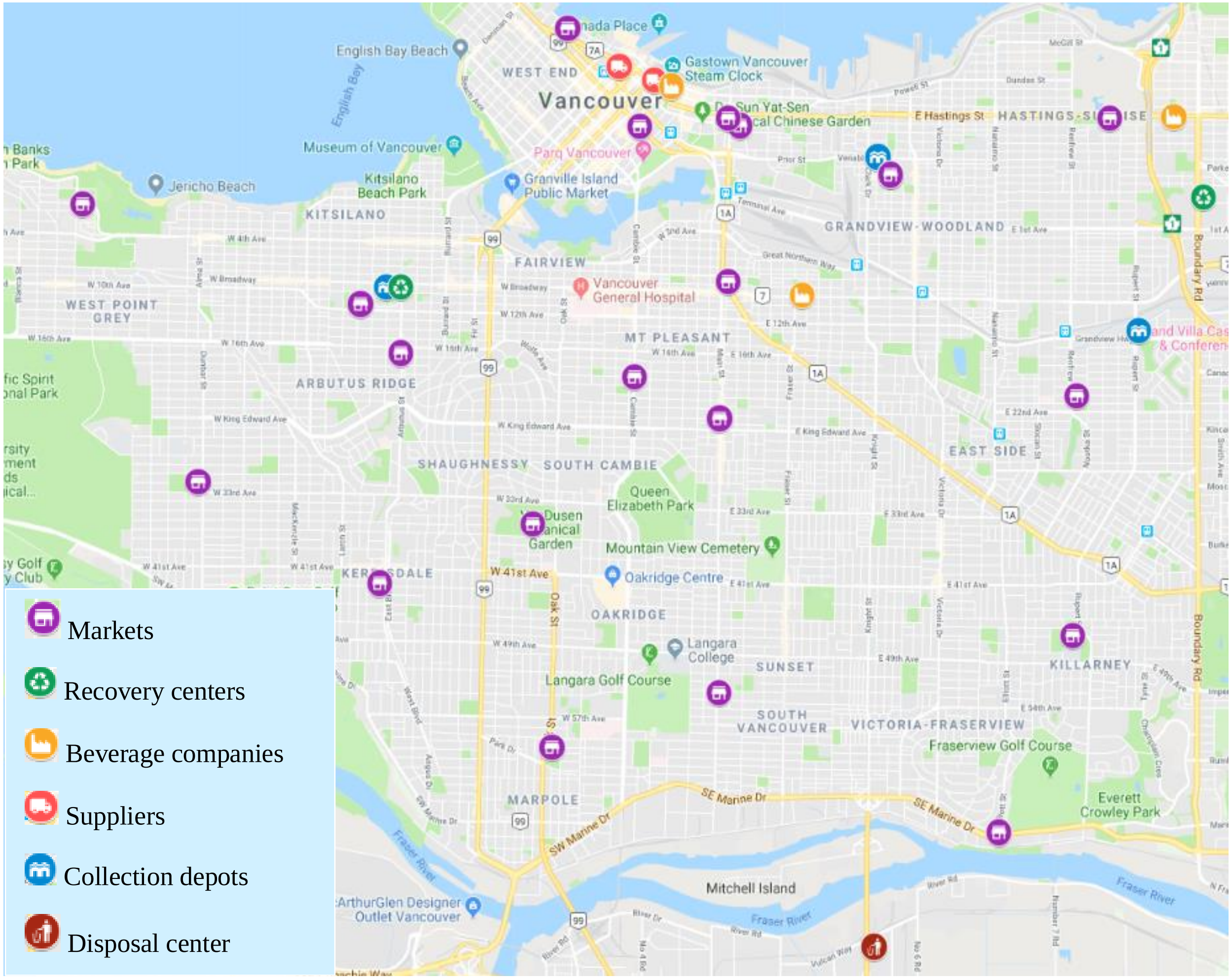

Fig. 5.6. The optimal network of beverage container RL in Vancouver

Nowadays, businesses are influenced by governmental and provincial regulations to tackle the environmental impact of their operations. However, there is not a single method to overcome such issues. Some decision-makers believe that employing technological innovation (i.e., eco-product design and using eco-technology in operations) can be a decent approach, while others emphasize on carbon tax policy instead (Tasker, 2019). Therefore, we first configure the beverage container RL network to minimize the total cost, which is the traditional objective in CLSC and RL network. In this regard, the impact of uncertainty on the total cost is investigated through some sensitivity analyses, and then an integrated approach (i.e., stochastic possibilistic method) is presented in Section 5.4.2. Thereafter, all three objective functions are considered simultaneously to optimize the beverage container RL network.

In real life, it is likely that unpredictable changes happen in the values of parameters involved in the configuration of networks (Esnaf and Küçükdeniz, 2009; Liu and Xu, 2011; Abdallah et al., 2012; Conceição et al., 2012; Tabrizi and Razmi, 2013; Subulan et al., 2015; Yang and Liu, 2015; Bai and Liu, 2016; Haddadsisakht and Ryan, 2018; Vlajic et al., 2018). As a result, the effectiveness of facilities' locations may be affected, if such unexpected changes are not considered. With this respect, we analyze the impacts of random changes in demand and return on the total cost of the beverage container RL network. As illustrated in Table 5.3, the total cost of beverage container RL is very sensitive to such fluctuations. The percentage of change is computed with regard to the original solution (e.g., (4,144,979 - 3,768,800)/ 3,768,800 = 9.98% for the 1st scenario). By comparison between Scenarios 5 and 6, it can be concluded that the increase in demand leads to an increase in the total cost. Conversely, comparing Scenarios 7 and 8 shows that as return increases, the total cost decreases due to the cost-saving because of the product recovery. Furthermore, as demand and return change, the numbers of the selected facilities may vary. In Section 5.4.2, we advance the optimization model to the stochastic possibilistic model to handle such uncertainties.

Table 5.3
The impact of random fluctuations in demand and return on total cost and selected facilities

Scenarios	Objective value	Change%	Selected facilities
1. 10% increase in demand and return	$Z_1 = 4{,}144{,}979$	9.98%	$v_1, v_4, v_5 - w_1, w_4, w_7 - x_3, x_5 - y_3, y_4, y_5$
2. 10% increase in demand and 10% decrease in return	$Z_1 = 4{,}162{,}048$	10.43%	$v_1, v_4, v_5 - w_1, w_4, w_7 - x_3, x_5 - y_3, y_4, y_5$
3. 10% decrease in demand and 10% increase in return	$Z_1 = 3{,}375{,}574$	-10.43%	$v_1, v_5 - w_3, w_7 - x_5 - y_3, y_4$
4. 10% decrease in demand and return	$Z_1 = 3{,}392{,}327$	-9.99%	$v_1, v_5 - w_3, w_7 - x_5 - y_3, y_4$
5. 10% increase in demand, while return is not changed	$Z_1 = 4{,}153{,}252$	10.20%	$v_1, v_4, v_5 - w_1, w_4, w_7 - x_3, x_5 - y_3, y_4, y_5$
6. 10% decrease in demand, while return is not changed	$Z_1 = 3{,}383{,}800$	-10.22%	$v_1, v_5 - w_3, w_7 - x_5 - y_3, y_4$
7. 10% increase in return, while demand is not changed	$Z_1 = 3{,}760{,}551$	-0.22%	$v_1, v_5 - w_1, w_3, w_7 - x_3, x_5 - y_3, y_4, y_5$
8. 10% decrease in return, while demand is not changed	$Z_1 = 3{,}777{,}264$	0.22%	$v_1, v_5 - w_1, w_4, w_7 - x_3, x_5 - y_3, y_4, y_5$

As illustrated in Table 5.4, the disposal fraction rate is the other parameter that affects the total cost of the RL network. As the disposal fraction increases, the beverage companies lose the opportunity to reuse the recovered containers. Accordingly, the new products are supposed to be purchased to replace the discarded containers. Therefore, the total cost and the environmental impacts of the whole RL network are increased as a result of the increase in the defect rate.

Table 5.4
The total cost of beverage container associated with different disposal rate

e_i = 0.15	e_i = 0.25	e_i = 0.35	e_i = 0.45	e_i = 0.55	e_i = 0.65
Z_1 = 3,808,710	Z_1 = 3,888,938	Z_1 = 3,969,479	Z_1 = 4,049,901	Z_1 = 4,128,502	Z_1 = 4,206,610

Table 5.5 summarizes the impact of capacity levels on the total cost of the beverage container RL network. Accordingly, more facilities are required by decreasing the available capacity. Furthermore, Fig. 5.7 illustrates that the increase in capacity levels leads to a decrease in the total cost. In this regard, there is a nonlinear relationship between the total cost of the RL network and capacity levels. For example, the optimal network has great cost-saving as the capacity levels increase by 25% from Scenario1 to Scenario 2, since the number of the required facilities decrease from 13 to 11. However, the trend of cost-saving becomes slow, because the numbers of open facilities in the optimal network become stable from Scenario 3 to Scenario 5.

Table 5.5
Sensitivity analyses on the available capacity

Scenarios	Objective value	Change %	Selected facilities *
1. 50% decrease in the capacity of facilities	Z_1 = 3,805,564	0.98%	RD: y_3, y_4, y_5 – RC: x_3, x_5 – S: v_1, v_2, v_4, v_5 – BC: w_1, w_2, w_4, w_7
2. 25% decrease in the capacity of facilities	Z_1 = 3,775,466	0.18%	RD: y_3, y_4, y_5 – RC: x_3, x_5 – S: v_1, v_4, v_5 – BC: w_1, w_3, w_7
3. Original case	Z_1 = 3,768,800	0.00	RD: y_3, y_4, y_5 – RC: x_3, x_5 – S: v_1, v_5 – BC: w_1, w_4, w_7
4. 25% increase in the capacity of facilities	Z_1 = 3,766,923	-0.05%	RD: y_3, y_4, y_5 – RC: x_3, x_5 – S: v_1, v_5 – BC: w_1, w_4, w_7
5. 50% increase in the capacity of facilities	Z_1 = 3,765,133	-0.10%	RD: y_3, y_4, y_5 – RC: x_3, x_5 – S: v_1, v_5 – BC: w_1, w_4, w_7

* Regional depots (RD), Recovery centers (RC), Suppliers (S), Beverage companies (BC)

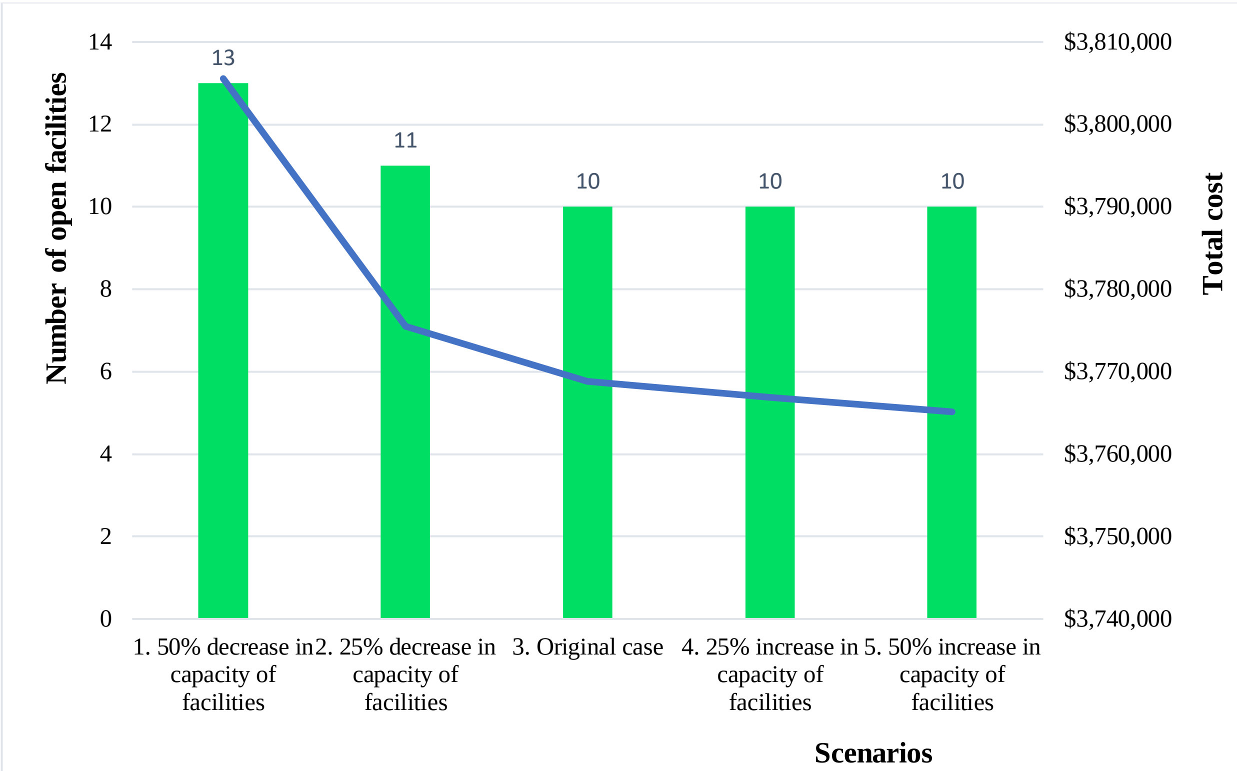

Fig. 5.7. The impact of capacity levels on the total cost and number of open facilities

5.4.2. Extension to stochastic possibilistic model

Scenario-based possibilistic method can be applied to handle imprecise parameters. On this matter, we consider different alternatives for the disposal rate and overcome the imprecise parameters through fuzzy programming. A hybrid solution approach is developed based on the methods proposed by Cadenas and Verdegay (1997), Parra et al., (2005), Snyder (2006), Jiménez et al., (2007), Peidro et al., (2009), Amin and Zhang (2013a), Pishvaee and Khalaf (2016). The new model includes different scenarios, fuzzy coefficients, and fuzzy right-hand sides. The general form of the proposed model is defined by Eqs. (5.13), (5.14), and (5.15).

$$Min\ z' = \sum_{\omega} \Psi_{\omega} \tilde{c}'_{\omega} x'_{\omega} + \tilde{d}' y' \qquad (5.13)$$

$$\tilde{a}'_{\omega} x'_{\omega} \geq \tilde{b}'_{\omega} \qquad \forall \omega \qquad (5.14)$$

$$\tilde{e}'_{\omega} x'_{\omega} = \tilde{f}'_{\omega} \qquad \forall \omega \qquad (5.15)$$

$$x'_{\omega} \geq 0, y' \in \{0,1\}$$

In this model, ω is the number of different scenarios for the disposal rate that may occur with probability Ψ_{ω}. Suppose that x'_{ω} and y' are the non-negative and binary variables. Moreover, $\tilde{c}'_{\omega}$ and $\tilde{d}'$ are variable and fixed costs, respectively. It is also assumed that $\tilde{a}'_{\omega}$, $\tilde{b}'_{\omega}$, $\tilde{e}'_{\omega}$, $\tilde{f}'_{\omega}$ are matrices. To reach an auxiliary crisp version of Eq. (5.13), the lateral margins associated with each imprecise parameter are computed. As illustrated in Fig. 5.8, $\Delta_{c'_{\omega}}$ and $\Delta'_{c'_{\omega}}$ represent the lateral margins associated with the triangular fuzzy number $\tilde{c}'_{\omega} = \left(c'^{l}_{\omega}, c'^{m}_{\omega}, c'^{u}_{\omega}\right)$ (Peidro et al., 2009).

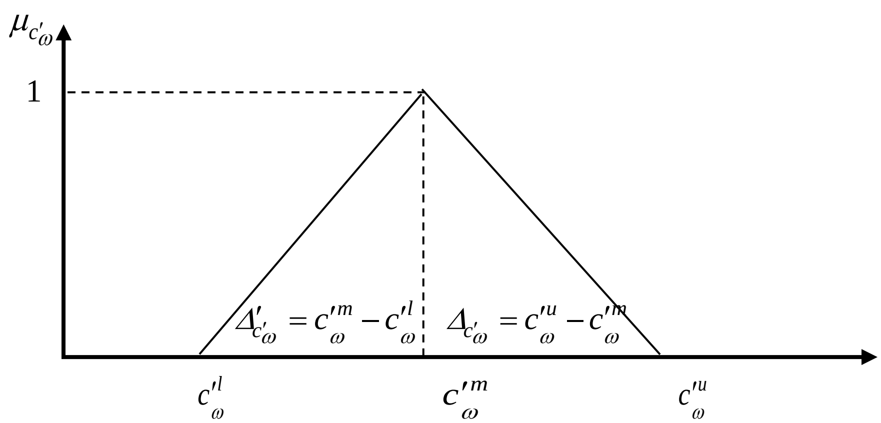

Fig. 5.8. Lateral margins of triangular fuzzy number (TFN) $\tilde{c}'_{\omega}$

Accordingly, the crisp version of Eq. (5.13) can be replaced by Eq. (5.16).

$$Min\ z' = \sum_{\omega} \Psi_{\omega} \left(c'_{\omega} + \frac{\Delta_{c'\omega} - \Delta'_{c'\omega}}{3} \right) x'_{\omega} + \left(d' + \frac{\Delta_{d'\omega} - \Delta'_{d'\omega}}{3} \right) y' \tag{5.16}$$

The possibilistic constraints of (5.14) and (5.15) can be converted to crisp versions of Eqs. (5.17), (5.18), and (5.19) based on Parra et al. (2005) and Jiménez et al. (2007).

$$\left[(1-\alpha) E_2^{a'_{\omega}} + \alpha E_1^{a'_{\omega}} \right] x'_{\omega} \geq \alpha E_2^{b'_{\omega}} + (1-\alpha) E_1^{b'_{\omega}} \qquad \forall \omega \tag{5.17}$$

$$\left[\left(1-\frac{\alpha}{2}\right) E_2^{e'_{\omega}} + \frac{\alpha}{2} E_1^{e'_{\omega}} \right] x'_{\omega} \geq \left(1-\frac{\alpha}{2}\right) E_1^{f'_{\omega}} + \frac{\alpha}{2} E_2^{f'_{\omega}} \qquad \forall \omega \tag{5.18}$$

$$\left[\left(1-\frac{\alpha}{2}\right)E_1^{e'_\omega}+\frac{\alpha}{2}E_2^{e'_\omega}\right]x'_\omega \le \left(1-\frac{\alpha}{2}\right)E_2^{f'_\omega}+\frac{\alpha}{2}E_1^{f'_\omega} \qquad \forall\omega \qquad (5.19)$$

In this model, α is the degree of feasibility, and the expected interval (EI) of $\tilde{a}'_\omega$ is equal to $\left[E_1^{a'_\omega},E_2^{a'_\omega}\right]=\left[\frac{1}{2}\left(a'^{l}_\omega+a'^{m}_\omega\right),\frac{1}{2}\left(a'^{m}_\omega+a'^{u}_\omega\right)\right]$. The equivalent crisp version of the objective function and Constraints (5.1) to (5.12) for ω scenarios are provided as follows:

$$Min\ z_1=\sum_d\sum_c\sum_i\sum_t\sum_\omega \Psi_\omega\left(\left(H_i+\frac{\Delta_{H_i}-\Delta'_{H_i}}{3}\right)+\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_{dc}\right)Y_{dci\omega t}+$$

$$\sum_c\sum_r\sum_i\sum_t\sum_\omega \Psi_\omega\left(-\left(J_i+\frac{\Delta_{J_i}-\Delta'_{J_i}}{3}\right)+\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_{cr}\right)V_{cri\omega t}$$

$$+\sum_s\sum_r\sum_i\sum_t\sum_\omega \Psi_\omega\left(\left(G_i+\frac{\Delta_{G_i}-\Delta'_{G_i}}{3}\right)+\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_{sr}\right)U_{sri\omega t}$$

$$+\sum_r\sum_m\sum_i\sum_t\sum_\omega \Psi_\omega\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_{rm}W_{rmi\omega t}+\sum_m\sum_d\sum_i\sum_t\sum_\omega \Psi_\omega\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_{md}X_{mdi\omega t}$$

$$+\sum_c\sum_i\sum_t\sum_\omega \Psi_\omega\left(\left(K_i+\frac{\Delta_{K_i}-\Delta'_{K_i}}{3}\right)+\left(O_i+\frac{\Delta_{O_i}-\Delta'_{O_i}}{3}\right)L_c\right)Z_{ci\omega t}+$$

$$\sum_r\left(B_r+\frac{\Delta_{B_r}-\Delta'_{B_r}}{3}\right)w_r+\sum_c\left(A_c+\frac{\Delta_{A_c}-\Delta'_{A_c}}{3}\right)x_c+\sum_d\left(F_d+\frac{\Delta_{F_d}-\Delta'_{F_d}}{3}\right)y_d+\sum_s\left(E_s+\frac{\Delta_{E_s}-\Delta'_{E_s}}{3}\right)v_s$$

$$Min\ z_2 = \left(u + \frac{\Delta_u - \Delta'_u}{3} \right) \times$$

$$\left(\begin{array}{l} \sum_s \sum_r \sum_i \sum_t \sum_\omega \Psi_\omega (L_{sr}) \frac{U_{sri\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} + \sum_r \sum_m \sum_i \sum_t \sum_\omega \Psi_\omega (L_{rm}) \frac{W_{rmi\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} + \\ \sum_m \sum_d \sum_i \sum_t \sum_\omega \Psi_\omega (L_{md}) \frac{X_{mdi\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} + \sum_d \sum_c \sum_i \sum_t \sum_\omega \Psi_\omega (L_{dc}) \frac{Y_{dci\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} + \\ \sum_c \sum_r \sum_i \sum_t \sum_\omega \Psi_\omega (L_{cr}) \frac{V_{cri\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} + \sum_c \sum_i \sum_t \sum_\omega \Psi_\omega (L_c) \frac{Z_{ci\omega t}}{\left(g + \frac{\Delta_g - \Delta'_g}{3} \right)} L_c \end{array} \right)$$

s.t.

$$\sum_m W_{rmi\omega t} = \sum_s U_{sri\omega t} + \sum_c V_{cri\omega t} \qquad \forall r,i,\omega,t \qquad (5.20)$$

$$\sum_r W_{rmi\omega t} \geq \alpha \left(\frac{N^m_{mit} + N^u_{mit}}{2} \right) + (1-\alpha) \left(\frac{N^l_{mit} + N^m_{mit}}{2} \right) \qquad \forall m,i,\omega,t \qquad (5.21)$$

$$\sum_d X_{mdi\omega t} \geq \left(1 - \frac{\alpha}{2} \right) \left(\frac{P^l_{mit} + P^m_{mit}}{2} \right) + \left(\frac{\alpha}{2} \right) \left(\frac{P^m_{mit} + P^u_{mit}}{2} \right) \qquad \forall m,i,\omega,t \qquad (5.22)$$

$$\sum_d X_{mdi\omega t} \leq \left(1 - \frac{\alpha}{2} \right) \left(\frac{P^m_{mit} + P^u_{mit}}{2} \right) + \left(\frac{\alpha}{2} \right) \left(\frac{P^l_{mit} + P^m_{mit}}{2} \right) \qquad \forall m,i,\omega,t \qquad (5.23)$$

$$\sum_c Y_{dci\omega t} = \sum_m X_{mdi\omega t} \qquad \forall d,i,\omega,t \qquad (5.24)$$

$$e_{i\omega} \sum_d Y_{dci\omega t} \leq Z_{ci\omega t} \qquad \forall c,i,\omega,t \qquad (5.25)$$

$$\sum_d Y_{dci\omega t} = \sum_r V_{cri\omega t} + Z_{ci\omega t} \qquad \forall c,i,\omega,t \qquad (5.26)$$

$$\sum_s \sum_i U_{sri\omega t} + \sum_c \sum_i V_{cri\omega t} \leq W_r \sum_i k_{ri} \qquad \forall r,\omega,t \qquad (5.27)$$

$$\sum_d \sum_i Y_{cdi\omega t} \leq x_c \sum_i f_{ci} \qquad \forall c, \omega, t \qquad (5.28)$$

$$\sum_r \sum_i U_{sri\omega t} \leq v_s \sum_i p_{si} \qquad \forall s, \omega, t \qquad (5.29)$$

$$\sum_m \sum_i X_{mdi\omega t} \leq Y_d \sum_i l_{di} \qquad \forall d, \omega, t \qquad (5.30)$$

$$w_r, x_c, y_d, v_s \in \{0,1\} \qquad \forall r, c, d, s \qquad (5.31)$$

$$U_{sri\omega t}, V_{cri\omega t}, W_{rmi\omega t}, X_{mdi\omega t}, Y_{dci\omega t}, Z_{ci\omega t} \geq 0 \qquad \forall s, r, c, m, d, i, \omega, t \qquad (5.32)$$

To solve the proposed stochastic possibilistic model, we estimate the lower and upper values of each TFN as 25 percent decrease and increase of its nominal value (see Table 5.B.2 in Appendix 5.B). Furthermore, 3 scenarios of 5%, 10%, and 15% for the disposal rate are taken into account with probabilities of 0.30, 0.40, and 0.30, respectively. According to the different levels of α-cut, various objective values can be obtained. On this matter, the decision-makers play a prominent role to decide about the appropriate pair of (α, z). Table 5.6 includes the optimal solutions of the proposed model for the beverage container RL network.

Table 5.6
The optimal solutions based on different levels of α-cut

α	Total profit	Selected entities
0.1	3,374,938.83	v_1, $v_5 - w_3$, $w_7 - x_5 - y_3$, y_4
0.2	3,472,233.29	v_1, $v_5 - w_1$, w_3, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.3	3,569,370.79	v_1, $v_5 - w_1$, w_3, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.4	3,666,517.02	v_1, $v_5 - w_1$, w_3, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.5	3,763,631.81	v_1, $v_5 - w_1$, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.6	3,860,603.04	v_1, $v_5 - w_1$, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.7	3,957,575.60	v_1, $v_5 - w_1$, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.8	4,054,564.33	v_1, $v_5 - w_1$, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
0.9	4,152,806.63	v_1, v_4, $v_5 - w_1$, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5

Types of uncertain parameters should be taken into account to determine the degree of feasibility (Pishvaee and Khalaf, 2016). A large value of α is applied when fulfilling the constraint is more important than minimizing the objective. Therefore, it is required to examine whether entities are able to handle unpredictable changes in market demand and return. On this matter, capability to increase the production by suppliers, beverage companies, regional depots, and container recovery centers should be examined by the decision-makers. As illustrated in Table 5.6, increasing the degree of feasibility causes a rise in the total cost of the RL due to the increase in demand and return. In addition, an increase in α may lead to opening new facilities on account of the limited capacity. Accordingly, as α increases from 0.1 to 0.2, the 1st beverage company, 3rd container recovery center, and 5th regional depot are supposed to be selected. The same interpretation can be taken into account for 4th supplier when α increases from 0.8 to 0.9. Table 5.7 shows how changing α may have an impact on the selected entities. As α changes from 0.2 to 0.8, a load of products between suppliers and beverage companies (i.e., U_{srit}) increases from 899,532 to 1,070,278, but it is still less than 1,080,000 which is the total capacity of Suppliers 1 and 5. Therefore, there is no need to open an extra supplier. However, as α increases to 0.9, the load of products increases to 1,098,735 which is greater than the capacity of Suppliers 1 and 5. In this regard, it is required to select a new supplier (i.e., v_4) for the purpose of increasing the available capacity of resources.

Table 5.7
The impact of α on the required capacity of suppliers

α-cut	Load of products between suppliers and beverage companies	Required capacity	Available capacity of selected entities
0.2	$U_{17i\omega t}$ = 540,000 & $U_{51i\omega t}$ = 135,491 & $U_{57i\omega t}$ = 224,041	899,532	1,080,000 = $v_1 + v_5$ = $(30,000)_{2*3}$ for all ω and t (ω = 3 & t = 2)
0.8	$U_{17i\omega t}$ = 540,000 & $U_{51i\omega t}$ = 247,574 & $U_{57i\omega t}$ = 282,704	1,070,278	1,080,000 = $v_1 + v_5$ = $(30,000)_{2*3}$ for all ω and t (ω = 3 & t = 2)
0.9	$U_{17i\omega t}$ = 540,000 & $U_{41i\omega t}$ = 18,735 $U_{51i\omega t}$ = 238,163 & $U_{57i\omega t}$ = 301,837	1,098,735	1,620,000 = $v_1 + v_4 + v_5$ = $(30,000)_{3*3}$ for all ω and t (ω = 3 & t = 2)

Table 5.8 indicates the sensitivity analysis of the proposed model regarding the probability of the disposal rate (Ψ_ω) in each scenario (i.e., 5%, 10%, 15%). In this regard, the minimum total cost

can be obtained when the large portion of the probability (0.8) is associated with the lowest disposal rate.

Table 5.8
The total cost with regard to different alternatives for probability of disposal rate

Alternatives	Ψ_ω = (0.8, 0.1, 0.1)	Ψ_ω = (0.1, 0.8, 0.1)	Ψ_ω = (0.1, 0.1, 0.8)
Total cost	3,733,735.29	3,763,637.52	3,793,301.11

5.4.3. Distance method and non-dominated solutions

To configure a sustainable beverage container RL, environmental issues (e.g., amount of carbon emissions due to transportation between facilities) and social responsibility and technological innovation of third parties should be considered as well. Therefore, developing a multi-objective model is necessary to address different aspects of economic, environmental, and social associated with a sustainable beverage container RL. The distance method is the popular method to find the non-dominated solutions (Pareto fronts) in multi-objective problems (Branke and Miettinen, 2008; Mirzapour Al-E-Hashem et al., 2011). As indicated by Eq. (5.33), $z_i^*$and w_i are applied as the best values and distance metrics, respectively. Accordingly, z_1, z_2 and z_3 must be solved separately to reach z_i^*. Then, the ideal values are replaced in Eq. (5.34). By changing different pairs of w_i, various non-dominated solutions can be obtained. While, α-value is equal to 0.5, the 1st, 2nd, and 3rd objective functions are 3,763,631.81, 754,081.93, and 210,907.02, respectively. Table 5.9 illustrates the non-dominated solutions for the proposed multi-objective model. The values of non-dominated solutions are influenced by changing distance metrics.

$$z = \left(\sum_i w_i^\tau \left(\frac{z_i - z_i^*}{z_i^*} \right)^\tau \right)^{\frac{1}{\tau}} \qquad \forall\ i = 1,\ 2 \ldots, \infty \tag{5.33}$$

$$Min\ z = \left(w_1^\tau \left(\frac{z_1 - z_1^*}{z_1^*} \right)^\tau + w_2^\tau \left(\frac{z_2 - z_2^*}{z_2^*} \right)^\tau \right)^{\frac{1}{\tau}} \tag{5.34}$$

s.t.

Constraints (5.20) to (5.32).

Table 5.9
The non-dominated solutions of 1st, 2nd, and 3rd objectives

	Distance metrics			Objectives' values			Facilities
Set	w_1	w_2	w_3	z_1	z_2	z_3	Open
1	0.80	0.10	0.10	3,813,000	876,730	63,424	$v_1, v_4 - w_1, w_3, w_4, w_7 - x_2, x_3, x_4, x_5 - y_1, y_2, y_3, y_4, y_5, y_7, y_8, y_9, y_{10}$
2	0.10	0.80	0.10	3,784,200	755,340	30,179	$v_1, v_2, v_5 - w_1, w_2, w_4, w_7 - x_3, x_4, x_5 - y_2, y_3, y_4, y_5, y_9, y_{10}$
3	0.10	0.10	0.80	4,542,800	1,907,800	174,910	$v_3, v_4 - w_1, w_2, w_4, w_5, w_6, w_7 - x_1 - y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9, y_{10}$
4	0.33	0.33	0.33	3,819,800	863,990	72,107	$v_2, v_4, v_5 - w_1, w_2, w_3, w_4, w_7 - x_2, x_3, x_4, x_5 - y_3, y_4, y_5, y_6, y_8, y_9, y_{10}$

To analyze the trade-off between non-dominated solutions, the value path analysis (VPA) can be utilized. According to the properties of VPA, neither of the value paths is dominated, if they have intersections (Wadhwa and Ravinsdran, 2007; Amin and Zhang, 2014).

In this study, there are different types of objective functions (i.e., minimizing total cost and CO_2 emissions along with maximizing the social responsibility and technological innovation of third parties) in the proposed model. Hence, some modifications are required to apply the VPA. In this regard, the non-dominated solutions are converted to normalized scales. In case of minimization, the inferior value of each objective among all sets is divided by its value in each non-dominated solution (e.g., normalized scale of z_1: 4,542,800 / 3,813,000 = 1.19 and normalized scale of z_2: 1,907,800 / 876,730 = 2.18 for the 1st set). In the case of maximization, the objective value of certain alternatives is divided by the minimum value among all alternatives (e.g., the normalized scale of z_3: 63,424 / 30,179 = 2.10 for the 1st set). Accordingly, a larger normalized scale gives rise to a more desirable result. Fig. 5.9 demonstrates that all value paths (i.e., Linear sets 1, 2, 3, and 4) have intersections. Therefore, neither of the non-dominated solutions is superior.

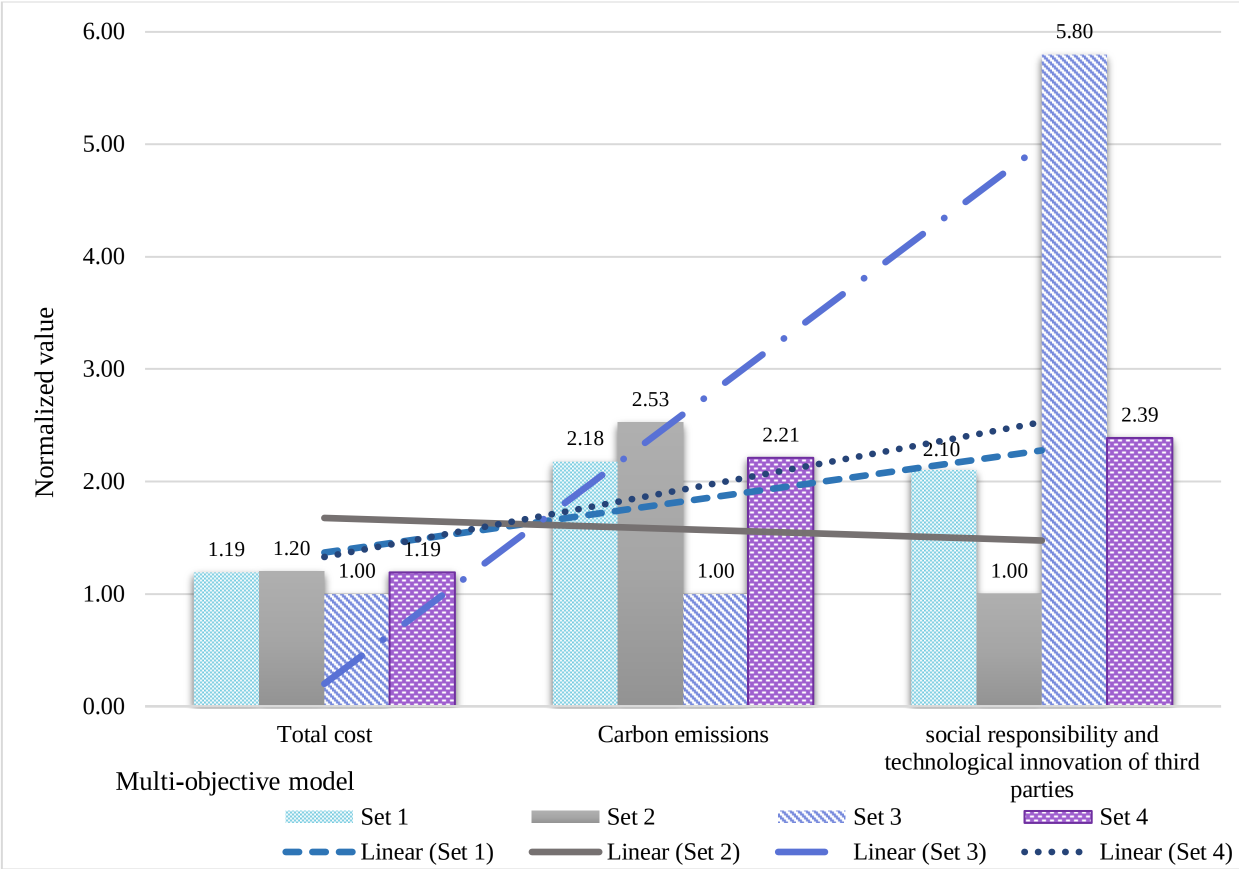

Fig. 5.9. The trade-off relations among non-dominated solutions

Two bi-objective models are analyzed to examine the impact of carbon emissions and social responsibility and technological innovation of third parties on the total cost of network. Table 5.10 illustrates that the value of carbon emissions ((754,120 - 756,140) / 756,140 = - 0.27% for the 1st set) cannot be improved, unless the total cost is increased ((3,787,800 - 3,778,400) / 3,778,400 = 0.25% for the 1st set). Table 5.11 also indicates that total cost must be increased ((4,001,800 - 3,910,600) / 3,910,600 = 2.33%) to grow the impact of third parties on society ((165,400 - 126,390) / 126,390 = 30.86%).

Table 5.10
The non-dominated solutions of 1st and 2nd objectivities

	Distance metrics		Objectives' values		Comparison with regard to base-case		Facilities
Set	w_1	w_2	z_1	z_2	Change in z_1	Change in z_2	Open
1	0.20	0.80	3,787,800	754,120	0.25%	- 0.27%	v_1, v_2, $v_5 - w_1$, w_2, w_3, w_4, $w_7 - x_3$, x_4, $x_5 - y_2$, y_3, y_4, y_5, y_9, y_{10}
2	0.30	0.70	3,778,400	756,140	base-case	base-case	v_1, v_2, $v_5 - w_1$, w_2, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5
3	0.50	0.50	3,779,300	755,460	0.02%	0.09%	v_1, v_2, $v_5 - w_1$, w_2, w_4, $w_7 - x_3$, $x_5 - y_3$, y_4, y_5, y_9

Table 5.11
The non-dominated solutions of 1st and 3rd objectives

	Distance metrics		Objectives' values		Comparison with regard to base-case		Facilities
Set	w_1	w_3	z_1	z_3	Change in z_1	Change in z_3	Open
1	0.20	0.80	4,345,400	174,910	11.12%	38.39%	v_3, $v_4 - w_1$, $w_7 - x_1 -$ y_2, y_3, y_4, y_5, y_8, y_9
2	0.80	0.20	4,001,800	165,400	2.33%	30.86%	v_3, $v_4 - w_1$, w_4, $w_7 -$ $x_1 - y_3$, y_5, y_9
3	0.90	0.10	3,910,600	126,390	base-case	base-case	v_3, v_4, $v_5 - w_1$, w_3, w_4, $w_7 - x_2$, x_3, x_4, x_5 $- y_1$, y_2, y_3, y_4, y_5, y_6, y_7, y_9

Fig. 5.10, Fig. 5.11, and Fig. 5.12 indicate the Pareto fronts of the proposed multi-objective optimization model. Pareto fronts are shown for three bi-objective models to investigate the effect of every certain objective function on the other objectives in the beverage container RL network. As described previously, the normalized scales are applied to plot the Pareto fronts due to different types of objective functions. As demonstrated by the trade-off surface, a certain value of one objective function (e.g., carbon emissions) is not improved unless the value of another objective (e.g., total cost) is degraded.

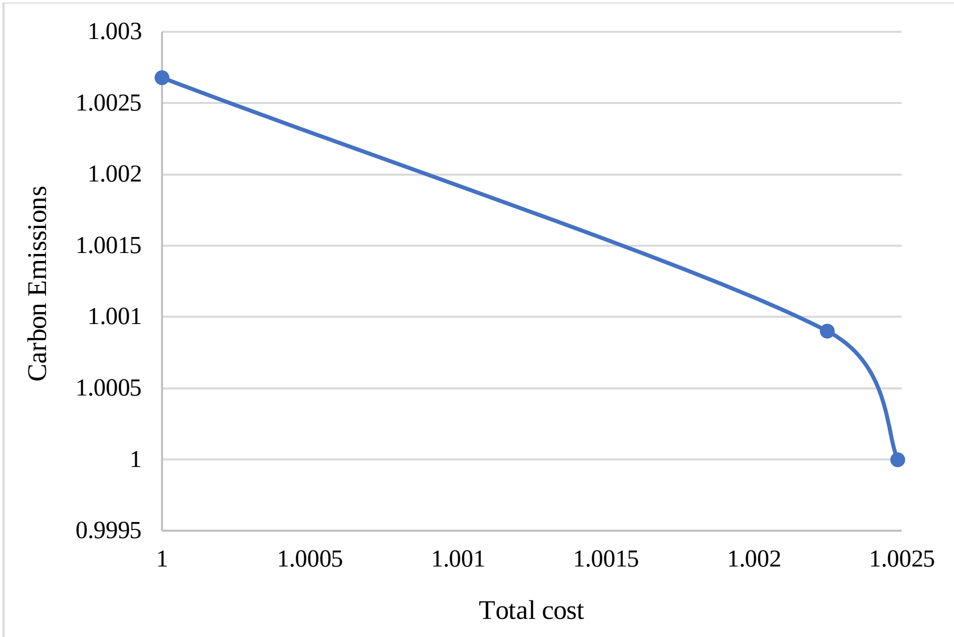

Fig. 5.10. The Pareto front of carbon emissions and total cost

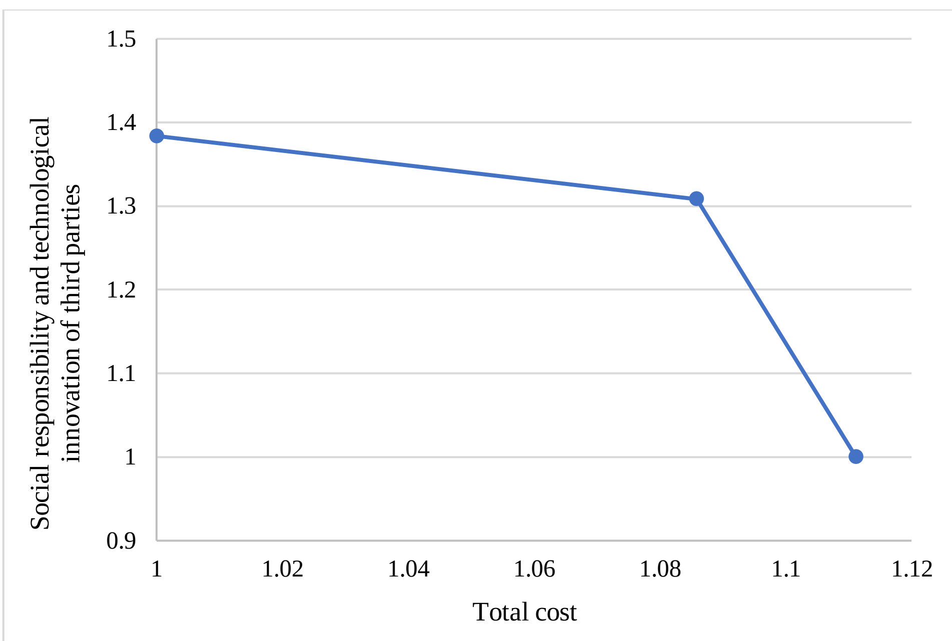

Fig. 5.11. The Pareto front of the total cost, social responsibility and technological innovation of third parties

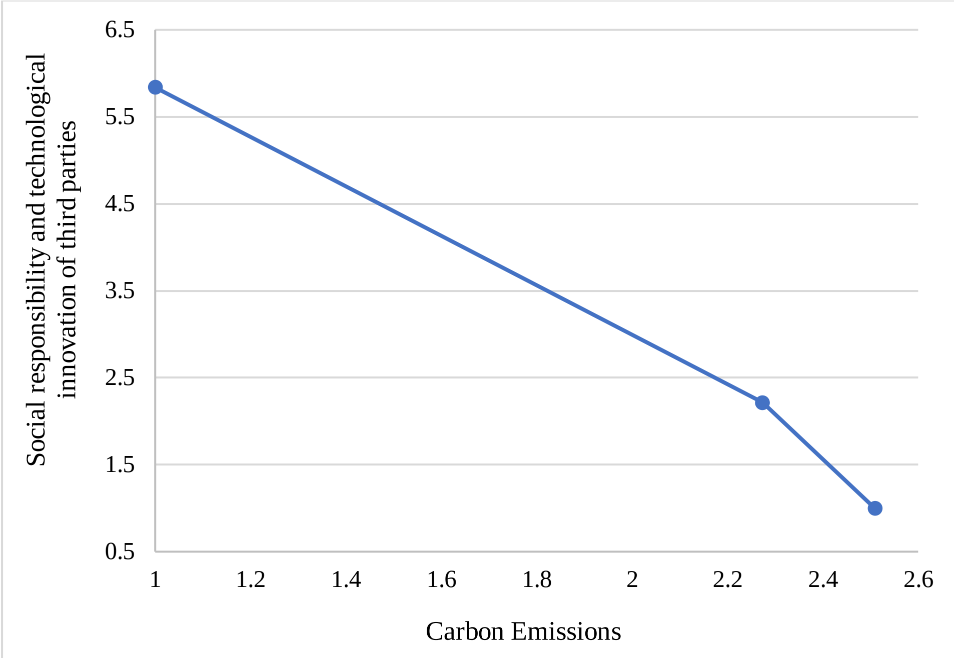

Fig. 5.12. The Pareto front of carbon emissions, social responsibility and technological innovation of third parties

5.5. Managerial implications

The application of RL networks has been expanded prominently for two reasons. First, customers are considering the environmental practices of companies (e.g., involving a recycling plan) in addition to environmental attributes of the products (e.g., recyclable). Second, government policies and regulations have led companies to hold environmentally friendly business frameworks. In his regard, companies have been motivated to be a part of RL networks to benefit from either tangible or intangible competitive advantages of such a strategic decision (Jayaraman and Luo, 2007). For example, the recovery of used products creates values as the return on investments for returned products. In addition, companies can deliver an environmentally friendly image to the community by adopting an RL network (e.g., offering return options).

However, the design of real RL networks is a strategic decision which can be affected by several dynamic factors. Those unpredictable factors result in some risks and complexities for the businesses in the long-term (Kumar et al., 2017; Van Engeland et al., 2020).

As mentioned previously, the concept of sustainability includes the economic, environmental, and social pillars. Therefore, there are several objectives involved in designing of RL network which may have conflict in practice. This study attempts to offer valuable insights to managers.

In Table 5.2, we provided the results of the optimal network based on the minimization of total cost regardless of carbon emissions, social responsibility and technological innovation of third parties. Fig. 5.13 illustrates the comparison between selected facilities while decision-makers allocate different relative importance to the objectives (z_1, z_2, and z_3). As indicated in the original case, 2 suppliers (i.e., v_1 and v_5), 3 beverage companies (i.e., w_1, w_4, and w_7), and 2 recovery centers (i.e., x_3 and x_5) are selected when the total cost has the highest priority. However, the configuration of the network is significantly changed, if the highest weight is considered for z_3 (i.e., Set 3 of Table 5.9). Suppliers 1 and 5 are replaced by Suppliers 3 and 4 which have the highest priority in Table 5.A.7 in the aspect of social responsibility and technological innovation. Similarly, Recovery centers 3 and 5 are replaced by Recovery center 1 (i.e., the highest rank in Table 5.A.8).

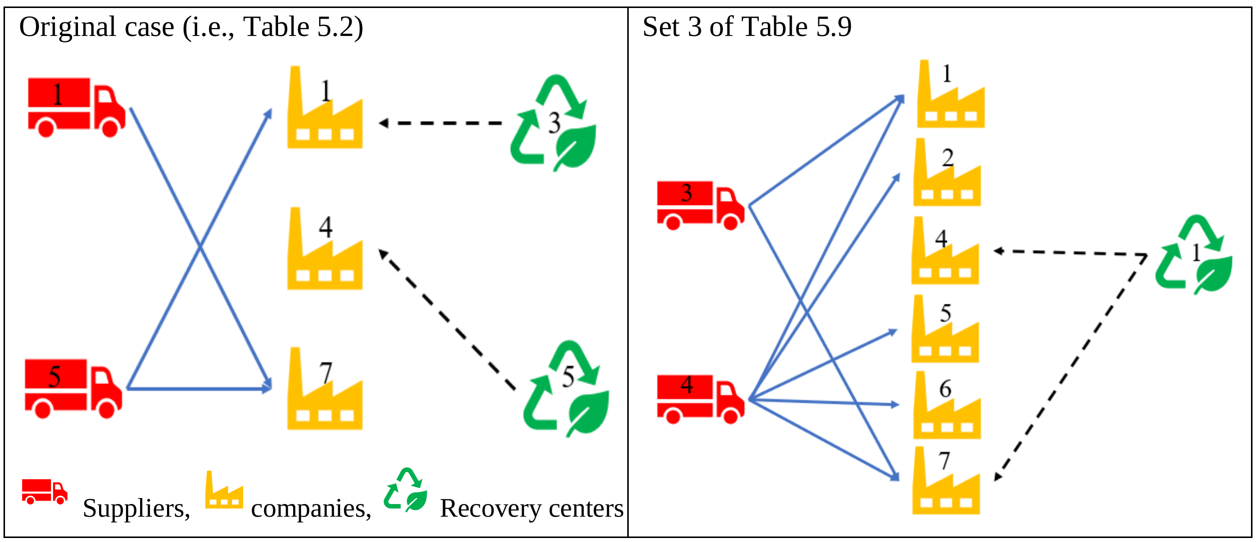

Fig. 5.13. The network design of original case (i.e., Table 5.2) and Set 3 of Table 5.9.

Furthermore, Fig. 5.14 depicts the selected facilities in two scenarios while all objectives are assumed to have the same priority. In the 1st scenario (i.e., Set 4 of Table 5.9), 3 suppliers (i.e., v_2, v_4 and v_5), 5 beverage companies (i.e., w_1, w_2, w_3, w_4, and w_7), and 4 recovery centers (i.e., x_2, x_3, x_4 and x_5) are selected when z_1, z_2, and z_3 are equal to 3,819,800, 863,990, 72,107, respectively. However, it is likely that one facility becomes disrupted in practice. Therefore, it is assumed that the 2nd Recovery center (i.e., a higher rank in comparison with 3rd, 4th, 5th Recovery centers in Table 5.A.8) becomes unavailable. In this regard, z_1, z_2, and z_3 are equal to 3,813,100, 852,850, 71,026, respectively. Accordingly, the total cost and CO_2 emissions of the network are improved, while the social responsibility and technological innovation of third parties are degraded. The proposed MOM enables decision-makers to investigate the configuration of facility location models with multiple objectives under uncertainty.

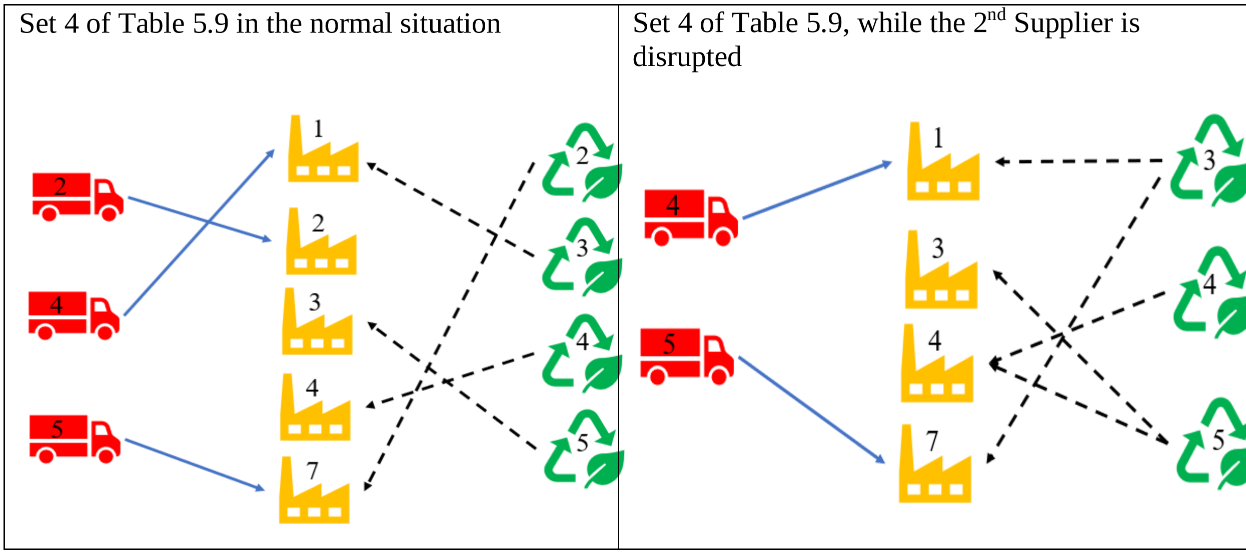

Fig. 5.14. The network design of Set 4 of Table 5.9 in the normal situation and in the case of disruption

5.6. Conclusions

In this study, a multi-objective, multi-echelon, multi-product, multi-period model has been developed to find the optimal configuration of a beverage container RL network (i.e., Encorp's stewardship plan) in Vancouver. The proposed model offers a solution approach to optimize the total cost, generated carbon emissions, social responsibility and technological innovation of third parties. The network includes container suppliers, beverage companies, markets, regional depots, and container recovery centers. On this matter, various activities such as transportation, production, recovery, and disposal have been considered. These activities may have a significant impact on the sustainability of Encorp's stewardship plan.

The main objective of recycling programs is to reduce the environmental impact through the social responsibility and technological innovation (e.g., the application of eco-technology in production, and environmental compliance). It is noticeable that the total cost of networks should be taken into account for the viability of such environmental programs in the long-term. With this respect, there are a variety of ambiguities related to imprecise parameters. To handle these issues, a stochastic possibilistic model has been developed for an RL network. Triangular fuzzy numbers were used in the optimization model to account for uncertainty in demands, returns, fixed and variable costs. In this research, scenario-based programming has been integrated with fuzzy optimization to examine the probable rate of disposal fraction.

Based on the sensitivity analyses in this study, reducing the defect rate can decrease the total cost of RL significantly. As the disposal fraction decreases, beverage companies can reuse the recovered containers instead of purchasing new containers from suppliers. Furthermore, the environmental impact associated with disposing of the unrecoverable containers is reduced as well.

To protect both environment and community, minimizing the carbon emissions along with maximizing the social responsibility of third parties are prominent factors. Because of this point, we have extended the optimization model to a multi-objective programming model. Then, the distance method has been employed to reach a trade-off surface. The non-dominated solutions have indicated that different facilities may be selected by changing the relative importance weight associated with objectives. To our knowledge, this research is among the first studies that has developed a multi-objective stochastic possibilistic optimization model to configure a beverage container RL network in Vancouver. According to our findings, the proposed model is an effective method to manage imprecise parameters in the recovery processes.

This research can be extended in different directions. The proposed multi-objective model can be extended to consider on-time delivery, and efficiency rate in container recovery centers as the objective functions. Furthermore, transportation modes (e.g., rail, road) can be considered and examined in this optimization model.

Chapter 6. A robust optimization model for designing a wastewater treatment network under uncertainty: Multi-objective approach

6.1. Introduction

Nowadays, companies are expected to run their operations in a sustainable manner. Sustainability refers to the usage of resources in a way that future generations can benefit from them as well (Ahi et al., 2016; Moore et al., 2017). Environmental practices are prominent parts of sustainability. On this subject, recently, sustainable environmental strategies (SES) have been considered to design facility location models. SES are those applied to reduce companies' environmental impact while still leading to cost-saving. In this regard, SES are led to optimize the companies' utilization rate of resources which give rise to advance their economic performance (Marsillac, 2008; Sarkis et al., 2010).

In the specific case of the oil and gas industry, hydraulic fracturing is utilized to access shale gas reserves. This operation involves the high-pressure injection of mixed carriers (i.e., water with a low volume of additives such as friction reducer, proppants, biocide, etc.) into a deep rock. As a result, fractures are created in the shale rock, and then gas releases. However, a large volume of fluids flows back to the ground surface after hydraulic fracturing operations. A great deal of concern is associated with improperly injection of polluted flowback fluids in landfills. Furthermore, pollution and depletion of water resources lead to the decline of available water for different users (e.g., industry and municipalities). Therefore, designing the wastewater treatment facilities includes a variety of benefits such as saving water resources and diverting waste from landfills and waterways.

Accordingly, there are many challenges to configure such facilities with regard to an uncertain amount of required fracturing fluids and flowback rates in different periods. Therefore, the application of deterministic assumptions has not been sufficient to design wastewater treatment network (Yang et al., 2014; Bartholomew and Mauter, 2016; Mohammad-Pajooh et al., 2018). In this study, a robust optimization model is developed to cope with several sources of uncertainty in facility location design.

6.1.1. Literature review

The type of uncertainty dictates the required optimization methods (e.g., robust optimization, possibilistic, and stochastic programming). Kim et al. (2018) classified the environment of decision-making to certain, risky, and uncertain situations. Deterministic mathematical programming models (MPMs) are applicable to solve problems whose parameters are known with certainty. Stochastic MPMs are applicable when, some or all, those parameters are random with known probability distributions (Gren et al., 2012; Kenne et al., 2012; Roghanian and Pazhoheshfar, 2014; Garrido et al., 2015; Yu and Foggo, 2017; Amin et al., 2017; Moreno et al., 2018; Snoeck et al., 2019). Possibilistic MPMs are suitable when the system parameters are uncertain (Wu et al., 2018). Such models are riskier than stochastic ones. Robust optimization is attractive when the range of uncertainty is definable (i.e., ellipsoidal, polyhedral, and box uncertainty sets) (Ben-Tal et al., 2005; Bohle et al., 2010; Pishvaee et al., 2011; Li and Liu, 2013; Hasani et al., 2015; Moarefdoost et al., 2016; Eshtehadi et al., 2017; Yu et al., 2017; Caunhye and Cardin, 2018).

6.1.1.1. Application of stochastic models in network design problems

The characteristics of data sets should be considered to develop appropriate methods in uncertain situations. Stochastic programming is applicable when the statistical distribution of data sets is known for all scenarios. Pishvaee et al. (2009) proposed a stochastic model to design a forward and reverse logistics network for different scenarios. Mete and Zabinsky (2010) utilized a stochastic mathematical model to select the storage locations of medical supplies. Amin and Zhang (2013a) presented a bi-objective scenario-based optimization model to minimize the total cost of a closed-loop supply chain network (CLSCN) under demand and return vagueness. Vahdani and Mohammadi (2015) proposed a robust stochastic model to minimize the total cost and waiting time of a CLSCN. Shabani and Sowlati (2016) proposed a robust stochastic method to maximize the profit of the biomass supply chain with regard to the uncertainty of biomass quality and availability. Keyvanshokooh et al. (2016) developed a robust stochastic model to configure a CLSCN. They applied scenario-based programming to deal with the volatility of transportation costs, and polyhedral uncertainty sets to define ranges for imprecise demand and return. Rezaee et al. (2017) developed a stochastic model to configure a green supply chain in a carbon trading environment. Tosarkani et al. (2019) utilized a bi-objective scenario-based optimization approach to design an electronic RLN under uncertainty. In their proposed model, the recovery rate of returned electronics was examined as a random parameter.

6.1.1.2. Application of possibilistic programming in network design problems

In some cases, it is not possible to estimate the probability of different scenarios. In this regard, possibilistic programming is applied to address uncertainty. Torabi and Hassini (2008) applied a possibilistic model to consider imprecise parameters (e.g., market demand, cost, time, and capacity) in a supply chain network (SCN) design. Aviso et al. (2010) used a fuzzy optimization model to optimize wastewater reuse in designing of an eco-industrial park. Pishvaee and Razmi (2012) introduced a fuzzy optimization model to configure an SCN. They applied an interactive fuzzy solution method to handle uncertainty. Subulan et al. (2015) formulated a scenario-based possibilistic method to consider financial and collection risks. They considered two types of uncertainty (i.e., randomness and epistemic) to design a lead-acid battery CLSCN. Zare and Lotfi (2015) utilized a possibilistic mixed-integer linear programming (MILP) in a CLSCN design. Govindan et al. (2016) presented a fuzzy MOM to design a sustainable reverse logistics network (RLN) under uncertainty. Talaei et al. (2016) developed a bi-objective possibilistic mathematical model to minimize the total cost and environmental impacts of a CLSCN. Tosarkani and Amin (2019) applied possibilistic programming to deal with uncertain fixed and variable costs in a battery CLSCN design.

6.1.1.3. Application of robust optimization in network design problems

Facility location design is a strategic decision which has costly consequences in case of unexpected changes. Robust optimization is a new approach that is extensively applied to deal with imprecise parameters due to its computational flexibility. Xu et al. (2016) applied a robust optimization model to design regional solid waste management under uncertainty. Bai and Liu (2016) utilized possibility distributions to address uncertain demand and transportation costs through a robust possibilistic optimization model in the food industry.

Guo et al. (2016) employed robust optimization to configure an automotive supply chain with regard to the uncertain macroeconomic environment. Aalaei and Davoudpour (2017) presented a robust optimization model to design a facility location for a cellular manufacturing system. Zokaee et al. (2017) considered a robust approach to address the uncertainty in demand, costs of transportation, and shortage in a bread SCN. Ghelichi et al. (2018) employed a robust optimization model to design a water distribution network. The total cost of the network was minimized concerning the uncertain amount of rainfall and demand.

Kim et al. (2018) configured a robust CLSCN in the fashion industry considering uncertainty in a reverse flow and customer demand. Orgut et al. (2018) investigated a donated food supply chain using a robust optimization approach. Aras and Bilge (2018) examined a robust multi-product SCN in the food industry. Prakash et al. (2018) considered the impact of uncertain demand on designing a furniture CLSCN by robust optimization. Sy et al. (2018) applied a robust MOM to configure a hybrid bio-refinery.

6.1.1.4. Application of green criteria in network design problems

In overall, economic criteria (e.g., profitability) have been taken into account as a primary objective in facility location problems. However, considering the green criteria is necessary due to the growing environmental concern (e.g., water contamination, soil and land pollution, carbon emissions).

Wang et al. (2011) proposed a multi-objective mathematical model to find non-dominated solutions of the total cost and environmental influence for a green SCN. Büyüközkan and Berkol (2011) applied a multi-criteria decision making (MCDM) method to design a green SCN. Azevedo et al. (2011) examined the impact of green practices on the performance of a supply chain in the automotive industry. Elhedhli and Merrick (2012) explored the impact of vehicle weight on CO_2 emissions in a green SCN. Kumar et al. (2012) introduced an environmental model to improve an SCN in the aspect of sustainability. Luthra et al. (2013) proposed a ranking model to prioritize green strategies in a manufacturing SCN.

Saffar et al. (2015) applied a fuzzy MOM to minimize the total costs and environmental issues associated with a green SCN. Coskun et al. (2016) configured a green SCN in accordance with customers' environmental concerns. Zhalechian et al. (2016) proposed a sustainable CLSCN concerning CO_2 emissions, fuel consumption, and wasted energy. Heidari-Fathian and Pasandideh (2018) examined sustainability in designing a multi-objective blood SCN to minimize the total cost and environmental impact. Hombach et al. (2018) mentioned that 22% of global CO_2 emissions are associated with the transportation sector. To address this issue, they applied a multi-objective scenario-based model to design a sustainable biodiesel SCN. López-Díaz et al. (2018)

designed a water network for shale gas production considering both economic and environmental criteria. Tosarkani and Amin (2018b) developed a multi-objective MCDM model for an electronic RLN. The proposed MOM was used to select third parties in an RLN regarding optimizing the total profit, sustainability, on-time delivery, and quality of remanufacturing operations. Table 6.1 comprises a list of criteria and mathematical approaches associated with some related papers.

Based on our knowledge and Table 6.1, most of the existing literature has considered one type of solution approach (e.g., possibilistic or stochastic programming) to design facility location models under uncertainty. However, several sources of uncertainty exist in practice based on types of parameters (e.g., bounded uncertainty sets, random parameters, and possibilistic uncertainty). As a result, an integrated solution approach is required to consider these types of imprecise parameters simultaneously. We will address such issues in this research.

Table 6.1
Applied mathematical approaches to deal with uncertainties

Authors	Uncertain parameters	Field of study	Multi-objective	Criteria *	Mathematical approach **	Real map
Pishvaee et al. (2009)	Demand, return, transportation costs	Numerical example		EC	SP	
Mete and Zabinsky (2010)	Demand, supply, transportation time	Medical supply		EC	SP	✓
Amin and Zhang (2013a)	Demand, return	Numerical example	✓	EC	SP	
Saffar et al. (2015)	Fixed and variable costs, demand, return	Numerical example	✓	GC, EC	FP	
Subulan et al. (2015)	Fixed and variable costs, demand, return	Lead-acid battery	✓	EC	SP and FP	✓
Bai and Liu (2016)	Demand, transportation costs	Food industry		EC	RO and FP	
Zhalechian et al. (2016)	Demand, return, lead time	LCD and LED TV industry	✓	GC, EC	SP and FP	✓
Shabani and Sowlati (2016)	Biomass quality and availability	Forest biomass power plant			SP and RO	
Aras and Bilge (2018)	Demand	Food industry		EC	RO	
Hombach et al. (2018)	Price, emission	Biodiesel sector	✓	GC, EC	RO	
Heidari-Fathian and Pasandideh (2018)	Demand, supply	Blood supply	✓	GC, EC	RO	
Kim et al. (2018)	Recycled products and demand	Fashion industry		EC	RO	
Prakash et al. (2018)	Demand	Furniture items		EC	RO	
Proposed model	Fixed and variable costs, demand, capacity of resources	Hydraulic fracturing	✓	GC, EC	Robust flexible chance-constrained model, and a new iterative approach to solve the MOM	✓

* Green criteria (GC), Economic criteria (EC).
** Stochastic programming (SP), Fuzzy programming (FP), Robust optimization (RO).

6.1.2. Aims and contributions of research

The objective of this research is to configure a wastewater treatment network the shale gas production. In this study, a bi-objective optimization model is proposed to consider the total cost and CO_2 emissions associated with wastewater treatment facilities. It is aimed to develop a robust flexible chance-constrained optimization model to find solutions in uncertain situations. Our overall solution framework is shown in Fig. 6.1.

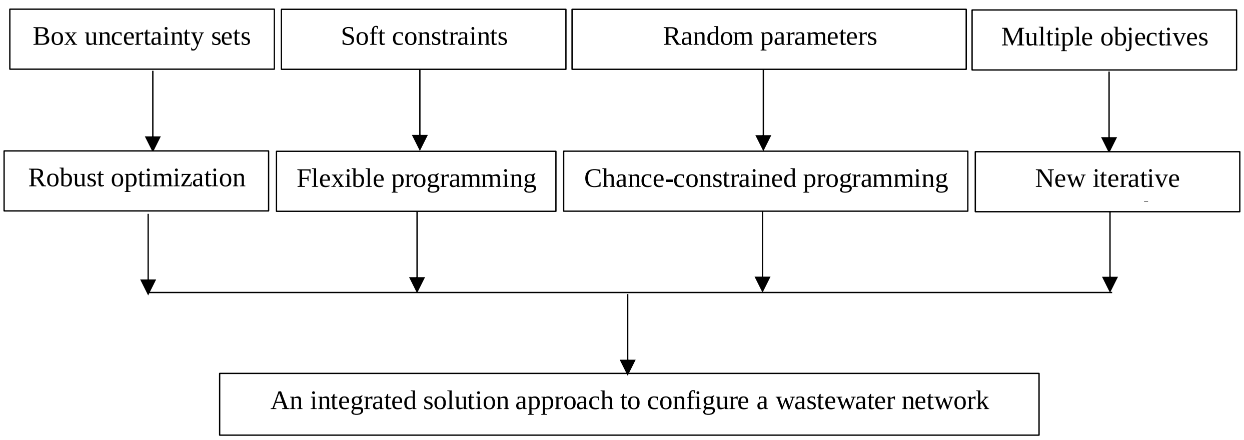

Fig. 6.1. An overall solution framework to develop the proposed model

The main contributions of this research are as follows:

- To design a wastewater treatment network in Alberta based on relevant information (e.g., consumed water in hydraulic fracturing operations) utilized from Fracfocus (2018).
- To propose a robust flexible chance-constrained model (RFCCM). To the best of our knowledge, this hybrid method is novel in the network design literature. In this respect, various sources of uncertainty are taken into account to configure a wastewater treatment network.
- To reduce environmental issues (e.g., CO_2 emissions) by developing a multi-objective approach. Two main sources of CO_2 emissions (i.e., transportation and operations) are considered to optimize the bi-objective model.
- To calculate the non-dominated solutions of the bi-objective problem using a new iterative approach. In addition, the distance method is applied to evaluate the performance and efficiency of this method in computing the non-dominated solutions.

This study is organized as follows: The problem statement is provided in Section 6.2. The optimization model and the solution approach are discussed in Sections 6.3 and 6.4, respectively. In Section 6.5, the values of parameters and solutions are provided. The new iterative approach is introduced and applied in Section 6.6. Finally, conclusions are summarized in Section 6.7.

6.2. Problem statement

In hydraulic fracturing operations, water consumption is mainly depended on the geologic formation. Fig. 6.2 illustrates the major deep shale gas prospective horizons in Alberta. In the case of thick shales, a large volume of water is required for hydraulic fracturing operations. However, the availability of groundwater and surface water sources varies in different regions. As a result, there is a growing concern that such amount of water required for hydraulic fracturing may have an impact on other users (i.e., agriculture, industry, and municipalities). Furthermore, there are some regulations to protect water sources from pollution in Alberta. Accordingly, flowback fluids are not allowed to be released to surface water bodies. They can be reused in oil and gas operations, or they must be disposed to deep subsurface (i.e., below the groundwater protection zone in which TDS is greater than 4,000 mg/L) (Canadian Water Regulations, 2016).

Accordingly, dealing with such a large volume of flowback fluids is the main environmental concern in hydraulic fracturing operations. Therefore, three different approaches can be considered to manage flowback fluids including deep well injection, indirect discharge to a wastewater treatment plant (WWTP), and basic separation to reuse. Disposal of entire flowback fluids increases the overall emissions as a result of trucks' travels. Furthermore, this approach may become an infeasible solution depending on geographic features, and the availability of disposal wells. Disposal costs of flowback fluids vary extremely depending on moving distance (Jiang et al., 2011; Slutz et al., 2012). Treating flowback fluids at WWTP can be a feasible approach if they have low salinity and toxicity (e.g., heavy metals). Basic separation to reuse is another solution to manage the flowback fluids which has received growing attention in recent years. In this approach, the treatment process is specifically designed for hydraulic fracturing operations. This process is based on basic separation or desalination and can be utilized at on-site facilities. On-site basic separation units (e.g., chemical precipitation, dissolved air floatation) have high water recovery and low treatment costs. However, the treated water from this process contains a high concentration of total dissolved solids (TDS) or salinity.

Therefore, application of mentioned approaches for the purpose of wastewater treatment in hydraulic fracturing operations depends on many factors, such as flowback fluids specifications, the proximity of water source(s) to the well pads, number of operating well pads, economic evaluation, environmental regulation, and geographical condition (e.g., the existence of nearby brine disposal well) (Slutz et al., 2012; Baudendistel et al., 2015; Bonapace et al., 2015).

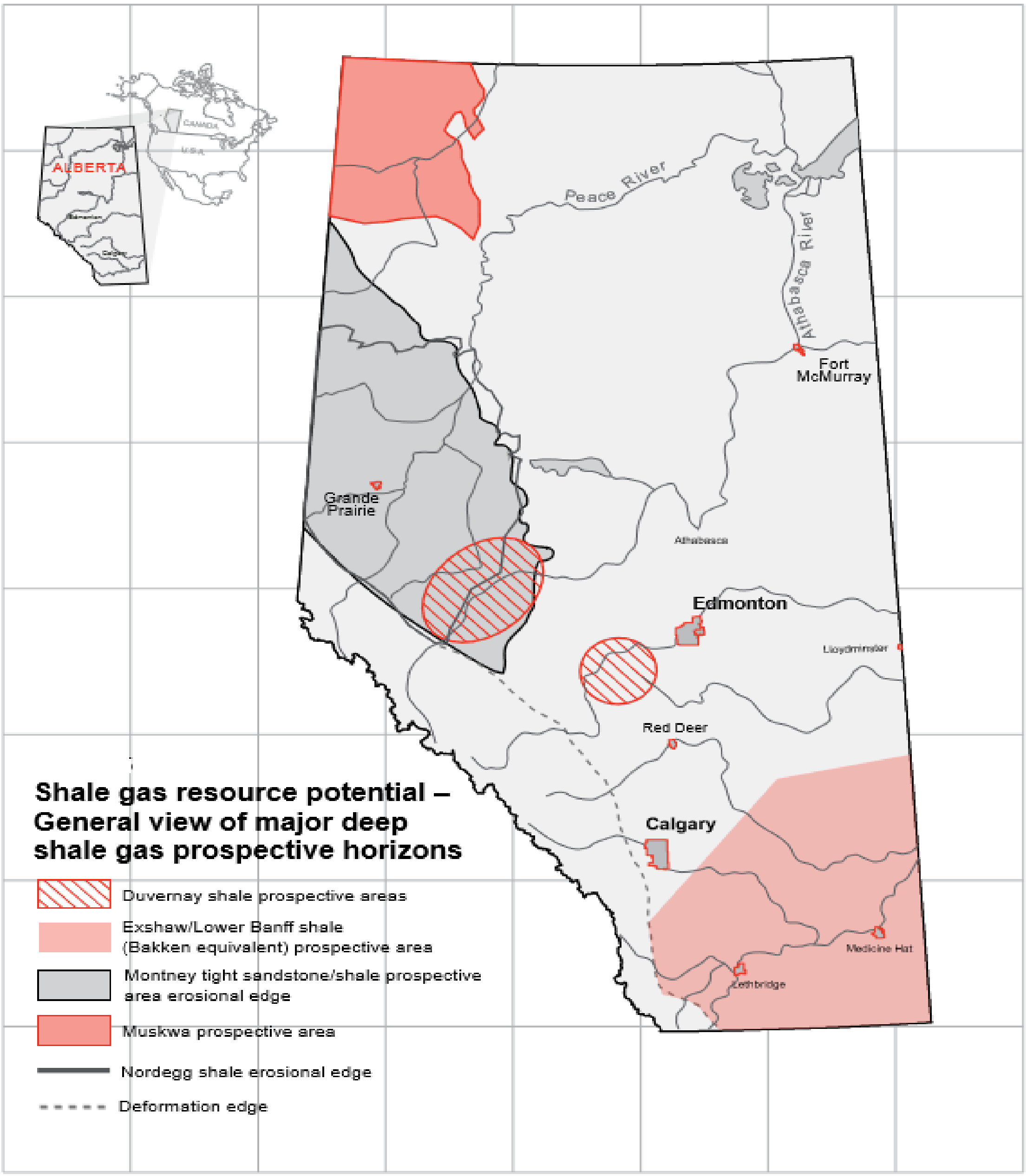

Fig. 6.2. Unconventional gas reserves in Alberta (Alberta Energy Regulator, 2014)

In this problem, a wastewater treatment network is designed and optimized. This network includes well pad(s), flowback fluid storage(s), on-site facility(s), WWTP(s), and disposal well(s). In this regard, there are several imprecise parameters (e.g., variable costs, the capacity of facilities, and volatility in water consumption) interfering with designing an optimal network. As illustrated in Fig. 6.3, a volume of fluids (i.e., U_{mnt}) is required for the hydraulic fracturing operations. This volume is mainly provided from the treatment process (i.e., J_{qmt} and X_{pmt}) performed by either WWTP(s) or on-site facility(s). However, water sources can be utilized in case of any shortages (i.e., S_{lmt}). After hydraulic fracturing operations, the flowback fluids (i.e., V_{not}) are transferred to the fluid storage(s). According to the mentioned treatment approaches, some recyclable ratios of flowback fluids are transferred to the on-site facility(s) and WWTP(s) based on their chemistry. The unrecyclable volumes are shipped to the location of disposal well(s).

In this study, the following questions are considered:

- Which and how many water source(s), fracturing blender(s), flowback fluids storage(s), on-site facility(s), water treatment unit(s), disposal well(s) must be selected?
- How much water must be provided by water source(s) to fulfill the amount of required fracturing fluids with regard to water recovery by on-site facility(s) and WWTP(s)?

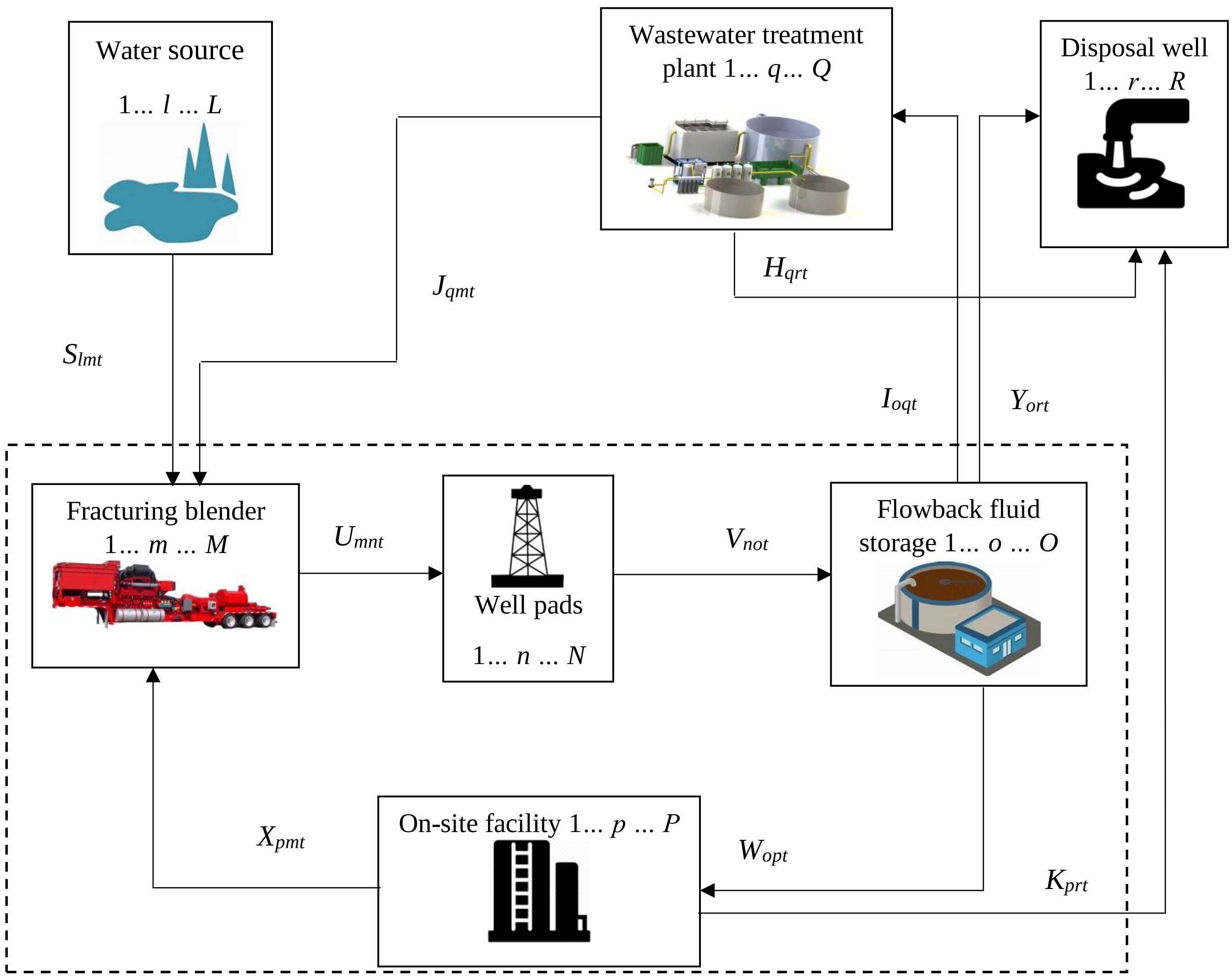

Fig. 6.3. A wastewater treatment network designed for hydraulic fracturing operations

6.3. Optimization model

In this section, an optimization model is developed to minimize the total cost and CO_2 emissions associated with hydraulic fracturing operations. To configure the wastewater treatment RL network, some facilities are considered on-site (depicted inside the dashed box in Fig. 6.3), and the others are assumed off-site. The definitions of elements involved in the mathematical model are written in Tables 6.2, 6.3, and 6.4.

Table 6.2
Definitions of sets

L: Set of potential locations for water sources ($l \in L$)
M: Set of fracturing blenders ($m \in M$)
N: Set of well pads ($n \in N$)
O: Set of flowback fluid storages ($o \in O$)
P: Set of on-site facilities ($p \in P$)
Q: Set of water treatment units ($q \in Q$)
R: Set of disposal wells ($r \in R$)
T: Set of time periods ($t \in T$)

Table 6.3
Definitions of parameters

A_l: Fixed-cost related to purchase, or rent and service of equipment holding in water source l
B_q: Fixed-cost related to construction and maintenance of WWTP q
C_r: Fixed-cost related to construction of disposal well r
E_m: Fixed-cost related to purchase, or rent and service of fracturing blender m
F_o: Fixed-cost related to service of flowback fluid storage o
G_p: Fixed-cost related to service of on-site facility p
a_{lm}: Distance between water storage l and fracturing blender m
b_{oq}: Distance between flowback fluid storage o and WWTP q
c_{or}: Distance between flowback fluid storage o and disposal well r
d_{qm}: Distance between WWTP q and fracturing blender m
v_{qr}: Distance between WWTP q and disposal well r
z_{pr}: Distance between on-site facility p and disposal well r
h_t: Unit cost of transportation in period t
e_l: Unit cost of operation related to provision of fluids from water source l
f_m: Unit cost of operation related to process in fracturing blender m
g_n: Unit cost of operation related to pumping fracturing fluids into well pad n
ς_o: Unit cost of transferring flowback fluids into storage o
i_p: Unit cost of operation related to process in on-site facility p
j_q: Unit cost of operation related to process in WWTP q
k_r: Unit cost of operation related to injection in disposal well r
ω_t: Flowback rate in period t
β_t: Injection rate to disposal well in period t
ζ_t: Recycling rate through the utilization of on-site facility(s) in period t
υ_t: Recycling rate through the utilization of WWTP(s) in period t
γ_t: Disposal rate of on-site facility(s) in period t
θ_t: Disposal rate of WWTP(s) in period t
Γ_o: Unit cost of holding flowback fluid in storage o
D_{nt}: Volume of required fracturing fluids for pumping into well pad n in period t
CW_{lt}: Capacity of water source l in period t

CD_{rt}: Capacity of disposal well r in period t
CU_{qt}: Capacity of WWTP q in period t
CB_{mt}: Capacity of fracturing blender m in period t
CF_{ot}: Capacity of flowback fluid storage o in period t
CO_{pt}: Capacity of on-site facility p in period t
CT: Truck capacity
s: Truck CO_2 emission per km
u: CO_2 emission due to operation of fracturing blender(s)
w: CO_2 emission due to process at well pads
x: CO_2 emission due to process in on-site facility(s)
y: CO_2 emission due to process in WWTP(s)

Table 6.4
Definitions of decision variables

S_{lmt}: Volume of fluids transferred to fracturing blender m from water source l in period t
U_{mnt}: Volume of fluids transferred to well pad n from fracturing blender m in period t
V_{not}: Volume of fluids returned to flowback fluid storage o from well pad n in period t
W_{opt}: Volume of fluids transferred to onsite facility p from flowback fluid storage o in period t
X_{pmt}: Volume of fluids returned to fracturing blender m from on-site facility p in period t
Y_{ort}: Volume of disposable fluids sent to disposal well r from flowback fluid storage o in period t
I_{oqt}: Volume of fluids sent to WWTP q from flowback fluid storage o in period t
J_{qmt}: Volume of fluids returned to fracturing blender m from WWTP q in period t
H_{qrt}: Volume of disposable fluids sent to disposal well r from WWTP q in period t
K_{prt}: Volume of disposable fluids sent to disposal well r from on-site facility p in period t
Φ_{ot}: Volume of flowback fluids holding in storage o in period t
ξ_l: 1, if the regional water source located in site l is utilized to provide required fluids, 0, otherwise.
ρ_r: 1, if the disposal well is selected at potential site r, 0, otherwise.
ψ_q: 1, if the water treatment unit is selected at potential site q, 0, otherwise.
κ_m: 1, if the fracturing blender m is selected, 0, otherwise.
λ_o: 1, if the flowback fluid storage o is selected, 0, otherwise.
δ_p: 1, if the on-site facility p is selected, 0, otherwise.

$$
\begin{aligned}
Min\ Z_1^c = & \sum_l \sum_m \sum_t (e_l + f_m + h_t.a_{lm}) S_{lmt} + \sum_q \sum_m \sum_t \left(f_m + h_t.d_{qm} \right) J_{qmt} + \\
& \sum_p \sum_m \sum_t (f_m) X_{pmt} + \sum_q \sum_r \sum_t \left(k_r + h_t.v_{qr} \right) H_{qrt} + \sum_p \sum_r \sum_t \left(k_r + h_t.z_{pr} \right) K_{prt} + \\
& \sum_o \sum_r \sum_t (k_r + h_t.c_{or}) Y_{ort} + \sum_m \sum_n \sum_t (g_n) U_{mnt} + \sum_n \sum_o \sum_t (\varsigma_o) V_{not} + \\
& \sum_o \sum_t (\Gamma_o) \Phi_{ot} + \sum_o \sum_q \sum_t \left(j_q + h_t.b_{oq} \right) I_{oqt} + \sum_o \sum_p \sum_t \left(i_p \right) W_{opt} + \\
& \left(\sum_l A_l \xi_l \right) + \left(\sum_q B_q \psi_q \right) + \left(\sum_r C_r \rho_r \right) + \left(\sum_m E_m \kappa_m \right) + \left(\sum_o F_o \lambda_o \right) + \left(\sum_p G_p \delta_p \right) \quad (6.1)
\end{aligned}
$$

$$
\begin{aligned}
Min\ Z_2^e = s&\left(\begin{aligned}&\sum_l\sum_m\sum_t\left(\frac{S_{lmt}}{CT}\right)a_{lm} + \sum_q\sum_r\sum_t\left(\frac{H_{qrt}}{CT}\right)v_{qr} + \sum_o\sum_r\sum_t\left(\frac{Y_{ort}}{CT}\right)c_{or} + \\ &\sum_o\sum_q\sum_t\left(\frac{I_{oqt}}{CT}\right)b_{oq} + \sum_q\sum_m\sum_t\left(\frac{J_{qmt}}{CT}\right)d_{qm} + \sum_p\sum_r\sum_t\left(\frac{K_{prt}}{CT}\right)z_{pr}\end{aligned}\right) + \\
u&\left(\sum_l\sum_m\sum_t S_{lmt} + \sum_q\sum_m\sum_t J_{qmt} + \sum_p\sum_m\sum_t X_{pmt}\right) + w\left(\sum_m\sum_n\sum_t U_{mnt}\right) + \\
x&\left(\sum_o\sum_p\sum_t W_{opt}\right) + y\left(\sum_o\sum_q\sum_t I_{oqt}\right)
\end{aligned} \tag{6.2}
$$

s.t.

$$\sum_l S_{lmt} + \sum_q J_{qmt} + \sum_p X_{pmt} = \sum_n U_{mnt} \qquad \forall m,t \tag{6.3}$$

$$\sum_m U_{mnt} \geq D_{nt} \qquad \forall n,t \tag{6.4}$$

$$\sum_m (U_{mnt})\omega_t = \sum_o V_{not} \qquad \forall n,t \tag{6.5}$$

$$\Phi_{ot} = \Phi_{o(t-1)} + \sum_n V_{not} - \left(\sum_q I_{oqt} + \sum_r Y_{ort} + \sum_p W_{opt}\right) \qquad \forall o,t \tag{6.6}$$

$$(\Phi_{ot})\beta_t \leq \sum_r Y_{ort} \qquad \forall o,t \tag{6.7}$$

$$(\Phi_{ot})\upsilon_t \leq \sum_q I_{oqt} \qquad \forall o,t \tag{6.8}$$

$$(\Phi_{ot})\zeta_t \leq \sum_p W_{opt} \qquad \forall o,t \tag{6.9}$$

$$\sum_o W_{opt} = \sum_m X_{pmt} + \sum_r K_{prt} \qquad \forall p,t \tag{6.10}$$

$$\left(\sum_o W_{opt}\right)\gamma_t \leq \sum_r K_{prt} \qquad \forall p,t \tag{6.11}$$

$$\sum_o I_{oqt} = \sum_m J_{qmt} + \sum_r H_{qrt} \qquad \forall q,t \tag{6.12}$$

$$\left(\sum_{o} I_{oqt}\right)\theta_t \leq \sum_{r} H_{qrt} \qquad \forall q,t \qquad (6.13)$$

$$\sum_{m} S_{lmt} \leq \xi_l \left(CW_{lt}\right) \qquad \forall l,t \qquad (6.14)$$

$$\sum_{o} I_{oqt} \leq \psi_q \left(CU_{qt}\right) \qquad \forall q,t \qquad (6.15)$$

$$\sum_{p} K_{prt} + \sum_{q} H_{qrt} + \sum_{o} Y_{ort} \leq \rho_r \left(CD_{rt}\right) \qquad \forall r,t \qquad (6.16)$$

$$\sum_{l} S_{lmt} + \sum_{q} J_{qmt} + \sum_{p} X_{pmt} \leq \kappa_m \left(CB_{mt}\right) \qquad \forall m,t \qquad (6.17)$$

$$\sum_{n} V_{not} + \Phi_{ot} \leq \lambda_o \left(CF_{ot}\right) \qquad \forall o,t \qquad (6.18)$$

$$\sum_{o} W_{opt} \leq \delta_p \left(CO_{pt}\right) \qquad \forall p,t \qquad (6.19)$$

$$\xi_l, \rho_r, \psi_q, \kappa_m, \lambda_o, \delta_p \in \{0,1\} \qquad \forall l,r,q,m,o,p \qquad (6.20)$$

$$S_{lmt}, U_{mnt}, V_{not}, W_{opt}, X_{pmt}, Y_{ort}, I_{oqt}, J_{qmt}, H_{qrt}, K_{prt}, \Phi_{ot}, \qquad \forall l,m,n,o,p,r,q,t \qquad (6.21)$$

In this study, Eq. (6.1) (i.e., Z_1^c) is employed to minimize the variable and fixed costs associated with wastewater treatment facilities. Furthermore, Eq. (6.2) (i.e., Z_2^e) is taken into account to minimize CO_2 emissions caused by transportation and operations required for the shale gas production.

Constraint (6.3) indicates the total fresh or recycled water used by blenders to make fracturing fluids. Constraint (6.4) shows the fluids required for hydraulic fracturing in well pad *n* in period *t*. Constraint (6.5) denotes the ratio of fluids returning to the surface. Constraint (6.6) describes that the holding fluids in period *t* is equal to holding fluids in period (*t*-1) plus the subtraction of output from input in flowback fluid storage(s) in period *t*. Constraints (6.7), (6.8), and (6.9) represent the portions of flowback fluids sent to disposal well(s), WWTP(s), and on-site facility(s). Constraints (6.10) and (6.11) imply trade-off relations between flowback fluids (W_{opt}), treated water (X_{pmt}), and disposable fluids (K_{prt}) in on-site facility(s). Constraints (6.12) and (6.13) balance the relations among the input and output flows in WWTP(s). Constraints (6.14), (6.15), (6.16), (6.17), (6.18), and (6.19) are capacity constraints of water source(s), WWTP(s), disposal well(s), fracturing blender(s), flowback fluid storage(s), and on-site facility(s), respectively. Constraints (6.20) and (6.21) define the binary and non-negative decision variables.

6.4. Solutions approach

We develop a novel RFCCM to deal with uncertain parameters. To describe the solution approach, Model (6.22) is considered (Ben-Tal and Nemirovski, 2000; Ben-Tal et al., 2005; Pishvaee and Khalaf, 2016).

$$\begin{aligned}
&Min\ p'\ddot{x} + q'\ddot{y} \\
&s.t. \\
&A'\ddot{x} \geq d', \\
&B'\ddot{x} \tilde{\leq} F'\ddot{y}, \\
&\ddot{y} \in \{0,1\}, \ddot{x} \geq 0.
\end{aligned} \tag{6.22}$$

In Model (6.22), vector p' shows variable costs, q' is related to fixed costs of opening or holding a facility, and d' denotes the required fracturing fluids. A', B', and F' are defined as the coefficient matrices in constraints. Besides, all binary and non-negative decision variables are defined by $\ddot{y}$, and $\ddot{x}$, respectively. In this study, all parameters related to the mentioned variable costs are varied in a specified bounded box, while the volume of fracturing fluids (i.e., d') complies with the normal distribution. The general form of uncertainty box is defined in Eq. (6.23).

$$u_{box} = \left\{ \Omega \in R^n : \left| \Omega_\iota - \bar{\Omega}_\iota \right| \leq \varphi \Delta_\iota, \iota = 1,\ldots,n \right\} \tag{6.23}$$

$\bar{\Omega}_\iota$ is the nominal value of the Ω_ι. Δ_ι defines the uncertainty scale, and φ > 0 denotes the uncertainty level. A specific case of interest is $\Delta_\iota = \bar{\Omega}_\iota$, where Ω_ι is allowed to deviate from the nominal value by the coefficient of φ. Accordingly, the robust counterpart of Model (6.22) can be written by Model (6.24).

$$
\begin{aligned}
&Min\ Z \\
&s.t. \\
&p'\ddot{x} + q'\ddot{y} \le Z \qquad \forall p' \in u_{box}^{p'} \\
&A'\ddot{x} \ge d' \qquad\qquad (6.24) \\
&B'\ddot{x} \tilde{\lessapprox} F'\ddot{y} \\
&\ddot{y} \in \{0,1\}, \ddot{x} \ge 0.
\end{aligned}
$$

The robust counterpart Model (6.24) can be replaced by the tractable equivalent version if the uncertain box is changed to a finite set. To this aim, Eq. (6.25) is applied based on the method of Ben-Tal et al. (2005).

$$p'\ddot{x} \le Z - q'\ddot{y}, \quad \forall p' \in u_{box}^{p'} \left| u_{box}^{p'} = \left\{ p' \in R^n : \left| p'_\iota - \bar{p}'_\iota \right| \le \varphi_{p'} \Delta_\iota^{p'}, \iota = 1, \dots, n_{p'} \right\}. \right. \qquad (6.25)$$

The left side of Eq. (6.25) includes uncertain parameters, while the parameters incorporating to the right side of the inequality are certain. Therefore, Model (6.26) can be developed to deal with uncertain bounded parameters as follows:

$$
\begin{aligned}
&Min\ Z \\
&s.t. \\
&\sum_\iota \left(\bar{p}'\ddot{x}_\iota + \eta_\iota \right) \le Z - q'\ddot{y} \\
&\varphi_{p'} \Delta_\iota^{p'} \ddot{x}_\iota \le \eta_\iota \qquad \forall \iota \in \{1, \dots, n_{p'}\}, \\
&\varphi_{p'} \Delta_\iota^{p'} \ddot{x}_\iota \ge -\eta_\iota \qquad \forall \iota \in \{1, \dots, n_{p'}\}. \\
&A'\ddot{x} \ge d' \qquad\qquad (6.26) \\
&B'\ddot{x} \tilde{\lessapprox} F'\ddot{y} \\
&\ddot{y} \in \{0,1\}, \ddot{x}, \eta_\iota \ge 0.
\end{aligned}
$$

To advance the described method, it is assumed that a random parameter is incorporated into the model with regard to soft constraints (i.e., capacities of resources). In Model (6.26), d' has the normal distribution and $B'\ddot{x} \tilde{\leq} F'\ddot{y}$ is the capacity constraint. If $\dot{X} \sim N\left(\dot{\mu},\dot{\sigma}^2\right)$, the density function can be represented by Eq. (6.27).

$$f\left(\dot{x}\right)=\frac{1}{\dot{\sigma}\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{\dot{x}-\dot{\mu}}{\dot{\sigma}}\right)^2},-\infty<\dot{x}<+\infty. \qquad (6.27)$$

$\dot{X}$ is converted to $\dot{Z}$, by the application of $\frac{\left(\dot{X}-\dot{\mu}\right)}{\dot{\sigma}}$. Eq. (6.28) illustrates the density function of $\dot{Z}$.

$$f\left(\dot{z}\right)=\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}\left(\dot{z}\right)^2},-\infty<\dot{z}<+\infty. \qquad (6.28)$$

In Model (6.24), $A'\ddot{x} \geq d'$, and $d' \sim N\left(\dot{\mu},\dot{\sigma}^2\right)$. The concept of chance-constrained programming is utilized to satisfy $A'\ddot{x} \geq d'$ with a probability of at least $1-\alpha$ (Hulsurkar et al., 1997; Bilsel and Ravindran, 2011; Roghanian and Pazhoheshfar, 2014). The deterministic equivalent of $P\left(A'\ddot{x} \geq d'\right) \geq 1-\alpha$ is obtained by $A'\ddot{x} \geq \dot{\sigma}\dot{z}_\alpha + \dot{\mu}$. The details of converting the chance constraint to the deterministic equivalent equation are provided in Appendix 6.A.

In this study, $\tilde{\leq}$ is utilized due to the uncertainty in the capacity of resources. With this respect, the left-hand side of a soft constraint is required to be less than or similar to the right-hand side value (Peidro et al., 2009). Therefore, $B'\ddot{x} \tilde{\leq} F'\ddot{y}$ can be converted to the crisp inequality constraint by $B'\ddot{x} \leq F'\ddot{y} + \left[\alpha'\left(1-\beta'\right)\right]\ddot{y}$. Where α' represents the maximum violation of soft constraint, and β' is the satisfaction level of such constraint (Cadenas and Verdegay, 1997). To control the degree of satisfaction level, θ' is used as the penalty cost for the violation of the soft constraint. Consequently, Model (6.26) can be replaced by Model (6.29).

$$
\begin{aligned}
& Min\ Z \\
& s.t. \\
& \sum_{\iota}\left(\bar{p}'\ddot{x}_{\iota}+\eta_{\iota}\right)\le Z-q'\ddot{y}-\theta'\left[\alpha'\left(1-\beta'\right)\right]\ddot{y} \\
& \varphi_{p'}\Delta_{\iota}^{p'}\ddot{x}_{\iota}\le\eta_{\iota} \qquad \forall\iota\in\left\{1,\ldots,n_{p'}\right\}, \\
& \varphi_{p'}\Delta_{\iota}^{p'}\ddot{x}_{\iota}\ge-\eta_{\iota} \qquad \forall\iota\in\left\{1,\ldots,n_{p'}\right\}. \\
& A'\ddot{x}\ge\dot{\sigma}\dot{z}_{\alpha}+\dot{\mu} \\
& B'\ddot{x}\le F'\ddot{y}+\left[\alpha'\left(1-\beta'\right)\right]\ddot{y} \\
& \ddot{y}\in\left\{0,1\right\},\ddot{x},\eta_{\iota}\ge 0,0\le\beta'\le 1.
\end{aligned}
\tag{6.29}
$$

Multiplication of $\ddot{y}$ by β' causes a nonlinear optimization model in Model (6.29). A non-negative auxiliary variable of $\nu'=\beta'\ddot{y}$ is applied to covert the nonlinear mathematical programming to the linear Model (6.30). Furthermore, Eqs. (6.31) to (6.34) are defined based on the method utilized by Pishvaee and Khalaf (2016). Eq. (6.31) forces ν' to be equal to 0 if $\ddot{y}=0$. Otherwise, Eqs. (6.32) to (6.33) force $\nu'=\beta'$ in case of $\ddot{y}=1$.

$$
\begin{aligned}
& min\ Z \\
& s.t. \\
& \sum_{\iota}\left(\bar{p}'\ddot{x}_{\iota}+\eta_{\iota}\right)\le Z-q'\ddot{y}-\theta'\left[\alpha'\left(\ddot{y}-\nu'\right)\right] \\
& \varphi_{p'}\Delta_{\iota}^{p'}\ddot{x}_{\iota}\le\eta_{\iota} \qquad \forall\iota\in\left\{1,\ldots,n_{p'}\right\}, \\
& \varphi_{p'}\Delta_{\iota}^{p'}\ddot{x}_{\iota}\ge-\eta_{\iota} \qquad \forall\iota\in\left\{1,\ldots,n_{p'}\right\}. \\
& A'\ddot{x}\ge\dot{\sigma}\dot{z}_{\alpha}+\dot{\mu} \\
& B'\ddot{x}\le F'\ddot{y}+\left[\alpha'\left(\ddot{y}-\nu'\right)\right]
\end{aligned}
\tag{6.30}
$$

$$\nu'\le M\ \ddot{y} \tag{6.31}$$

$$\nu'\ge M\left(\ddot{y}-1\right)+\beta' \tag{6.32}$$

$$\nu'\le\beta' \tag{6.33}$$

$$\ddot{y}\in\left\{0,1\right\},\ddot{x},\eta_{\iota},\nu'\ge 0,0\le\beta'\le 1 \tag{6.34}$$

Accordingly, the tractable form of the optimization model for the wastewater treatment network is written as follows:

$$
\begin{aligned}
Min\ Z_1^c &= \sum_l \sum_m \sum_t \left(\bar{e}_l S_{lmt} + \eta_{lmt}^e \right) + \sum_l \sum_m \sum_t \left(\bar{f}_m S_{lmt} + \eta_{lmt}^f \right) \\
&+ \sum_l \sum_m \sum_t \left(\left(\bar{h}_t . a_{lm} \right) S_{lmt} + \eta_{lmt}^h \right) + \sum_q \sum_m \sum_t \left(\bar{f}_m J_{qmt} + \eta_{qmt}^f \right) \\
&+ \sum_q \sum_m \sum_t \left(\left(\bar{h}_t . d_{qm} \right) J_{qmt} + \eta_{qmt}^h \right) + \sum_p \sum_m \sum_t \left(\bar{f}_m X_{pmt} + \eta_{pmt}^f \right) \\
&+ \sum_q \sum_r \sum_t \left(\bar{k}_r H_{qrt} + \eta_{qrt}^k \right) + \sum_q \sum_r \sum_t \left(\left(\bar{h}_t . v_{qr} \right) H_{qrt} + \eta_{qrt}^h \right) \\
&+ \sum_p \sum_r \sum_t \left(\bar{k}_r K_{prt} + \eta_{prt}^k \right) + \sum_p \sum_r \sum_t \left(\left(\bar{h}_t . z_{pr} \right) K_{prt} + \eta_{prt}^h \right) \\
&+ \sum_o \sum_r \sum_t \left(\bar{k}_r Y_{ort} + \eta_{ort}^k \right) + \sum_o \sum_r \sum_t \left(\left(\bar{h}_t . c_{or} \right) Y_{ort} + \eta_{ort}^h \right) \\
&+ \sum_m \sum_n \sum_t \left(\bar{g}_n U_{mnt} + \eta_{mnt}^g \right) + \sum_n \sum_o \sum_t \left(\bar{\varsigma}_o V_{not} + \eta_{not}^{\varsigma} \right) + \sum_o \sum_t \left(\bar{\Gamma}_o \Phi_{ot} + \eta_{ot}^{\Gamma} \right) \\
&+ \sum_o \sum_q \sum_t \left(\bar{j}_q I_{oqt} + \eta_{oqt}^j \right) + \sum_o \sum_q \sum_t \left(\left(\bar{h}_t . b_{oq} \right) I_{oqt} + \eta_{oqt}^h \right) + \sum_o \sum_p \sum_t \left(\bar{i}_p W_{opt} + \eta_{opt}^i \right) \\
&+ \left(\sum_l A_l \xi_l \right) + \left(\sum_q B_q \psi_q \right) + \left(\sum_r C_r \rho_r \right) + \left(\sum_m E_m \kappa_m \right) + \left(\sum_o F_o \lambda_o \right) + \left(\sum_p G_p \delta_p \right) + \\
&\theta_1' \left[\alpha_1' \sum_l \left(\xi_l - v_l^1 \right) \right] + \theta_2' \left[\alpha_2' \sum_q \left(\psi_q - v_q^2 \right) \right] + \theta_3' \left[\alpha_3' \sum_r \left(\rho_r - v_r^3 \right) \right] + \theta_4' \left[\alpha_4' \sum_m \left(\kappa_m - v_m^4 \right) \right] \\
&+ \theta_5' \left[\alpha_5' \sum_o \left(\lambda_o - v_o^5 \right) \right] + \theta_6' \left[\alpha_6' \sum_p \left(\delta_p - v_p^6 \right) \right] \qquad (6.35)
\end{aligned}
$$

s.t.

Constraints (6.3), (6.5) to (6.12), (6.20), (6.21)

$$\varphi_e \Delta_l^e S_{lmt} \le \eta_{lmt}^e \qquad \forall l,m,t \qquad (6.36)$$

$$\varphi_e \Delta_l^e S_{lmt} \ge -\eta_{lmt}^e \qquad \forall l,m,t \qquad (6.37)$$

$$\varphi_f \Delta_m^f S_{lmt} \le \eta_{lmt}^f \qquad \forall l,m,t \qquad (6.38)$$

$$\varphi_f \Delta_m^f S_{lmt} \ge -\eta_{lmt}^f \qquad \forall l,m,t \qquad (6.39)$$

$$\varphi_h\left(\Delta_t^h.a_{lm}\right)S_{lmt} \le \eta_{lmt}^h \qquad \forall l,m,t \qquad (6.40)$$

$$\varphi_h\left(\Delta_t^h.a_{lm}\right)S_{lmt} \ge -\eta_{lmt}^h \qquad \forall l,m,t \qquad (6.41)$$

$$\varphi_f\,\Delta_m^f J_{qmt} \le \eta_{qmt}^f \qquad \forall q,m,t \qquad (6.42)$$

$$\varphi_f\,\Delta_m^f J_{qmt} \ge -\eta_{qmt}^f \qquad \forall q,m,t \qquad (6.43)$$

$$\varphi_h\left(\Delta_t^h.d_{qm}\right)J_{qmt} \le \eta_{qmt}^h \qquad \forall q,m,t \qquad (6.44)$$

$$\varphi_h\left(\Delta_t^h.d_{qm}\right)J_{qmt} \ge -\eta_{qmt}^h \qquad \forall q,m,t \qquad (6.45)$$

$$\varphi_f\,\Delta_m^f X_{pmt} \le \eta_{pmt}^f \qquad \forall p,m,t \qquad (6.46)$$

$$\varphi_f\,\Delta_m^f X_{pmt} \ge -\eta_{pmt}^f \qquad \forall p,m,t \qquad (6.47)$$

$$\varphi_k\,\Delta_r^k H_{qrt} \le \eta_{qrt}^k \qquad \forall q,r,t \qquad (6.48)$$

$$\varphi_k\,\Delta_r^k H_{qrt} \ge -\eta_{qrt}^k \qquad \forall q,r,t \qquad (6.49)$$

$$\varphi_h\left(\Delta_t^h.v_{qr}\right)H_{qrt} \le \eta_{qrt}^h \qquad \forall q,r,t \qquad (6.50)$$

$$\varphi_h\left(\Delta_t^h.v_{qr}\right)H_{qrt} \ge -\eta_{qrt}^h \qquad \forall q,r,t \qquad (6.51)$$

$$\varphi_k\,\Delta_r^k K_{prt} \le \eta_{prt}^k \qquad \forall p,r,t \qquad (6.52)$$

$$\varphi_k\,\Delta_r^k K_{prt} \ge -\eta_{prt}^k \qquad \forall p,r,t \qquad (6.53)$$

$$\varphi_h\left(\Delta_t^h.z_{pr}\right)K_{prt} \le \eta_{prt}^h \qquad \forall p,r,t \qquad (6.54)$$

$$\varphi_h\left(\Delta_t^h.z_{pr}\right)K_{prt} \ge -\eta_{prt}^h \qquad \forall p,r,t \qquad (6.55)$$

$$\varphi_k\,\Delta_r^k Y_{ort} \le \eta_{ort}^k \qquad \forall o,r,t \qquad (6.56)$$

$$\varphi_k\,\Delta_r^k Y_{ort} \ge -\eta_{ort}^k \qquad \forall o,r,t \qquad (6.57)$$

$$\varphi_h\left(\Delta_t^h.c_{or}\right)Y_{ort} \le \eta_{ort}^h \qquad \forall o,r,t \qquad (6.58)$$

$$\varphi_h\left(\varDelta_t^h.c_{or}\right)Y_{ort} \geq -\eta_{ort}^h \qquad \forall o,r,t \qquad (6.59)$$

$$\varphi_g \varDelta_n^g U_{mnt} \leq \eta_{mnt}^g \qquad \forall m,n,t \qquad (6.60)$$

$$\varphi_g \varDelta_n^g U_{mnt} \geq -\eta_{mnt}^g \qquad \forall m,n,t \qquad (6.61)$$

$$\varphi_\varsigma \varDelta_o^\varsigma V_{not} \leq \eta_{not}^\varsigma \qquad \forall n,o,t \qquad (6.62)$$

$$\varphi_\varsigma \varDelta_o^\varsigma V_{not} \geq -\eta_{not}^\varsigma \qquad \forall n,o,t \qquad (6.63)$$

$$\varphi_\varGamma \varDelta_o^\varGamma \varPhi_{ot} \leq \eta_{ot}^\varGamma \qquad \forall o,t \qquad (6.64)$$

$$\varphi_\varGamma \varDelta_o^\varGamma \varPhi_{ot} \geq -\eta_{ot}^\varGamma \qquad \forall o,t \qquad (6.65)$$

$$\varphi_j \varDelta_q^j I_{oqt} \leq \eta_{oqt}^j \qquad \forall o,q,t \qquad (6.66)$$

$$\varphi_j \varDelta_q^j I_{oqt} \geq -\eta_{oqt}^j \qquad \forall o,q,t \qquad (6.67)$$

$$\varphi_h\left(\varDelta_t^h.b_{oq}\right)I_{oqt} \leq \eta_{oqt}^h \qquad \forall o,q,t \qquad (6.68)$$

$$\varphi_h\left(\varDelta_t^h.b_{oq}\right)I_{oqt} \geq -\eta_{oqt}^h \qquad \forall o,q,t \qquad (6.69)$$

$$\varphi_i \varDelta_p^i W_{opt} \leq \eta_{opt}^i \qquad \forall o,p,t \qquad (6.70)$$

$$\varphi_i \varDelta_p^i W_{opt} \geq -\eta_{opt}^i \qquad \forall o,p,t \qquad (6.71)$$

$$\sum_m U_{mnt} \geq \dot{\sigma}\dot{z}_\alpha + \dot{\mu} \qquad \forall n,t \qquad (6.72)$$

$$\sum_m S_{lmt} \leq \xi_l\left(CW_{lt}\right) + \left[\alpha_1'\left(\xi_l - \nu_l^1\right)\right] \qquad \forall l,t \qquad (6.73)$$

$$\nu_l^1 \leq M\,\xi_l \qquad \forall l \qquad (6.74)$$

$$\nu_l^1 \geq M\left(\xi_l - 1\right) + \beta_1 \qquad \forall l \qquad (6.75)$$

$$\nu_l^1 \leq \beta_1 \qquad \forall l \qquad (6.76)$$

$$\sum_o I_{oqt} \leq \psi_q\left(CU_{qt}\right) + \left[\alpha_2'\left(\psi_q - \nu_q^2\right)\right] \qquad \forall q,t \qquad (6.77)$$

$$\nu_q^2 \leq M\,\psi_q \qquad \forall q \qquad (6.78)$$

$$\nu_q^2 \geq M\left(\psi_q - 1\right) + \beta_2 \qquad \forall q \qquad (6.79)$$

$$\nu_q^2 \leq \beta_2 \qquad \forall q \qquad (6.80)$$

$$\sum_p K_{prt} + \sum_q H_{qrt} + \sum_o Y_{ort} \leq \rho_r \left(CD_{rt}\right) + \left[\alpha_3'\left(\rho_r - \nu_r^3\right)\right] \qquad \forall r,t \qquad (6.81)$$

$$\nu_r^3 \leq M\ \rho_r \qquad \forall r \qquad (6.82)$$

$$\nu_r^3 \geq M\left(\rho_r - 1\right) + \beta_3 \qquad \forall r \qquad (6.83)$$

$$\nu_r^3 \leq \beta_3 \qquad \forall r \qquad (6.84)$$

$$\sum_l S_{lmt} + \sum_q J_{qmt} + \sum_p X_{pmt} \leq \kappa_m \left(CB_{mt}\right) + \left[\alpha_4'\left(\kappa_m - \nu_m^4\right)\right] \qquad \forall m,t \qquad (6.85)$$

$$\nu_m^4 \leq M\ \kappa_m \qquad \forall m \qquad (6.86)$$

$$\nu_m^4 \geq M\left(\kappa_m - 1\right) + \beta_4 \qquad \forall m \qquad (6.87)$$

$$\nu_m^4 \leq \beta_4 \qquad \forall m \qquad (6.88)$$

$$\sum_n V_{not} + \Phi_{ot} \leq \lambda_o \left(CF_{ot}\right) + \left[\alpha_5'\left(\lambda_o - \nu_o^5\right)\right] \qquad \forall o,t \qquad (6.89)$$

$$\nu_o^5 \leq M\ \lambda_o \qquad \forall o \qquad (6.90)$$

$$\nu_o^5 \geq M\left(\lambda_o - 1\right) + \beta_5 \qquad \forall o \qquad (6.91)$$

$$\nu_o^5 \leq \beta_5 \qquad \forall o \qquad (6.92)$$

$$\sum_o W_{opt} \leq \delta_p \left(CO_{pt}\right) + \left[\alpha_6'\left(\delta_p - \nu_p^6\right)\right] \qquad \forall p,t \qquad (6.93)$$

$$\nu_p^6 \leq M\ \delta_p \qquad \forall p \qquad (6.94)$$

$$\nu_p^6 \geq M\left(\delta_p - 1\right) + \beta_6 \qquad \forall p \qquad (6.95)$$

$$\nu_p^6 \leq \beta_6 \qquad \forall p \qquad (6.96)$$

$$\eta_{lmt}^e, \eta_{lmt}^f, \eta_{lmt}^h, \eta_{qmt}^f, \eta_{qmt}^h, \eta_{pmt}^f, \eta_{qrt}^k, \eta_{qrt}^h, \eta_{prt}^k, \eta_{prt}^h, \eta_{ort}^k, \eta_{ort}^h, \eta_{mnt}^g, \eta_{not}^{\varsigma}, \eta_{ot}^{\Gamma}, \eta_{oqt}^j, \eta_{oqt}^h, \eta_{opt}^i \geq 0$$

$$\forall l,m,n,o,p,q,r,t \qquad (6.97)$$

$$\nu_l^1, \nu_q^2, \nu_r^3, \nu_m^4, \nu_o^5, \nu_p^6 \geq 0 \qquad \forall l, r, q, m, o, p \qquad (6.98)$$

$$0 \leq \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6 \leq 1 \qquad (6.99)$$

6.5. Values of parameters and solutions

The wastewater treatment network is configured based on the proposed RFCCM. The required volumes of fluids for hydraulic fracturing vary significantly due to the thickness of shale rocks. Fracturing records of shale gas reserves in the municipal district of Greenview are examined to estimate consumed fluids for hydraulic fracturing operations. IBM SPSS Statistics is employed to analyze data sets based on Fracfocus (2018). The descriptive statistics and the normality test associated with consumed fracturing fluids are demonstrated in Tables 6.5 and 6.6, respectively. According to the outputs of Kolmogorov-Smirnov and Shapiro-Wilk tests, the Sig. values are greater than 0.05. Therefore, it is verified that the data sets (i.e., consumed fracturing fluids) follow the normal distribution $D_{nt} \sim N$ ($\dot{\mu}$ = 50,505.38, $\dot{\sigma}$ = 9,281.66).

Table 6.5
Descriptive statistics using IBM SPSS Statistics

	Mean	Std. deviation	Sample size
Demand for consumed fracturing fluids	50,505.38	9,281.66	50

Table 6.6
Normality test using IBM SPSS Statistics

Types of tests	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Used water	0.105	52	0.200	0.970	52	0.213

To extend the sample space, the value of consumed fracturing fluids has been simulated by NORM.INV (probability, mean, standard deviation) in Microsoft Excel. The values of probability, mean, and standard deviation are defined as RAND (), 50505.38, and 9281.66, respectively. Fig. 6.4 indicates the frequency histogram for 100 data sets.

As demonstrated in Appendix 6.A, $\Phi\left(\dot{z}_{\alpha}\right)$ equals to$1-\alpha$. Therefore $P\left(\dot{X} \le 56{,}765.76\right)$ is $P\left(\frac{\dot{X}-\dot{\mu}}{\dot{\sigma}} \le \frac{56{,}765.76-50505.38}{9{,}281.66}\right) = \Phi\left(\frac{56{,}765.76-50505.38}{9{,}281.66}\right)$ = 75%. Fig. 6.4 shows that 75 data sets are less than $Z_{25\%}$.

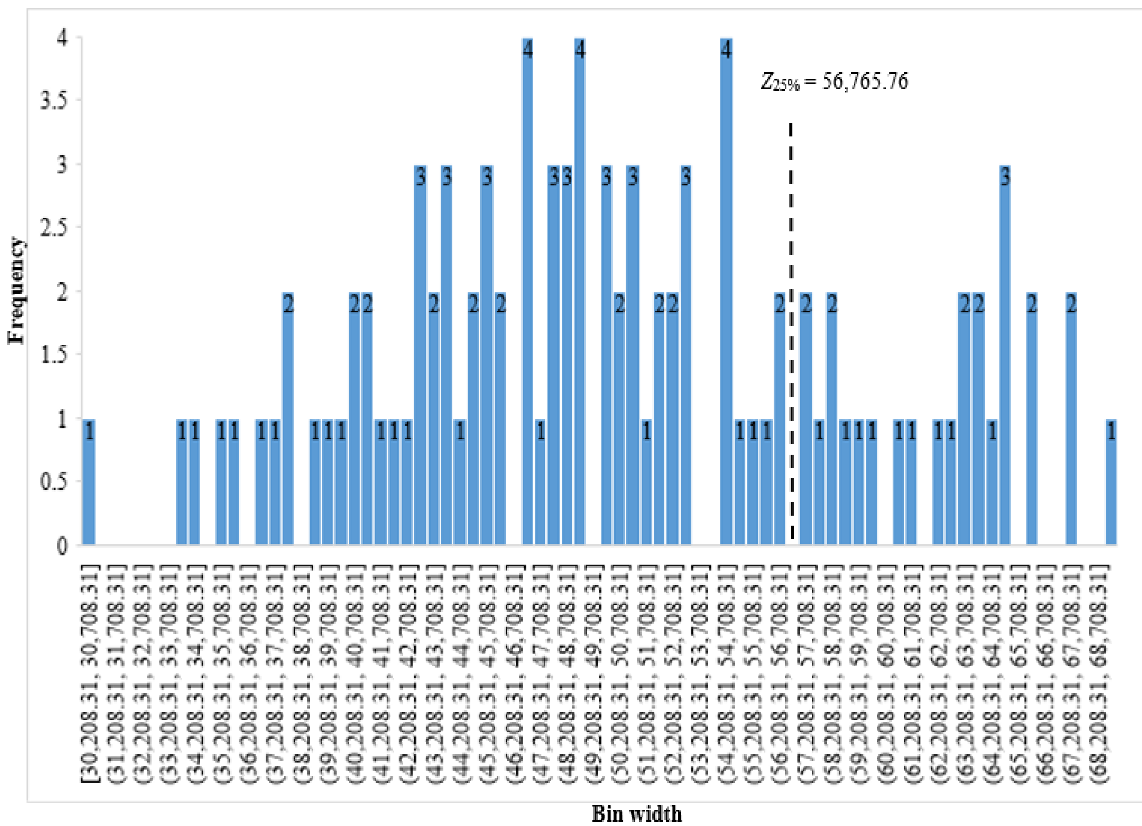

Fig. 6.4. The frequency histogram of consumed fracturing fluids

In this study, 5 regional water storages, 3 shale gas reserves, 4 locations as central WWTP(s), and 7 locations as disposal wells are considered. Transportation costs can be considered as functions of fuel prices and distances between potential locations. In this regard, Google Maps is employed to calculate the real driving distances that have a direct impact on transportation costs and carbon emissions. The values of the other parameters are written in Table 6.B.1 in Appendix 6.B.

IBM ILOG CPLEX 12.8.0 is employed to solve the proposed RFCCM. The mathematical model includes 861 constraints, 649 non-negative variables, 52 binary variables, and 3,305 non-zero coefficients. Table 6.7 includes the optimal solutions of the proposed model for different scenarios (i.e., α = 30 %, 25%, 20%, 15%, 10% and 5%). As α decreases, the minimum probability to satisfy the chance constraint (i.e., demand for the required fracturing fluids) increases on the well pads. The reason for choosing various α is showing that changes in the demand have a direct impact on variable costs or fixed costs or both of them. As the wastewater increases, the variable costs for treatment increase as well. However, changing fixed costs is only related to the required number of open facilities. For example, the optimal off-site network includes 1 location for the wastewater treatment plant, 1 disposal well, and 2 regional water sources in the case of α = 5%. With this respect, 2 basic treatment facilities, 6 fracturing blenders, and 2 flowback fluid storages are required. The optimal network of off-site facilities is illustrated in Fig. 6.5.

Table 6.7
Solutions of RFCCM for hydraulic fracturing operation

Objective value for Z_1^c (φ = 10%)	Selected WWTP	Selected on-site facility	Working fracturing blenders	Selected flowback fluid storage(s)	Selected disposal well	Selected regional water sources
7,597,029.25 (α = 30%) 7,767,870.53 (α = 25%) 7,958,111.68 (α = 20%)	ψ_1	δ_1	κ_2 to κ_6	λ_2	ρ_1	ξ_1, ξ_2
8,335,530.82 (α = 15%) 8,619,480.94 (α = 10%) 9,105,786.98 (α = 5%)	ψ_1	δ_1	κ_1 to κ_6	λ_1, λ_2	ρ_1	ξ_1, ξ_2

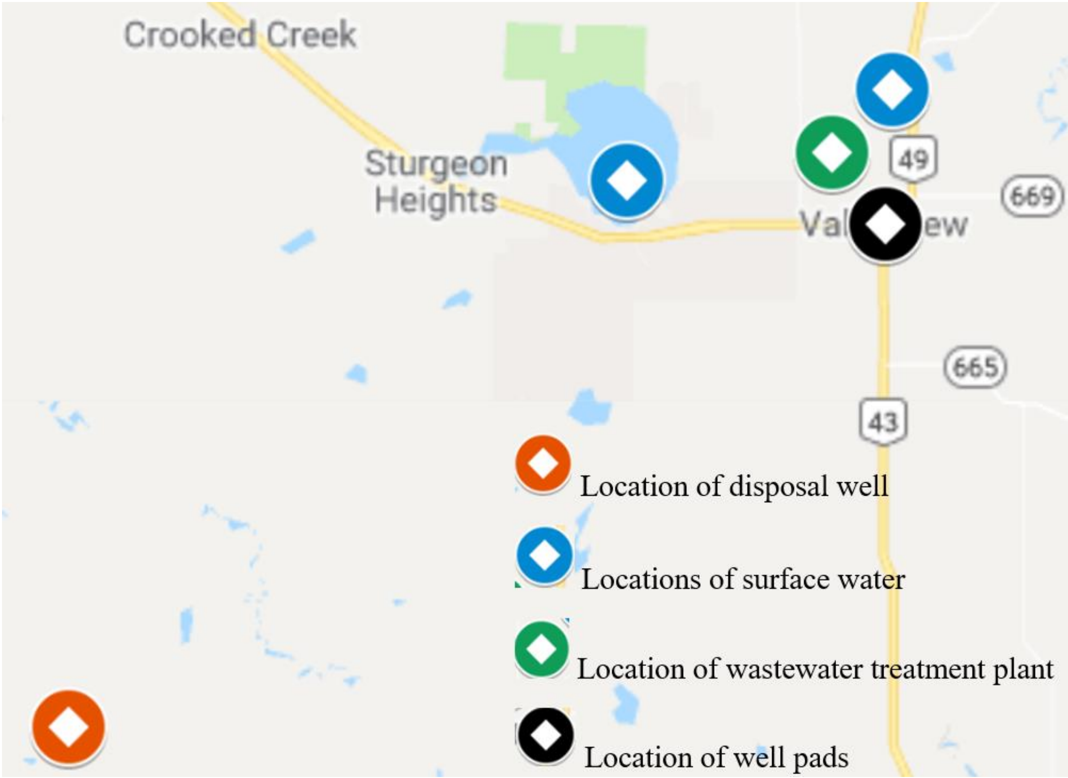

Fig. 6.5. The locations of the selected off-site facilities for the hydraulic fracturing operation

The RFCCM is solved for 100 data sets of consumed fracturing fluids. The optimal solutions are provided in Table 6.C.1 in Appendix 6.C. As illustrated in Table 6.7, the total cost associated with demand of 56,765.76 (α = 25%) and 65,772.35 (α = 5%) are 7,767,870.53 and 9,105,786.98, respectively. Fig. 6.6 also indicates that 75% of the objective values are less than 7,767,870, and 95% of them are less than 9,105,786. Therefore, demand for the required fracturing fluids has a significant impact on the total cost of hydraulic fracturing operations. In this regard, the regression analysis is also performed to show the predictability of the dependent variable (i.e., total cost) by the independent variable (i.e., demand for required fracturing fluids). Table 6.8 shows the relative importance of the independent variable and collinearity statistics. The unstandardized coefficient shows that a one-unit increase of the independent variable increases the dependent variable by 133.67 in addition to 229,291.38 as a constant value. Besides, the standardized coefficient indicates that the correlation between independent and dependent variables is almost 99 percent which is statistically significant.

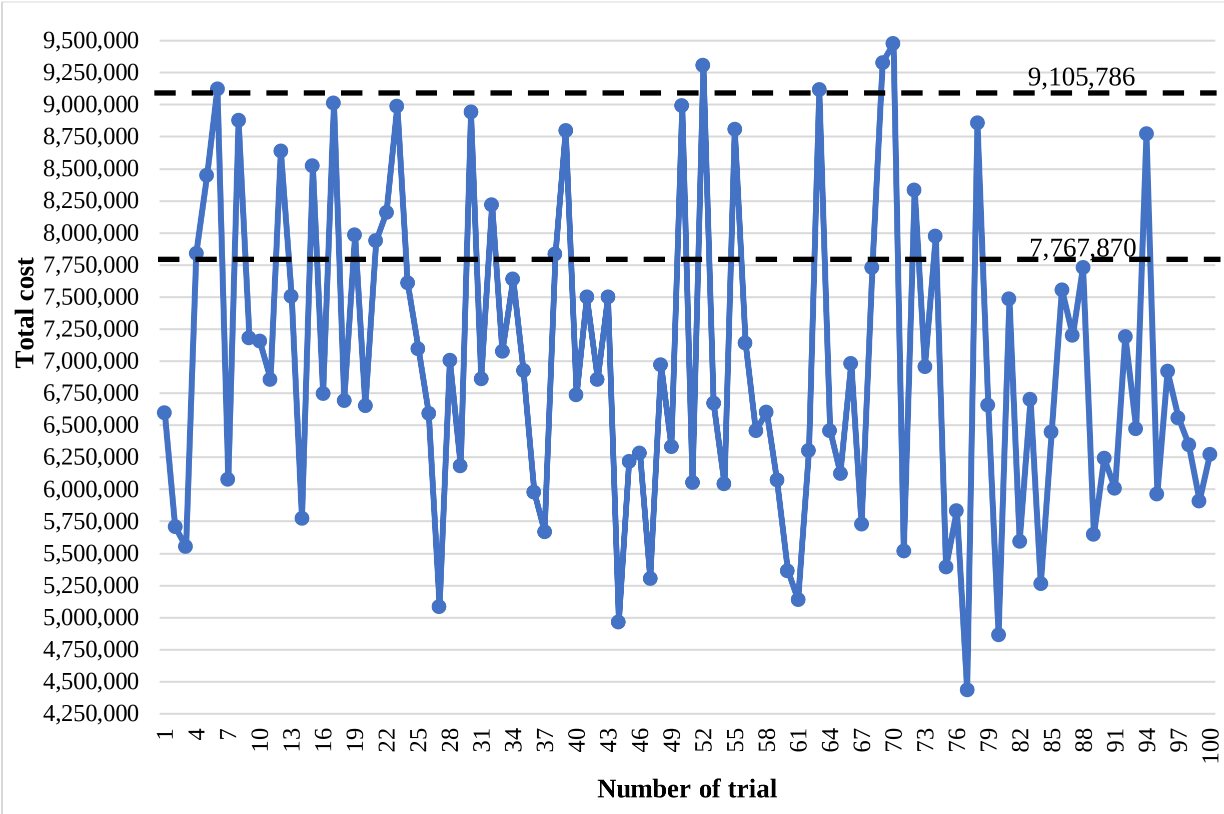

Fig. 6.6. The total cost related to 100 data sets

Table 6.8
Regression analysis using IBM SPSS Statistics

	Unstandardized coefficients		Standardized coefficients		
Model	B	Std.Error	Beta	t	Sig.
Constant	229,291.381	38,366.522		5.976	0.000
Demand for fracturing fluids	133.674	0.749	0.998	178.509	0.000

It is noticeable that the uncertainty level affects the total cost. The sensitivity analysis is conducted on the uncertainty level (i.e., φ) to show the behavior of the RFCCM. The value of φ is determined by decision-makers based on the type of parameters and the associated risk level. As defined in Model (6.30), $\varphi_{p'} \Delta_{\imath}^{p'} \ddot{x}_{\imath}$ is less than or equal to $\eta_{\imath}$ which is incorporated into the objective function. Table 6.9 illustrates that the value of total cost increases as φ increases.

Table 6.9
Sensitivity analysis with regard to uncertainty level

Z_1^c	φ = 20%	φ = 40%	φ = 60%	φ = 80%	φ = 1
α = 25%	8,384,040.58	9,616,380.68	10,848,720.77	12,081,060.87	13,313,400.97
α = 5%	9,824,494.89	11,261,910.71	12,699,326.52	14,136,742.34	15,574,158.16

A solution is called robust if there are both optimality robustness and feasibility robustness. The feasibility robustness is reached while solutions are feasible for all possible changes of imprecise parameters (Ben-Tal and Nemirovski, 2000; Pishvaee and Khalaf, 2016). Fig. 6.7 indicates that the total cost remains unchanged while α is equal to 2.5%, or 5% because the demand can be fulfilled by the nominal capacity of the resources. In the case of α = 1%, the total cost increases as the penalty cost increases due to the possible violation (α') of the soft constraint.

The proposed RFCCM enables decision-makers to deal with different types of imprecise parameters through the integration of different methods. Robust optimization has been applied for the bounded uncertainty sets (i.e., variable costs). In addition, chance-constrained programming has been utilized for the random parameter (i.e., the required amount of fracturing fluids). Besides, flexible programming has been utilized in this research for the soft constraints (i.e., the capacity of resources). Deviations from the nominal value on soft constraints have been handled by the penalty costs and the confidence level. Therefore, the values of the objective function depend on the decision-makers and their choices to determine the penalty costs and the degree of possible violation for the capacity of resources.

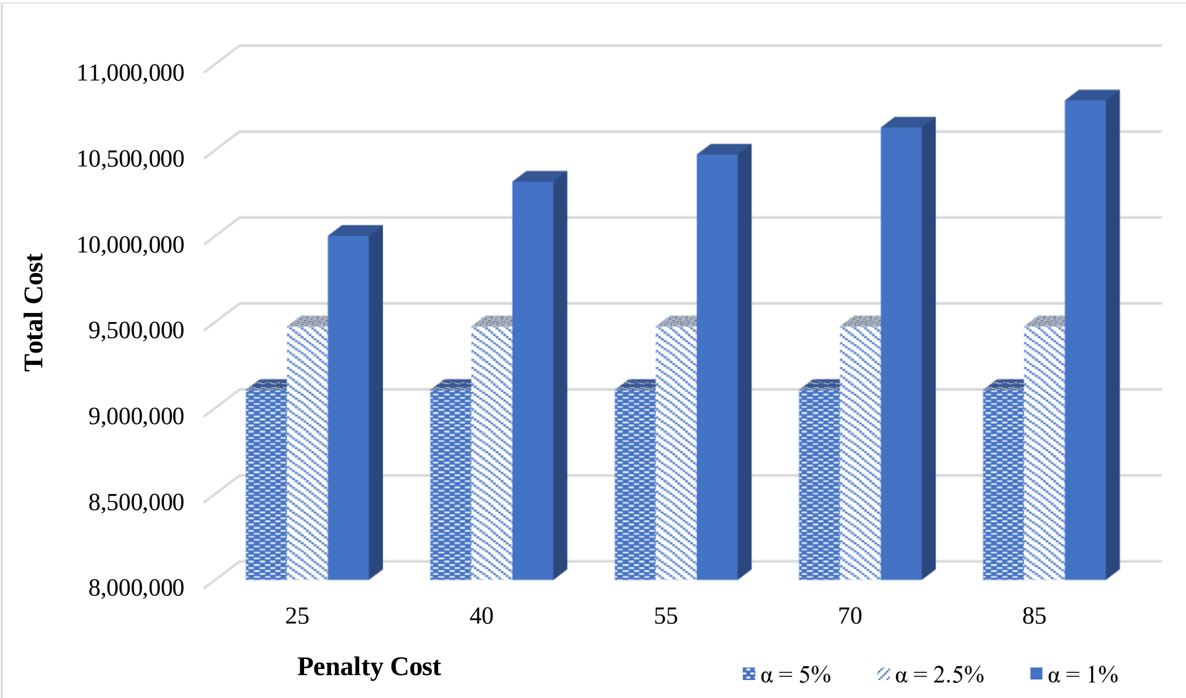

Fig. 6.7. The total cost deviation with regard to changes in penalty cost

To evaluate the performance of the proposed RFCCM in comparison with the deterministic model, simulation is conducted to generate different numerical scenarios. The NORM.INV function is utilized to simulate 100 random values for D_{nt}. This simulation is replicated 5 times. Then the minimum, average, and maximum of random values are taken into account for each scenario. In the next stage, the RFCCM and the deterministic model are solved with the minimum, average, and maximum values of D_{nt}.

Based on the results in Table 6.10, the deterministic model is not able to reach the optimal value in some scenarios. Therefore, the deterministic model is not sufficient to design the network under uncertain situations. The mentioned procedure is applied for the problem while the number of well pads increases from 3 to 4, and 5. Accordingly, the required volume of fluids for hydraulic fracturing operations increases as the number of well pads increases. In the RFCCM approach, decision-makers can handle the shortage of capacities associated with resources by increasing maximum violations (i.e., $\alpha'_{i'=1,\dots,6}$) of soft constraints. On the contrary, the deterministic model cannot find optimal solutions in case of the resource shortage. Tables 6.11 and 6.12 indicate that the rate of infeasibility grows in the deterministic model due to the insufficiency of the nominal capacity to fulfil the required fracturing fluids.

Table 6.10

Performances of deterministic and RFCCM (n = 3, φ = 5%, $\alpha'_{i'=1,...,6}$ = 5% of resource capacities)

Scenario	RFCCM Min	RFCCM Ave	RFCCM Max	Deterministic Min	Deterministic Ave	Deterministic Max
1	3,739,597.98	6,532,885.82	8,928,736.64	3,602,950.46	6,400,532.51	8,560,701.56
2	4,256,359.01	6,693,634.92	9,715,640.02	4,095,103.81	6,417,271.35	Infeasible
3	3,675,719.15	6,717,145.67	9,022,003.77	3,542,113.48	6,439,662.54	8,649,527.40
4	4,580,795.53	6,620,623.57	9,523,003.11	4,404,090.98	6,347,736.73	Infeasible
5	4,170,752.94	6,670,668.12	9,479,631.68	4,013,574.23	6,395,398.21	Infeasible

Table 6.11

Performances of deterministic and RFCCM (n = 4, φ = 5%, $\alpha'_{i'=1,...,6}$ = 50% of resource capacities)

Scenario	RFCCM Min	RFCCM Ave	RFCCM Max	Deterministic Min	Deterministic Ave	Deterministic Max
1	5,191,274.87	9,947,428.33	13,860,027.90	4,985,499.88	9,530,884.13	Infeasible
2	5,980,487.41	9,974,543.56	14,885,174.88	5,737,607.06	9,556,708.15	Infeasible
3	5,095,626.12	10,010,815.04	13,998,806.07	4,894,405.83	9,591,252.42	Infeasible
4	6,470,335.13	9,861,904.49	14,598,538.03	6,204,128.69	9,449,432.84	Infeasible
5	5,851,235.82	9,939,111.28	14,534,002.88	5,614,510.30	9,522,963.13	Infeasible

Table 6.12

Performances of deterministic and RFCCM (n = 5, φ = 5%, $\alpha'_{i'=1,...,6}$ = 75% of resource capacities)

Scenario	RFCCM Min	RFCCM Ave	RFCCM Max	Deterministic Min	Deterministic Ave	Deterministic Max
1	6,079,544.65	12,932,073.08	16,867,828.06	5,831,947.28	Infeasible	Infeasible
2	7,026,741.56	12,964,280.14	19,695,943.04	6,734,515.77	Infeasible	Infeasible
3	5,963,854.61	13,007,362.87	17,033,272.34	5,721,766.30	Infeasible	Infeasible
4	7,691,112.32	12,830489.12	19,350,498.24	7,396,020.78	Infeasible	Infeasible
5	6,871,229.75	12,922,194.21	17,775,626.71	6,586,409.28	Infeasible	Infeasible

6.6. Iterative approach

The solutions of a multi-objective model (MOM) are called non-dominated solutions (Branke et al., 2008; Mirzapour Al-E-Hashem et al., 2011). Li et al. (2006) defined Z^* as the ideal solution of MOM whose components are computed by the maximum value of each objective function which is written by Eq. (6.100). In the case of minimization, Z^- is defined by Eq. (6.101).

$$Z^* = \left[Z_1^*,\ldots,Z_N^* \right] = \left[max\, Z_1(x),\ldots,max\, Z_N(x) \right] \tag{6.100}$$

$$Z^- = \left[Z_1^-,\ldots,Z_N^- \right] = \left[min\, Z_1(x),\ldots,min\, Z_N(x) \right] \tag{6.101}$$

To solve a MOM, Zimmermann (1978) proposed the max-min approach represented in Model (6.M_1).

$$\begin{aligned} & Max\ \hat{\lambda} \\ & s.t. \\ & \hat{\lambda} \le u_k(x),\ k = 1,\ldots,N \\ & 0 \le \hat{\lambda} \le 1, 0 \le x \end{aligned} \tag{6.M_1}$$

As defined by Eq. (6.102), $u_k(x)$ is the membership function denoting the satisfaction level of each objective function. In this regard, the minimum value of each objective can be replaced as the initial solution (O_k) in the membership function.

$$u_k(x) = \begin{cases} 1, & Z_k(x) > Z_k^*, \\ 1 - \dfrac{Z_k^* - Z_k(x)}{Z_k^* - O_k} & O_k < Z_k(x) \le Z_k^*, \qquad k = 1,\ldots,N \\ 0, & Z_k(x) \le O_k, \end{cases} \tag{6.102}$$

Finding efficient solutions cannot be guaranteed using Model (6.M_1). For further information, it is worthy to refer to (Guua and Wu, 1999; Li et al., 2006). In this respect, we apply the idea of the ε-constraint method to develop a new iterative approach. Model (6.M_2) shows the behavior of the ε-constraint approach with two objectives. The objective with high priority is chosen as the main objective function. Then, ε_2 is changed iteratively to reach the various non-dominated solutions. The advantage of the ε-constraint method is to obtain non-dominated solutions in both convex and concave situations.

$$
\begin{aligned}
& Min\ Z_1(x) \\
& s.t. \\
& Z_2(x) \le \varepsilon_2, \qquad (6.M_2)
\end{aligned}
$$

Accordingly, the new iterative method is introduced by Model (6.M_3). The proposed bi-objective model minimizes the total cost (Z_1), and CO_2 emissions (Z_2). In this regard, ε_1 and ε_2 are ideal solutions of Z_1 and Z_2. Since it is impossible that both Z_1 and Z_2 have values less than or equal to their optimal values, $\hat{\lambda}$ is defined to control the feasibility of the bi-objective model.

$$
\begin{aligned}
& Min\ \hat{\lambda} \\
& s.t. \\
& Z_1 \le \hat{\lambda}\varepsilon_1, \\
& Z_2 \le \hat{\lambda}\varepsilon_2, \\
& 0 \le \lambda, \qquad (6.M_3)
\end{aligned}
$$

Constraints (6.3), (6.5) to (6.12), (6.20) and (6.21), (6.36) to (6.99).

The steps to find the non-dominated solutions through the new iterative approach for the proposed MOM are as follows:

Step 1: Each objective is solved separately with regard to the defined constraints to reach Z_1^* and Z_2^*. Table 6.13 includes the results. Then, the values of ε_1 and ε_2 are assumed to be equal to the optimal values of the associated objectives.

Table 6.13
Optimal solutions of the 1st and 2nd objectives

α	Total cost	CO_2 emissions
25%	7,767,870.53	52,853,004.67
5%	9,105,786.98	62,573,820.10

Step 2: Either ε_1 or ε_2 should be changed to compute various non-dominated solutions. The results of the proposed iterative approach and the max-min approach are provided and compared in Tables 6.14 and 6.15.

Table 6.14
The non-dominated solutions for the 1st and 2nd objectives for α = 25%

ε_1 ε_2	7,767,870.53 53,136,590	7,767,870.53 53,137,700	7,767,870.53 59,136,615	Max-min approach
$\hat{\lambda}$	1.0019	1.0023	1.0013	0.971
Total cost	7,782,400	7,785,600	7,777,700	7,946,400
CO_2 emissions	53,225,000	53,137,000	53,521,000	63,380,000
Selected facilities	$\psi_1 - \delta_1 - \kappa_2$ to $\kappa_6 - \lambda_2$ - $\rho_2 - \xi_1, \xi_2$	$\psi_1 - \delta_1 - \kappa_2$ to $\kappa_6 -$ $\lambda_2 - \rho_2 - \xi_2, \xi_5$	$\psi_1 - \delta_1 - \kappa_1$ to $\kappa_5 - \lambda_2 -$ $\rho_1 - \xi_2, \xi_5$	$\psi_1 - \delta_1 - \kappa_1$ to $\kappa_6 -$ $\lambda_2 - \rho_1, \rho_2 - \xi_1, \xi_2$

Table 6.15
The non-dominated solutions for the 1st and 2nd objectives for α = 5%

ε_1 ε_2	9,105,786.98 63,139,889	9,105,786.98 63,586,500	9,105,786.98 64,089,500	9,105,786.98 65,589,685	Max-min approach
$\hat{\lambda}$	1.0039	1.0020	1.0021	1.0003	0.966
Total cost	9,140,400	9,123,200	9,124,100	9,105,800	9,337,000
CO_2 emissions	63,142,000	63,647,000	63,587,000	64,092,000	74,655,000
Selected facilities	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 - \lambda_1, \lambda_2$ - ρ_2 $- \xi_2, \xi_5$	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 - \lambda_1, \lambda_2$ - ρ_2 $- \xi_1, \xi_2$	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 - \lambda_1, \lambda_2 - \rho_1$ $- \xi_2, \xi_5$	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 - \lambda_1, \lambda_2 - \rho_1$ $- \xi_1, \xi_2$	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 - \lambda_1, \lambda_2 - \rho_1, \rho_2,$ $\rho_6 - \xi_1, \xi_2$

Distance technique is a well-known method to solve MOM (Mirzapour Al-E-Hashem et al., 2011; Amin and Zhang, 2012). In this regard, this technique is applied to verify the performance of the proposed iterative approach. Eq. (6.103) represents the distance formula in which w_i is defined as the distance metric for Objective i. Eq. (6.104) shows the objective function for the bi-objective wastewater treatment network.

$$Z = \left(\sum_i w_i^{\tau} \left(\frac{Z_i - Z_i^*}{Z_i^*} \right)^{\tau} \right)^{\frac{1}{\tau}} \qquad \forall\ i = 1, 2, \ldots, \infty \tag{6.103}$$

$$Min\ Z = \left(w_1^{\tau} \left(\frac{Z_1 - Z_1^*}{Z_1^*} \right)^{\tau} + w_2^{\tau} \left(\frac{Z_2 - Z_2^*}{Z_2^*} \right)^{\tau} \right)^{\frac{1}{\tau}} \tag{6.104}$$

s.t.

Constraints (6.3), (6.5) to (6.12), (6.20) and (6.21), (6.36) to (6.99).

To estimate various non-dominated solutions for the bi-objective model, various pairs of w_i are tested with the condition of $\sum_i w_i = 1$. Tables 6.16 and 6.17 contain the non-dominated solutions of the total cost and CO_2 emissions. The same non-dominated solutions are obtained by the distance technique. However, the proposed iterative approach could compute more efficient solutions. Therefore, this method is selected.

Table 6.16
The non-dominated solutions for the 1st and 2nd objectives for α = 25% using distance technique

w_1	0.6	0.7
Total cost	7,782,400	7,785,600
CO_2 emissions	53,225,000	53,137,000
Selected facilities	$\psi_1 - \delta_1 - \kappa_2$ to $\kappa_6 - \lambda_2$ - $\rho_2 - \xi_1, \xi_2$	$\psi_1 - \delta_1 - \kappa_2$ to $\kappa_6 - \lambda_2$ - ρ_2 - ξ_2, ξ_5

Table 6.17
The non-dominated solutions for the 1st and 2nd objectives for α = 5% using distance technique

w_1	0.4	0.5	0.8
Total cost	9,140,400	9,127,400	9,105,800
CO_2 emissions	63,142,000	63,587,000	64,092,000
Selected facilities	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 -$ λ_1, λ_2 - $\rho_2 - \xi_2, \xi_5$	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 -$ $\lambda_1, \lambda_2 - \rho_1$ - ξ_2, ξ_5	$\psi_1 - \delta_1, \delta_2 - \kappa_1$ to $\kappa_6 -$ $\lambda_1, \lambda_2 - \rho_1 - \xi_1, \xi_2$

6.7. Conclusions

In hydraulic fracturing operations, there are different facilities (e.g., on-site facilities, WWTPs) with limited capacities. The number of such facilities is mainly depended on the demand (i.e., amount of fracturing fluids). In this regard, the value of demand has a direct impact on the configuration of the wastewater treatment network. This random parameter fluctuates based on the number of wells and the geologic formation in different areas. Therefore, it is not realistic to apply deterministic assumptions to design facility location models for hydraulic fracturing operations.

In this study, a new RFCCM has been developed. In addition, the application has been shown for a wastewater treatment network in Alberta, Canada. The mathematical model has been proposed for uncertain situations due to the presence of imprecise parameters in real-world problems. Chance-constrained programming has been applied to handle the stochastic nature of the required fluids for hydraulic fracturing operations. Furthermore, robust optimization and flexible programming have been utilized to address the uncertainty of variable costs and capacities of resources, respectively. The most important advantage of the proposed model is considering different sources of uncertainty simultaneously. The efficiency of the proposed RFCCM to compute the optimal solutions has been demonstrated in uncertain situations. As illustrated in Tables 6.10, 6.11, and 6.12, decision-makers can handle the shortage of capacities associated with resources by increasing maximum violations of soft constraints.

To reduce the environmental concern associated with hydraulic fracturing operations, a bi-objective optimization model has been developed. A new iterative approach has been introduced to find the non-dominated solutions. The efficient solutions have been obtained through two methods of iterative approach and distance method. The optimal network configuration mainly depends on the importance of the objectives in the view of decision-makers. It has been shown that the number of selected facilities may vary by changing the weight factors associated with the total cost and CO_2 emissions. The proposed bi-objective RFCCM introduces a novel approach to configure facility location models associated with hydraulic fracturing operations.

Some future research areas can be investigated based on this study. Demand is an important factor in this problem. As mentioned before, the demand for fracturing fluids depends on many factors. Multiple regression analysis can be performed to estimate the value of demand. In this study, a robust flexible chance-constrained approach has been proposed for a network design problem in multiple periods without financial factors. Financial indicators (e.g., discount rate) can be integrated with this multi-period model to examine their impacts.

Chapter 7. Conclusions, research contributions, and future research

This dissertation has introduced several important contributions by developing multi-objective optimization models to design facility location models. Five real RLNs in Canada have been investigated to optimize environmental practices, energy consumption, and cost-saving in recovery programs. The outcomes of this study will open several directions for future research in designing of RLNs.

7.1. Summary of research

In Chapter 2, the application of RLN was expanded prominently due to environmental issues, and profit related to the returned products. As mentioned previously, RLN includes all activities associated with product recovery such as repairing, recycling, refurbishing, and remanufacturing. Several partners are required to collaborate efficiently on account of obtaining optimal outcomes. In this sense, the selection of partners in RLN can be considered as an MCDM problem. Therefore, FANP was applied to convert the environmental qualitative factors to the quantitative parameters. Furthermore, an optimization model was introduced for a multi-echelon, multi-component, multi-product RLN in multiple periods. A multi-objective MILP programming model was employed to maximize the total profit, green practices, on-time delivery, and minimize defect rate in the proposed RLN. Finally, the multi-objective model was solved to achieve non-dominated solutions between the objectives.

As mentioned in Chapter 3, there are several parameters contributing to the configuration of facility locations that fluctuate in different situations and cause some risks and complexities for the businesses. Since a facility location design is a strategic decision, it is impossible to be changed in the short-term. Therefore, a fully fuzzy programming (FFP) method and scenario-based programming were integrated to address various scenarios to maximize the total profit of an LAB CLSC network. Furthermore, the second objective was introduced to maximize the environmental compliance of suppliers, plants, and battery recovery centers. Then, the distance technique was utilized for solving the fuzzy scenario-based multi-objective problem. The application of the proposed model was illustrated in a network in Winnipeg, Canada.

In Chapter 4, a novel scenario-based robust possibilistic approach was developed to optimize and configure an electronic RLN by considering the uncertainty associated with fixed and variable costs, the quantity of demand and return, and the quality of returned products. A Monte Carlo simulation was utilized to analyze the performance of the proposed model. Then, ANOVA test was conducted to statistically verify our model using the simulation results. The mathematical model was extended to the multi-objective optimization by maximizing the environmental compliance of the third parties. The efficient solutions of the multi-objective model were computed using the two-phase fuzzy compromise approach. The application of the proposed model was illustrated using a network in the Greater Toronto Area (GTA) in Canada.

In Chapter 5, a beverage container RLN was proposed to manage recycling activities associated with returned containers. A large number of used containers (e.g., aluminum can) can be utilized in the production of new products after recovery. On this matter, a hybrid optimization model was developed to configure a multi-echelon, multi-period beverage container RLN. A scenario-based possibilistic approach was implemented to handle the uncertainty associated with fixed and variable costs, the quantity of demand and return, and the quality of returned products. The model is then extended to a multi-objective one to reduce CO_2 emissions and maximize the social responsibility and technological innovation of third parties involved in a beverage container RLN. To illustrate the application of the proposed model, a network was examined in Vancouver, Canada.

In Chapter 6, a novel robust chance-constrained optimization model was developed to configure a wastewater treatment RLN considering the uncertainty of parameters (i.e., fixed and variable costs, required amount of fracturing fluids, and capacities of facilities). Simulation was conducted to analyze the robustness of the proposed model. To eliminate carbon emissions as a result of the operation and transportation, the mathematical model was extended to a multi-objective model. Non-dominated solutions of the multi-objective model were obtained by a new iterative approach. To illustrate the economic and environmental impact of the proposed model, a network was examined in Alberta, Canada.

7.2. Research contributions

According to the Canadian Environmental Protection Act and development of circular economy strategies, greater attention has been directed towards RLN design. In this regard, some stewardship plans in Canada were considered, such as the electronic recycling association (ERA), Canadian battery association (CBA), beverage container stewardship program regulation

(BCSPR), Ontario electronic stewardship (OES), and wastewater management. Then, a related RL network was proposed for each stewardship program based on its operation. Since there were various imprecise parameters affecting such RLNs, different solution approaches were integrated to address different sources of uncertainty, simultaneously. The main research contributions of this investigation can be summarized as follow:

- An MCDM model was developed to configure and optimize an electronic RLN in multiple periods. The mathematical model included multiple objectives, such as total profit of RLN, the environmental performance of third parties, on-time delivery, and defect rate.
- A fully fuzzy programming was proposed to design an integrated forward and RLN considering different scenarios. The proposed hybrid approach was extended to a bi-objective model for the purpose of considering the environmental compliance of third parties in the battery industry.
- A bi-objective scenario-based robust possibilistic model was introduced to configure a multi-echelon electronic RLN. A fuzzy TOPSIS method was employed to prioritize the facilities based on their green practices. The non-dominated solutions of the bi-objective model were computed by using the two-phase fuzzy compromise approach.
- A multi-echelon beverage container RLN was designed under uncertainty. A bi-objective hybrid model was developed by integration of the possibilistic programming method and scenario-based approach.
- A bi-objective robust flexible chance-constrained model was proposed to design a wastewater treatment RLN. A new iterative approach was introduced to calculate the non-dominated solutions of the bi-objective model.

Table 7.1 includes a summary of the proposed models to design multi-echelon RLs for real Canadian stewardship plans.

Table 7.1
Design of reverse logistics networks under uncertainty: Multi-objective approach

Title	Multi-objective	Type of products	Uncertainty	Mathematical approach*	Real location
1. A multi-objective model to configure an electronic reverse logistics network and third party selection	✓	Electronics		MILP, MOP	
2. An environmental optimization model to configure a hybrid forward and reverse supply chain network under uncertainty	✓	Battery	All parameters and decision variables	FFSP, MOP	✓
3. A scenario-based robust possibilistic model for a multi-objective electronic reverse logistics network	✓	Electronics	Selling price, fixed and variable costs, demand and return, capacity of plant(s), disposal rate	SRPM, MOP	✓
4. A novel multi-objective model to design and optimize a beverage container reverse logistics network	✓	Beverage container	Fixed and variable costs, demand and return, disposal rate	SPM, MOP	✓
5. A robust optimization model for designing a wastewater treatment network under uncertainty: Multi-objective approach	✓	Wastewater	Fixed and variable costs, demand, capacity of resources	RFCCM, MOP	✓

***** Mixed-integer linear programming (MILP), scenario-based possibilistic model (SPM), scenario-based robust possibilistic model (SRPM), fully fuzzy scenario-based programming (FFSP), robust flexible chance-constrained model (RFCCM)

7.3. Future research

The potential future research avenues for this study are as follow:

7.3.1. To develop a forecasting method for returned products

In this dissertation, it is assumed that the value of return can be estimated as ten percent of market demand (see, e.g., Fleischmann et al., 2001; Amin and Baki, 2017). There are different reasons to return products from a customer's perspective. The commercial returns include all non-defective products returned to the sellers within 30 to 90 days (Rogers and Tibben-Lembke, 2001). The end-of-use returns stem from the technological upgrade. With this respect, consumers prefer to replace outdated functional products with updated ones. The end-of-life returns consist of all products that are no longer applicable and become obsolete. Furthermore, there is another category of returns occurred due to repair, or warranty. In this regard, different factors must be considered to estimate the rate of return (e.g., product life cycle, type of industry). Therefore, developing a forecasting approach for returned products can be a future research direction for this study.

7.3.2. To develop the proposed models to consider different types of risk

Three types of risk should be considered in designing facility location models. The first type is associated with the uncertainty of parameters (e.g., demand, return, quality of returned products, fixed and variable costs) that have a significant impact on the configuration of RLN. This type of uncertainty was discussed in Chapters 3, 4, 5, and 6. The second type of risk may arise when some of the selected facilities become unavailable on account of disruptions such as natural disasters and production interruption. In this case, some operational consequences are concerned with disruption risks such as inventory shortages and order delays. The third type of risk stems from transportation disruptions. This type of risk is less severe than the facility failure leading to shut down operations. However, the material flow is interrupted between two echelons due to transportation disruptions. In this regard, different scenarios should be taken into account before configuring the RLN. Therefore, it is worthwhile to extend the proposed models for the purpose of considering the disruption risk.

7.3.3. To develop the proposed models to consider different objectives

Customer relationship management (CRM) is one of the well-known approaches leading to competitive advantages in business. The main goal of applying CRM is to establish useful relationships between companies and customers. With this respect, customers become loyal players to be engaged to return unwanted appliances to the regional collection centers. However, incorporating the CRM as the qualitative factor into the mathematical model can be a challenge in RLN. There are many MCDM tools (e.g., FANP) to convert the qualitative factors to the quantitative parameters to be applicable in mathematical functions. Therefore, incorporating CRM as a new objective in addition to the economic and environmental objectives may increase the rate of return.

7.3.4. To consider coordination efforts in the proposed models

The reverse supply chain is not led by a single company. A coherent mechanism is necessary to coordinate facilities for the aim of collecting and recovering (e.g., refurbishing, remanufacturing) unwanted products in RLNs. The coordination can be implemented in a centralized process that a certain decision-maker is in charge, or a decentralized process in which multiple entities play the role of decision-makers. Since the operation of product recovery is complicated, many factors are involved in the decision-making process, such as quality and quantity of returned products, locations, and variable cost of recovery. Furthermore, customers may be involved in the coordination model (e.g., bonus sharing technique) by offering some incentives for their efforts. Therefore, it is valuable to develop the proposed models to examine the effects of collaboration and competition between different players in the RL networks.

7.3.5. To consider a price competition between remanufactured and new products in the proposed models

As mentioned before, remanufacturing refers to disassembling, inspecting, and refurbishing of the recoverable parts of the returned products for reuse. The economic benefits of remanufacturing make companies motivated to be a part of this program regardless of the governmental policies and environmental regulations. For example, HP Inc., the large computer producer, has implemented a remanufacturing program (i.e., HP Renew Program) for refurbishing and remanufacturing the used products. This program certifies that the remanufactured products perform well, and can be substituted as the new products at a lower price (Wu, 2012). Integrating a price competition between the remanufactured and new products with the proposed model can be a future research avenue for this study.

7.3.6. To consider the quality degradation of remanufactured products in the proposed models

Degradation is defined as a reduction in the quality of materials with each recycling phase (Amini et. al., 2007). To reduce the weight of products, lightweight materials have been increasingly used in productions recently. In this regard, manufacturers are more willing to use different composite materials, polymers, and aluminum. However, recycling of some types of lightweight materials (e.g., polymers and composites) is economically unattractive. Furthermore, the recovered items may be contaminated due to the joints between various materials within products during disassembling. Hence, a large number of components are not recyclable indefinitely (Bazan et. al., 2017). Considering the quality degradation of recovered components can be another future research direction for this study.

Appendices

Appendix 2

2.A. Fuzzy ANP calculation related to suppliers

Table 2.A.1
Pairwise comparisons among criteria

W_1	C_1			C_2			C_3			C_4			W_c
C_1	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.50	2.00	2.50	0.359
C_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.338
C_3	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.167
C_4	0.40	0.50	0.67	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.136

Table 2.A.2
The inner dependence matrix and relative weight factor with respect to C_1

C_1	C_2			C_3			C_4			W_c
C_2	1.00	1.00	1.00	1.00	1.50	2.00	0.50	0.67	1.00	0.341
C_3	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.284
C_4	1.00	1.50	2.00	0.67	1.00	2.00	1.00	1.00	1.00	0.376

Table 2.A.3
The inner dependence matrix and relative weight factor with respect to C_2

C_2	C_1			C_3			C_4			W_c
C_1	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.392
C_3	0.67	1.00	2.00	1.00	1.00	1.00	1.50	2.00	2.50	0.450
C_4	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	0.158

Table 2.A.4
The inner dependence matrix and relative weight factor with respect to C_3

C_3		C_1			C_2			C_4		W_c
C_1	1.00	1.00	1.00	0.50	0.67	1.00	1.50	2.00	2.50	0.381
C_2	1.00	1.50	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.363
C_4	0.40	0.50	0.67	0.67	1.00	2.00	1.00	1.00	1.00	0.256

Table 2.A.5
The inner dependence matrix and relative weight factor with respect to C_4

C_4		C_1			C_2			C_3		W_c
C_1	1.00	1.00	1.00	0.50	0.67	1.00	0.40	0.50	0.67	0.147
C_2	1.00	1.50	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.448
C_3	1.50	2.00	2.50	0.50	0.67	1.00	1.00	1.00	1.00	0.405

Table 2.A.6
The interdependent ranking of the green performance criteria related to suppliers

W_2	C_1	C_2	C_3	C_4	W_1	$W_{criteria}$
C_1	1.00	0.39	0.38	0.15	0.359	0.287
C_2	0.34	1.00	0.36	0.45	0.338	0.291
C_3	0.28	0.45	1.00	0.41	0.167	0.238
C_4	0.38	0.16	0.26	1.00	0.136	0.183

Table 2.A.7
Pairwise comparisons among sub-criteria of C_1

C_1		Sc_1			Sc_2			Sc_3		W_c
Sc_1	1.00	1.00	1.00	1.00	1.50	2.00	0.50	0.67	1.00	0.305
Sc_2	0.50	0.67	1.00	1.00	1.00	1.00	2.00	2.50	3.00	0.454
Sc_3	1.00	1.50	2.00	0.33	0.40	0.50	1.00	1.00	1.00	0.241

Table 2.A.8
Pairwise comparisons among sub-criteria of C_2

C_2		Sc_4			Sc_5		W_c
Sc_4	1.00	1.00	1.00	1.00	1.50	2.00	0.684
Sc_5	0.50	0.67	1.00	1.00	1.00	1.00	0.316

Table 2.A.9
Pairwise comparisons among sub-criteria of C_3

C_3		Sc_6			Sc_7		W_c
Sc_6	1.00	1.00	1.00	0.50	1.00	1.50	0.500
Sc_7	0.67	1.00	2.00	1.00	1.00	1.00	0.500

Table 2.A.10
Pairwise comparisons among sub-criteria of C_4

C_4		Sc_8			Sc_9			Sc_{10}		W_c
Sc_8	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.685
Sc_9	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	0.224
Sc_{10}	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.091

Table 2.A.11
Overall priority of the sub-criteria of green performance for suppliers

Fuzzy ANP	$W_{criteria}$ obtained in Step 3	Sub-criteria	$W_{Sub\text{-}criteria}$ obtained in Step 4	Overall priority of the Sub-criteria
C_1: Eco-product design	0.287	Sc_1: Designing the recyclable product	0.305	0.088
		Sc_2: Application of less hazardous material in production	0.454	0.131
		Sc_3: Design of product for reduce consumption of material/energy	0.241	0.069
C_2: Environmental practice	0.291	Sc_4: Regulatory compliance audit	0.684	0.199
		Sc_5: ISO 14001 certificate	0.316	0.092
C_3: Sustainable packaging	0.238	Sc_6: Reusable packaging	0.500	0.119
		Sc_7: Packaging from recycled material	0.500	0.119
C_4: Supplier's characteristic	0.183	Sc_8: Supplier's reputation in green performance	0.685	0.126
		Sc_9: Environmental experience	0.224	0.041
		Sc_{10}: Legality	0.091	0.017

Table 2.A.12
Priority of each supplier with respect to Sc_1

Sc_1		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.50	0.67	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.50	1.00	1.50	0.239
Sup_2	1.00	1.50	2.00	1.00	1.00	1.00	1.50	2.00	2.50	1.00	1.50	2.00	0.67	1.00	2.00	0.250
Sup_3	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.221
Sup_4	0.33	0.40	0.50	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.67	1.00	2.00	0.129
Sup_5	0.67	1.00	2.00	0.50	1.00	1.50	0.33	0.40	0.50	0.50	1.00	1.50	1.00	1.00	1.00	0.162

Table 2.A.13
Priority of each supplier with respect to Sc_2

Sc_2		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	0.50	0.67	1.00	0.259
Sup_2	0.33	0.40	0.50	1.00	1.00	1.00	1.50	2.00	2.50	0.40	0.50	0.67	2.50	3.00	3.50	0.232
Sup_3	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.205
Sup_4	0.40	0.50	0.67	1.50	2.00	2.50	0.33	0.40	0.50	1.00	1.00	1.00	2.00	2.50	3.00	0.212
Sup_5	1.00	1.50	2.00	0.29	0.33	0.40	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.091

Table 2.A.14
Priority of each supplier with respect to Sc_3

Sc_3		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.40	0.50	0.67	2.00	2.50	3.00	1.00	1.50	2.00	0.50	1.00	1.50	0.222
Sup_2	1.50	2.00	2.50	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.33	0.40	0.50	0.252
Sup_3	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.67	1.00	2.00	0.132
Sup_4	0.50	0.67	1.00	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.190
Sup_5	0.67	1.00	2.00	2.00	2.50	3.00	0.50	1.00	1.50	0.33	0.40	0.50	1.00	1.00	1.00	0.204

Table 2.A.15
Priority of each supplier with respect to Sc_4

Sc_4		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.33	0.40	0.50	1.00	1.50	2.00	0.40	0.50	0.67	0.50	1.00	1.50	0.136
Sup_2	2.00	2.50	3.00	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.00	1.50	2.00	0.297
Sup_3	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.67	1.00	2.00	0.158
Sup_4	1.50	2.00	2.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.269
Sup_5	0.67	1.00	2.00	0.50	0.67	1.00	0.50	1.00	1.50	0.33	0.40	0.50	1.00	1.00	1.00	0.140

Table 2.A.16
Priority of each supplier with respect to Sc_5

Sc_5		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.50	0.67	1.00	1.50	2.00	2.50	2.00	2.50	3.00	0.33	0.40	0.50	0.241
Sup_2	1.00	1.50	2.00	1.00	1.00	1.00	0.67	1.00	2.00	1.00	1.50	2.00	0.50	1.00	1.50	0.230
Sup_3	0.40	0.50	0.67	0.50	1.00	1.50	1.00	1.00	1.00	0.50	1.00	1.50	0.50	0.67	1.00	0.130
Sup_4	0.33	0.40	0.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.40	0.50	0.67	0.101
Sup_5	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.50	2.00	1.50	2.00	2.50	1.00	1.00	1.00	0.298

Table 2.A.17
Priority of each supplier with respect to Sc_6

Sc_6		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.40	0.50	0.67	0.50	1.00	1.50	0.33	0.40	0.50	0.50	1.00	1.50	0.116
Sup_2	1.50	2.00	2.50	1.00	1.00	1.00	1.50	2.00	2.50	1.00	1.50	2.00	0.50	0.67	1.00	0.253
Sup_3	0.67	1.00	2.00	0.40	0.50	0.67	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.232
Sup_4	2.00	2.50	3.00	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	1.50	2.00	2.50	0.232
Sup_5	0.67	1.00	2.00	1.00	1.50	2.00	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	0.166

Table 2.A.18

Priority of each supplier with respect to Sc_7

Sc_7		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	1.00	1.50	2.00	1.50	2.00	2.50	2.00	2.50	3.00	0.50	0.67	1.00	0.282
Sup_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.50	1.00	1.50	1.00	1.50	2.00	0.207
Sup_3	0.40	0.50	0.67	0.50	0.67	1.00	1.00	1.00	1.00	0.33	0.40	0.50	1.00	1.50	2.00	0.113
Sup_4	0.33	0.40	0.50	0.67	1.00	2.00	2.00	2.50	3.00	1.00	1.00	1.00	0.50	1.00	1.50	0.219
Sup_5	1.00	1.50	2.00	0.50	0.67	1.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.178

Table 2.A.19

Priority of each supplier with respect to Sc_8

Sc_8		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	1.50	2.00	2.50	0.67	1.00	2.00	1.50	2.00	2.50	0.67	1.00	2.00	0.257
Sup_2	0.40	0.50	0.67	1.00	1.00	1.00	2.00	2.50	3.00	0.50	1.00	1.50	2.00	2.50	3.00	0.272
Sup_3	0.50	1.00	1.50	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.190
Sup_4	0.40	0.50	0.67	0.67	1.00	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.67	1.00	2.00	0.156
Sup_5	0.50	1.00	1.50	0.33	0.40	0.50	0.50	0.67	1.00	0.50	1.00	1.50	1.00	1.00	1.00	0.125

Table 2.A.20

Priority of each supplier with respect to Sc_9

Sc_9		Sup_1			Sup_2			Sup_3			Sup_4			Sup_5		W_c
Sup_1	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	2.00	2.50	3.00	0.67	1.00	2.00	0.252
Sup_2	0.67	1.00	2.00	1.00	1.00	1.00	1.50	2.00	2.50	1.00	1.50	2.00	0.40	0.50	0.67	0.221
Sup_3	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.164
Sup_4	0.33	0.40	0.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.67	1.00	2.00	0.156
Sup_5	0.50	1.00	1.50	1.50	2.00	2.50	0.50	0.67	1.00	0.50	1.00	1.50	1.00	1.00	1.00	0.207

Table 2.A.21
Priority of each supplier with respect to Sc_{10}

Sc_{10}	Sup_1			Sup_2			Sup_3			Sup_4			Sup_5			W_c
Sup_1	1.00	1.00	1.00	2.00	2.50	3.00	0.50	1.00	1.50	1.50	2.00	2.50	1.00	1.50	2.00	0.283
Sup_2	0.33	0.40	0.50	1.00	1.00	1.00	2.00	2.50	3.00	0.33	0.40	0.50	0.67	1.00	2.00	0.182
Sup_3	0.67	1.00	2.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.172
Sup_4	0.40	0.50	0.67	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.267
Sup_5	0.50	0.67	1.00	0.50	1.00	1.50	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.096

Table 2.A.22
Overall priority of each supplier according to each sub-criterion

W_4	Priority of each supplier with respect to each sub-criterion									
	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}
Sup_1	0.239	0.259	0.222	0.136	0.241	0.116	0.282	0.257	0.252	0.283
Sup_2	0.250	0.232	0.252	0.297	0.230	0.253	0.207	0.272	0.221	0.182
Sup_3	0.221	0.205	0.132	0.158	0.130	0.232	0.113	0.190	0.164	0.172
Sup_4	0.129	0.212	0.190	0.269	0.101	0.232	0.219	0.156	0.156	0.267
Sup_5	0.162	0.091	0.204	0.140	0.298	0.166	0.178	0.125	0.207	0.096

2.B. Fuzzy ANP calculation related to ERCs

Table 2.B.1
Pairwise comparisons among criteria

W_1	C_1			C_2			C_3			C_4			W_c
C_1	1.00	1.00	1.00	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.50	2.00	0.361
C_2	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	0.50	0.67	1.00	0.130
C_3	0.50	1.00	1.50	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.334
C_4	0.50	0.67	1.00	1.00	1.50	2.00	0.33	0.40	0.50	1.00	1.00	1.00	0.175

Table 2.B.2
The inner dependence matrix and relative weight factor with respect to C_1

C_1	C_2			C_3			C_4			W_c
C_2	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.591
C_3	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.212
C_4	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.198

Table 2.B.3
The inner dependence matrix and relative weight factor with respect to C_2

C_2	C_1			C_3			C_4			W_c
C_1	1.00	1.00	1.00	1.50	2.00	2.50	2.00	2.50	3.00	0.764
C_3	0.40	0.50	0.67	1.00	1.00	1.00	0.50	1.00	1.50	0.083
C_4	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.153

Table 2.B.4
The inner dependence matrix and relative weight factor with respect to C_3

C_3		C_1			C_2			C_4		W_c
C_1	1.00	1.00	1.00	1.00	1.50	2.00	0.50	0.67	1.00	0.305
C_2	0.50	0.67	1.00	1.00	1.00	1.00	2.00	2.50	3.00	0.454
C_4	1.00	1.50	2.00	0.33	0.40	0.50	1.00	1.00	1.00	0.241

Table 2.B.5
The inner dependence matrix and relative weight factor with respect to C_4

C_4		C_1			C_2			C_3		W_c
C_1	1.00	1.00	1.00	0.50	1.00	1.50	1.50	2.00	2.50	0.419
C_2	0.67	1.00	2.00	1.00	1.00	1.00	0.67	1.00	2.00	0.342
C_3	0.40	0.50	0.67	0.50	1.00	1.50	1.00	1.00	1.00	0.239

Table 2.B.6
The interdependent ranking of the green performance criteria related to ERCs

W_2	C_1	C_2	C_3	C_4	W_1	$W_{criteria}$
C_1	1.00	0.764	0.305	0.419	0.361	0.318
C_2	0.591	1.00	0.454	0.342	0.130	0.277
C_3	0.212	0.083	1.00	0.239	0.334	0.232
C_4	0.198	0.153	0.241	1.00	0.175	0.174

Table 2.B.7
Pairwise comparisons among sub-criteria of C_1

C_1		Sc_1			Sc_2		W_c
Sc_1	1.00	1.00	1.00	1.00	1.50	2.00	0.684
Sc_2	0.50	0.67	1.00	1.00	1.00	1.00	0.316

Table 2.B.8
Pairwise comparisons among sub-criteria of C_2

C_2		Sc_3			Sc_4		W_c
Sc_3	1.00	1.00	1.00	0.50	1.00	1.50	0.500
Sc_4	0.67	1.00	2.00	1.00	1.00	1.00	0.500

Table 2.B.9
Pairwise comparisons among sub-criteria of C_3

C_3		Sc_5			Sc_6			Sc_7		W_c
Sc_5	1.00	1.00	1.00	1.00	1.50	2.00	0.50	1.00	1.50	0.354
Sc_6	0.50	0.67	1.00	1.00	1.00	1.00	2.00	2.50	3.00	0.434
Sc_7	0.67	1.00	2.00	0.33	0.40	0.50	1.00	1.00	1.00	0.212

Table 2.B.10
Pairwise comparisons among sub-criteria of C_4

C_4		Sc_8			Sc_9			Sc_{10}		W_c
Sc_8	1.00	1.00	1.00	0.50	1.00	1.50	1.50	2.00	2.50	0.419
Sc_9	0.67	1.00	2.00	1.00	1.00	1.00	0.67	1.00	2.00	0.342
Sc_{10}	0.40	0.50	0.67	0.50	1.00	1.50	1.00	1.00	1.00	0.239

Table 2.B.11
Overall priority of the sub-criteria of green performance for ERCs

Fuzzy ANP	$W_{criteria}$ obtained in Step 3	Sub-criteria	$W_{Sub\text{-}criteria}$ obtained in Step 4	Overall priority of the Sub-criteria
C_1: Green recycling	0.318	Sc_1: Application of sustainable method to reduce scrap rate	0.684	0.217
		Sc_2: Recovery Center's environmental management system	0.316	0.100
C_2: Eco-technology	0.277	Sc_3: Utilizing eco-tech for recovery (compatible with renewable source of energy)	0.500	0.139
		Sc_4: Utilizing eco-tech for recovery (producing less carbon emission)	0.500	0.139
C_3: Green transportation	0.232	Sc_5: Collaborating with collection centers to standardize packaging or reducing empty running	0.354	0.082
		Sc_6: Non-damaged transport	0.434	0.100
		Sc_7: Enhancing vehicle operating efficiency and improving vehicle routing using GPS	0.212	0.049
C_4: Social-cultural enablers	0.174	Sc_8: Green organizational culture	0.419	0.073
		Sc_9: Environmental education and training	0.342	0.059
		Sc_{10}: Employee involvement	0.239	0.042

Table 2.B.12

Priority of each ERC with respect to Sc_1

Sc_1	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	0.50	0.67	1.00	1.00	1.50	2.00	0.33	0.40	0.50	0.50	1.00	1.50	0.67	1.00	2.00	0.140
ERC_2	1.00	1.50	2.00	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.00	1.50	2.00	0.50	1.00	1.50	0.219
ERC_3	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	2.00	2.50	3.00	0.174
ERC_4	2.00	2.50	3.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.50	0.67	1.00	0.173
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.154
ERC_6	0.50	1.00	1.50	0.67	1.00	2.00	0.33	0.40	0.50	1.00	1.50	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.140

Table 2.B.13

Priority of each ERC with respect to Sc_2

Sc_2	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	0.50	1.00	1.50	0.50	0.67	1.00	0.210
ERC_2	0.33	0.40	0.50	1.00	1.00	1.00	0.50	0.67	1.00	1.00	1.50	2.00	1.00	1.50	2.00	2.00	2.50	3.00	0.185
ERC_3	0.50	0.67	1.00	1.00	1.50	2.00	1.00	1.00	1.00	2.00	2.50	3.00	1.50	2.00	2.50	0.50	1.00	1.50	0.210
ERC_4	0.40	0.50	0.67	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.115
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	0.40	0.50	0.67	0.67	1.00	2.00	1.00	1.00	1.00	0.67	1.00	2.00	0.140
ERC_6	1.00	1.50	2.00	0.33	0.40	0.50	0.67	1.00	2.00	0.50	0.67	1.00	0.50	1.00	1.50	1.00	1.00	1.00	0.140

Table 2.B.14

Priority of each ERC with respect to Sc_3

Sc_3	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	0.50	0.67	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.50	1.00	1.50	2.50	3.00	3.50	0.236
ERC_2	1.00	1.50	2.00	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	1.00	1.50	2.00	0.50	1.00	1.50	0.222
ERC_3	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.33	0.40	0.50	1.00	1.50	2.00	0.099
ERC_4	0.50	0.67	1.00	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	1.50	2.00	2.50	0.188
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	2.00	2.50	3.00	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	0.175
ERC_6	0.29	0.33	0.40	0.67	1.00	2.00	0.50	0.67	1.00	0.40	0.50	0.67	0.50	0.67	1.00	1.00	1.00	1.00	0.080

Table 2.B.15
Priority of each ERC with respect to Sc_4

Sc_4	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	0.50	1.00	1.50	2.00	2.50	3.00	0.253
ERC_2	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.00	1.50	2.00	0.33	0.40	0.50	0.138
ERC_3	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.33	0.40	0.50	2.00	2.50	3.00	0.50	1.00	1.50	0.137
ERC_4	0.40	0.50	0.67	0.50	0.67	1.00	2.00	2.50	3.00	1.00	1.00	1.00	0.50	1.00	1.50	1.50	2.00	2.50	0.183
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.163
ERC_6	0.33	0.40	0.50	2.00	2.50	3.00	0.67	1.00	2.00	0.40	0.50	0.67	0.33	0.40	0.50	1.00	1.00	1.00	0.125

Table 2.B.16
Priority of each ERC with respect to Sc_5

Sc_5	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	1.50	2.00	2.50	0.50	0.67	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.67	1.00	2.00	0.215
ERC_2	0.40	0.50	0.67	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.50	1.00	1.50	0.50	1.00	1.50	0.164
ERC_3	1.00	1.50	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.50	0.67	1.00	1.00	1.50	2.00	0.160
ERC_4	0.33	0.40	0.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.180
ERC_5	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.50	2.00	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.164
ERC_6	0.50	1.00	1.50	0.67	1.00	2.00	0.50	0.67	1.00	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.117

Table 2.B.17
Priority of each ERC with respect to Sc_6

Sc_6	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	1.00	1.50	2.00	0.67	1.00	2.00	1.50	2.00	2.50	0.50	1.00	1.50	0.33	0.40	0.50	0.171
ERC_2	0.50	0.67	1.00	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	0.50	1.00	1.50	0.208
ERC_3	0.50	1.00	1.50	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.40	0.50	0.67	0.126
ERC_4	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.177
ERC_5	0.67	1.00	2.00	0.40	0.50	0.67	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.132
ERC_6	2.00	2.50	3.00	0.67	1.00	2.00	1.50	2.00	2.50	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.185

Table 2.B.18

Priority of each ERC with respect to Sc_7

Sc_7	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.50	0.67	1.00	0.50	1.00	1.50	0.67	1.00	2.00	0.191
ERC_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.00	1.50	2.00	0.50	0.67	1.00	0.174
ERC_3	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	2.00	2.50	3.00	1.00	1.50	2.00	0.178
ERC_4	1.00	1.50	2.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.50	1.00	1.50	0.172
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	0.67	1.00	0.113
ERC_6	0.50	1.00	1.50	1.00	1.50	2.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.50	2.00	1.00	1.00	1.00	0.172

Table 2.B.19

Priority of each ERC with respect to Sc_8

Sc_8	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	0.40	0.50	0.67	1.00	1.50	2.00	0.67	1.00	2.00	0.50	1.00	1.50	0.50	0.67	1.00	0.140
ERC_2	1.50	2.00	2.50	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	1.00	1.50	2.00	0.267
ERC_3	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	1.50	2.00	2.50	0.158
ERC_4	0.50	1.00	1.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.40	0.50	0.67	0.124
ERC_5	0.67	1.00	2.00	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.175
ERC_6	1.00	1.50	2.00	0.50	0.67	1.00	0.40	0.50	0.67	1.50	2.00	2.50	0.33	0.40	0.50	1.00	1.00	1.00	0.136

Table 2.B.20

Priority of each ERC with respect to Sc_9

Sc_9	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	1.00	1.50	2.00	1.50	2.00	2.50	0.50	0.67	1.00	0.50	1.00	1.50	1.50	2.00	2.50	0.200
ERC_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.33	0.40	0.50	1.00	1.50	2.00	0.50	1.00	1.50	0.151
ERC_3	0.40	0.50	0.67	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	2.00	2.50	3.00	0.178
ERC_4	1.00	1.50	2.00	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.50	1.00	1.50	0.197
ERC_5	0.67	1.00	2.00	0.50	0.67	1.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.154
ERC_6	0.40	0.50	0.67	0.67	1.00	2.00	0.33	0.40	0.50	0.67	1.00	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.120

Table 2.B.21
Priority of each ERC with respect to Sc_{10}

Sc_{10}	ERC_1			ERC_2			ERC_3			ERC_4			ERC_5			ERC_6			W_c
ERC_1	1.00	1.00	1.00	0.40	0.50	0.67	1.00	1.50	2.00	0.50	1.00	1.50	1.00	1.50	2.00	0.67	1.00	2.00	0.170
ERC_2	1.50	2.00	2.50	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	1.00	1.50	2.00	1.00	1.50	2.00	0.255
ERC_3	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	2.00	2.50	3.00	0.188
ERC_4	0.67	1.00	2.00	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.159
ERC_5	0.50	0.67	1.00	0.50	0.67	1.00	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.50	2.00	2.50	0.154
ERC_6	0.50	1.00	1.50	0.50	0.67	1.00	0.33	0.40	0.50	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	0.072

Table 2.B.22
Overall priority of each ERC according to each sub-criterion

W_4	Priority of each ERC with respect to each sub-criterion									
	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}
ERC_1	0.140	0.210	0.236	0.253	0.215	0.171	0.191	0.140	0.200	0.170
ERC_2	0.219	0.185	0.222	0.138	0.164	0.208	0.174	0.267	0.151	0.255
ERC_3	0.174	0.210	0.099	0.137	0.160	0.126	0.178	0.158	0.178	0.188
ERC_4	0.173	0.115	0.188	0.183	0.180	0.177	0.172	0.124	0.197	0.159
ERC_5	0.154	0.140	0.175	0.163	0.164	0.132	0.113	0.175	0.154	0.154
ERC_6	0.140	0.140	0.080	0.125	0.117	0.185	0.172	0.136	0.120	0.072

2.C. Fuzzy ANP calculation related to ERPs

Table 2.C.1
Pairwise comparisons among criteria

W_1	C_1			C_2			C_3			C_4			W_c
C_1	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.50	1.00	1.50	0.326
C_2	0.33	0.40	0.50	1.00	1.00	1.00	0.67	1.00	2.00	2.50	3.00	3.50	0.296
C_3	0.50	0.67	1.00	0.50	1.00	1.50	1.00	1.00	1.00	0.50	1.00	1.50	0.188
C_4	0.67	1.00	2.00	0.29	0.33	0.40	0.67	1.00	2.00	1.00	1.00	1.00	0.190

Table 2.C.2
The inner dependence matrix and relative weight factor with respect to C_1

C_1	C_2			C_3			C_4			W_c
C_2	1.00	1.00	1.00	1.00	1.50	2.00	0.50	1.00	1.50	0.363
C_3	0.50	0.67	1.00	1.00	1.00	1.00	1.50	2.00	2.50	0.381
C_4	0.67	1.00	2.00	0.40	0.50	0.67	1.00	1.00	1.00	0.256

Table 2.C.3
The inner dependence matrix and relative weight factor with respect to C_2

C_2	C_1			C_3			C_4			W_c
C_1	1.00	1.00	1.00	1.00	1.50	2.00	0.33	0.40	0.50	0.253
C_3	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.236
C_4	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.00	1.00	0.512

Table 2.C.4
The inner dependence matrix and relative weight factor with respect to C_3

C_3		C_1			C_2			C_4		W_c
C_1	1.00	1.00	1.00	0.67	1.00	2.00	0.50	1.00	1.50	0.325
C_2	0.50	1.00	1.50	1.00	1.00	1.00	1.50	2.00	2.50	0.412
C_4	0.67	1.00	2.00	0.40	0.50	0.67	1.00	1.00	1.00	0.263

Table 2.C.5
The inner dependence matrix and relative weight factor with respect to C_4

C_4		C_1			C_2			C_3		W_c
C_1	1.00	1.00	1.00	0.40	0.50	0.67	1.50	2.00	2.50	0.361
C_2	1.50	2.00	2.50	1.00	1.00	1.00	0.67	1.00	2.00	0.426
C_3	0.40	0.50	0.67	0.50	1.00	1.50	1.00	1.00	1.00	0.213

Table 2.C.6
The interdependent ranking of the green performance criteria related to ERPs

W_2	C_1	C_2	C_3	C_4	W_1	$W_{criteria}$
C_1	1.00	0.253	0.325	0.361	0.326	0.265
C_2	0.363	1.00	0.412	0.426	0.296	0.286
C_3	0.381	0.236	1.00	0.213	0.188	0.211
C_4	0.256	0.512	0.263	1.00	0.190	0.237

Table 2.C.7
Pairwise comparisons among sub-criteria of C_1

C_1		Sc_1			Sc_2		W_c
Sc_1	1.00	1.00	1.00	1.00	1.50	2.00	0.684
Sc_2	0.50	0.67	1.00	1.00	1.00	1.00	0.316

Table 2.C.8
Pairwise comparisons among sub-criteria of C_2

C_2		Sc_3			Sc_4		W_c
Sc_3	1.00	1.00	1.00	0.50	1.00	1.50	0.500
Sc_4	0.67	1.00	2.00	1.00	1.00	1.00	0.500

Table 2.C.9
Pairwise comparisons among sub-criteria of C_3

C_3		Sc_5			Sc_6			Sc_7		W_c
Sc_5	1.00	1.00	1.00	2.50	3.00	3.50	0.50	1.00	1.50	0.543
Sc_6	0.29	0.33	0.40	1.00	1.00	1.00	0.50	1.00	1.50	0.115
Sc_7	0.67	1.00	2.00	0.67	1.00	2.00	1.00	1.00	1.00	0.342

Table 2.C.10
Pairwise comparisons among sub-criteria of C_4

C_4		Sc_8			Sc_9			Sc_{10}		W_c
Sc_8	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.685
Sc_9	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	0.224
Sc_{10}	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.091

Table 2.C.11
Overall priority of the sub-criteria of green performance for ERPs

Fuzzy ANP	$W_{criteria}$ obtained in Step 3	Sub-criteria	$W_{Sub\text{-}criteria}$ obtained in Step 4	Overall priority of the Sub-criteria
C_1: Green purchasing	0.265	Sc_1: Collaborating with supplier for protecting the environment	0.684	0.182
		Sc_2: Purchasing from Suppliers having ISO 14001 Standard - Environmental Management Systems	0.316	0.084
C_2: Operational performance	0.286	Sc_3: Optimum design	0.500	0.143
		Sc_4: Capacity utilization	0.500	0.143
C_3: Internal environmental management	0.211	Sc_5: Solid and septic waste management	0.543	0.115
		Sc_6: Reduction of emission	0.115	0.024
		Sc_7: Responsible Recycling© (R2) Certification	0.342	0.072
C_4: Green ethical approach	0.237	Sc_8: Green marketing	0.685	0.162
		Sc_9: Returning the package to suppliers for reuse	0.224	0.053
		Sc_{10}: Investment recovery	0.091	0.022

Table 2.C.12
Priority of each ERP with respect to Sc_1

Sc_1	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	2.00	2.50	3.00	0.50	1.00	1.50	1.50	2.00	2.50	0.67	1.00	2.00	0.269
ERP_2	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.00	1.50	2.00	0.212
ERP_3	0.67	1.00	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	2.00	2.50	3.00	0.227
ERP_4	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.149
ERP_5	0.50	1.00	1.50	0.50	0.67	1.00	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.143

Table 2.C.13
Priority of each ERP with respect to Sc_2

Sc_2	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	2.00	2.50	3.00	0.50	0.67	1.00	1.50	2.00	2.50	0.33	0.40	0.50	0.229
ERP_2	0.33	0.40	0.50	1.00	1.00	1.00	1.50	2.00	2.50	1.00	1.50	2.00	1.00	1.50	2.00	0.224
ERP_3	1.00	1.50	2.00	0.40	0.50	0.67	1.00	1.00	1.00	2.00	2.50	3.00	0.67	1.00	2.00	0.227
ERP_4	0.40	0.50	0.67	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	0.101
ERP_5	2.00	2.50	3.00	0.50	0.67	1.00	0.50	1.00	1.50	0.67	1.00	2.00	1.00	1.00	1.00	0.218

Table 2.C.14
Priority of each ERP with respect to Sc_3

Sc_3	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	1.50	2.00	2.50	2.00	2.50	3.00	1.50	2.00	2.50	1.00	1.50	2.00	0.341
ERP_2	0.40	0.50	0.67	1.00	1.00	1.00	1.00	1.50	2.00	2.00	2.50	3.00	0.67	1.00	2.00	0.246
ERP_3	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	1.50	2.00	2.50	0.163
ERP_4	0.40	0.50	0.67	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	2.00	2.50	3.00	0.190
ERP_5	0.50	0.67	1.00	0.50	1.00	1.50	0.40	0.50	0.67	0.33	0.40	0.50	1.00	1.00	1.00	0.060

Table 2.C.15
Priority of each ERP with respect to Sc_4

Sc_4		ERP_1			ERP_2			ERP_3			ERP_4			ERP_5		W_c
ERP_1	1.00	1.00	1.00	1.50	2.00	2.50	2.00	2.50	3.00	1.50	2.00	2.50	0.50	1.00	1.50	0.307
ERP_2	0.40	0.50	0.67	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	1.50	2.00	2.50	0.233
ERP_3	0.33	0.40	0.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	2.00	2.50	3.00	0.188
ERP_4	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.138
ERP_5	0.67	1.00	2.00	0.40	0.50	0.67	0.33	0.40	0.50	0.67	1.00	2.00	1.00	1.00	1.00	0.134

Table 2.C.16
Priority of each ERP with respect to Sc_5

Sc_5		ERP_1			ERP_2			ERP_3			ERP_4			ERP_5		W_c
ERP_1	1.00	1.00	1.00	0.67	1.00	2.00	1.00	1.50	2.00	2.00	2.50	3.00	0.50	0.67	1.00	0.233
ERP_2	0.50	1.00	1.50	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	0.33	0.40	0.50	0.224
ERP_3	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.156
ERP_4	0.33	0.40	0.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.164
ERP_5	1.00	1.50	2.00	2.00	2.50	3.00	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.222

Table 2.C.17
Priority of each ERP with respect to Sc_6

Sc_6		ERP_1			ERP_2			ERP_3			ERP_4			ERP_5		W_c
ERP_1	1.00	1.00	1.00	1.50	2.00	2.50	1.00	1.50	2.00	1.50	2.00	2.50	0.50	1.00	1.50	0.276
ERP_2	0.40	0.50	0.67	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	2.00	2.50	3.00	0.293
ERP_3	0.50	0.67	1.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.145
ERP_4	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.50	2.00	2.50	0.186
ERP_5	0.67	1.00	2.00	0.33	0.40	0.50	0.50	0.67	1.00	0.40	0.50	0.67	1.00	1.00	1.00	0.099

Table 2.C.18
Priority of each ERP with respect to Sc_7

Sc_7	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	1.00	1.50	2.00	0.50	0.67	1.00	1.50	2.00	2.50	0.50	1.00	1.50	0.228
ERP_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.67	1.00	2.00	1.00	1.50	2.00	0.213
ERP_3	1.00	1.50	2.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.50	0.67	1.00	0.183
ERP_4	0.40	0.50	0.67	0.50	1.00	1.50	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.176
ERP_5	0.67	1.00	2.00	0.50	0.67	1.00	1.00	1.50	2.00	0.67	1.00	2.00	1.00	1.00	1.00	0.201

Table 2.C.19
Priority of each ERP with respect to Sc_8

Sc_8	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	0.67	1.00	2.00	0.33	0.40	0.50	1.50	2.00	2.50	0.33	0.40	0.50	0.160
ERP_2	0.50	1.00	1.50	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	0.278
ERP_3	2.00	2.50	3.00	0.33	0.40	0.50	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.222
ERP_4	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.140
ERP_5	2.00	2.50	3.00	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.199

Table 2.C.20
Priority of each ERP with respect to Sc_9

Sc_9	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	1.00	1.50	2.00	0.67	1.00	2.00	2.00	2.50	3.00	0.50	1.00	1.50	0.253
ERP_2	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.50	0.67	1.00	0.195
ERP_3	0.50	1.00	1.50	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.33	0.40	0.50	0.140
ERP_4	0.33	0.40	0.50	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	1.00	1.50	2.00	0.170
ERP_5	0.67	1.00	2.00	1.00	1.50	2.00	2.00	2.50	3.00	0.50	0.67	1.00	1.00	1.00	1.00	0.243

Table 2.C.21
Priority of each ERP with respect to Sc_{10}

Sc_{10}	ERP_1			ERP_2			ERP_3			ERP_4			ERP_5			W_c
ERP_1	1.00	1.00	1.00	2.00	2.50	3.00	1.00	1.50	2.00	1.50	2.00	2.50	1.00	1.50	2.00	0.316
ERP_2	0.33	0.40	0.50	1.00	1.00	1.00	1.00	1.50	2.00	0.33	0.40	0.50	1.50	2.00	2.50	0.175
ERP_3	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.164
ERP_4	0.40	0.50	0.67	2.00	2.50	3.00	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.225
ERP_5	0.50	0.67	1.00	0.40	0.50	0.67	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.120

Table 2.C.22
Overall priority of each ERP according to each sub-criterion

W_4	Priority of each ERP with respect to each sub-criterion									
	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}
ERP_1	0.269	0.229	0.341	0.307	0.233	0.276	0.228	0.160	0.253	0.316
ERP_2	0.212	0.224	0.246	0.233	0.224	0.293	0.213	0.278	0.195	0.175
ERP_3	0.227	0.227	0.163	0.188	0.156	0.145	0.183	0.222	0.140	0.164
ERP_4	0.149	0.101	0.190	0.138	0.164	0.186	0.176	0.140	0.170	0.225
ERP_5	0.143	0.218	0.060	0.134	0.222	0.099	0.201	0.199	0.243	0.120

Appendix 4

4.A. Volatility in Canadian fuel price

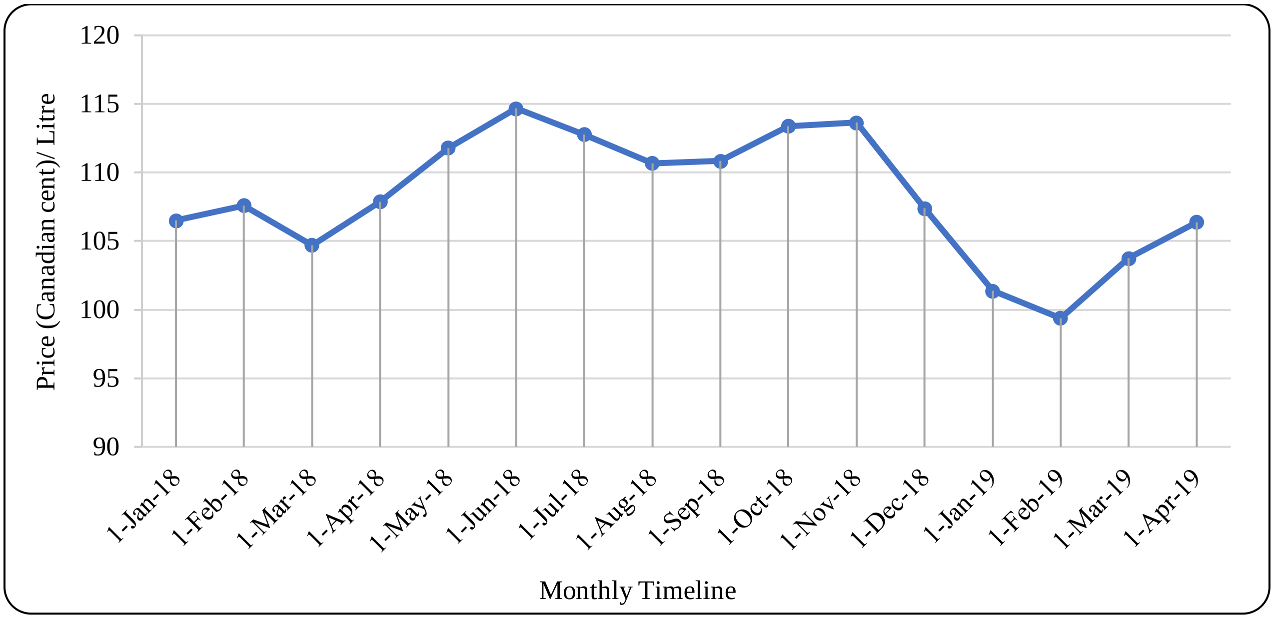

Fig. 4.A.1. The volatility in Canadian fuel price (The Historical Trend in Canadian Fuel Pricing, 2019)

4.B. Value of parameters

Table 4.B.1
The values of the parameters in the mathematical model

$J = 3$	$\widetilde{A}_s = (9{,}000, 10{,}000, 11{,}000)$	$\tilde{p}_j = \tilde{h}_j = \tilde{g}_j = \tilde{l}_j = \tilde{a}_j = (0.087, 0.097, 0.107)$
$\underset{\cdot}{N} = 5$	$\widetilde{B}_c = (9{,}000, 10{,}000, 11{,}000)$	$\tilde{o}_n = \tilde{k}_n = \tilde{e}_n = (0.0184, 0.0194, 0.0204)$
$\underset{\cdot}{S} = 6$	$\widetilde{C}_i = (39{,}000, 40{,}000, 41{,}000)$	$\widetilde{H}_{fn} = (55{,}000, 60{,}000, 65{,}000)$
$\underset{\cdot}{M} = 25$	$\tilde{Y}_r = (90{,}000, 100{,}000, 110{,}000)$	$U_{cj} = 1{,}000$
$\underset{\cdot}{R} = 5$	$\widetilde{D}_f = (390{,}000, 400{,}000, 410{,}000)$	$W_{rj} = 15{,}000$
$\acute{\text{Ç}} = 25$	$\widetilde{E}_{sn} = (8, 10, 12)$,	$\Gamma_{sn} = 50{,}000$
$\dot{F}=4$	$\widetilde{F}_j = (12, 15, 18)$	$\Lambda_{ij} = 300{,}000$
$\underset{\cdot}{I} = 7$	$\widetilde{R}_j = (180, 200, 220)$	$\varphi = 0.3$
$\Omega = 5$	$\widetilde{G}_j = (30, 35, 40)$	$\eta = 200$
$\text{Ŧ} = 2$	$\tilde{T}_n = (2, 5, 8)$	$\pi_1 = \pi_2 = 100$
$\Delta = 100$	$\gamma = 200$	$\sigma = 200$
$\upsilon_j = 0.25$	K_{sn} *, M_{fn} **, N_{rn} ***	Φ_ω ; $\Phi_1 = 0.15$, $\Phi_2 = 0.20$, $\Phi_3 = 0.30$, $\Phi_4 = 0.20$, $\Phi_5 = 0.15$ ****

*, **, *** are provided in Tables 4.C.11, 4.C.12, and 4.C.13, respectively.

**** The scenario-based programming has been applied in different studies to consider the impact of various scenarios with pre-determined probabilities on network design (Snyder, 2006; Pishvaee et al., 2009; Amin and Zhang 2013a). ω was defined earlier as scenarios representing different rates of disposal fractions with the probability of Φ_ω to consider the various types of quality in returns. We consider five scenarios including $\varepsilon_{n0.2}$, $\varepsilon_{n0.4}$, $\varepsilon_{n0.6}$, $\varepsilon_{n0.8}$, $\varepsilon_{n1,}$ where $\varepsilon_{n\omega}$ is defined as the disposal fraction of component n in scenario ω. For example, if one module is unrecyclable, the disposal fraction becomes 20%. Disposal fractions of 40%, 60%, 80%, and 100% can be interpreted similarly. Given our real-world observations, it is fair to assume that most of the time, 3 out of 5 (i.e., 60%) modules are unusable for reassembling with new modules. Therefore, a higher probability has been assigned to the 3rd Scenario (i.e., $\Phi_3 = 0.30$). Similarly, it is rare that all 5 modules are unusable for remanufacturing operations. Therefore, a lower probability has been assigned to the 5th Scenario (i.e., $\Phi_5 = 0.15$).

4.C. The related calculations for green practices of third parties (i.e., K_{sn}, M_{fn}, and N_{rn})

Three decision-makers rank the potential suppliers, recovery centers, and remanufacturing plants regarding environmental practices. To this aim, we apply a fuzzy TOPSIS method which has been developed by Junior et al. (2014). Two types of linguistic scales are utilized for the purpose of comparison. Table 4.C.1 is applied to rank each criterion, and Table 4.C.2 is applied to rank each alternative.

Table 4.C.1
Linguistic scale to rank each criterion

Linguistic scale	TFNs
Unimportant	(0, 0, 0.25)
Moderately important	(0, 0.25, 0.50)
Important	(0.25, 0.50, 0.75)
Very important	(0.50, 0.75, 1)
Absolutely important	(0.75, 1, 1)

Table 4.C.2
Linguistic scale to rank each alternative

Linguistic scale	TFNs
Very low	(0, 0, 2.5)
Low	(0, 2.5, 5)
Good	(2.5, 5, 7.5)
High	(5, 7.5, 10)
Excellent	(7.5, 10, 10)

Step 1: As illustrated in Tables 4.C.3, 4.C.4, and 4.C.5, six potential suppliers are ranked by the decision-makers based on each criterion. Then, each criterion is ranked based on the associated linguistic scale.

Step 2: The average of each scale is computed in relation to each alternative. Similarly, the average weight of each criterion is calculated. The results are provided in Table 4.C.6.

Table 4.C.3
Rating of suppliers by the first decision-maker (DM1)

DM1	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	5	7.5	10	5	7.5	10	2.5	5	7.5	5	7.5	10	0	0	2.5
Supplier 2	7.5	10	10	7.5	10	10	5	7.5	10	7.5	10	10	5	7.5	10
Supplier 3	5	7.5	10	5	7.5	10	7.5	10	10	2.5	5	7.5	2.5	5	7.5
Supplier 4	2.5	5	7.5	5	7.5	10	2.5	5	7.5	5	7.5	10	5	7.5	10
Supplier 5	2.5	5	7.5	5	7.5	10	7.5	10	10	2.5	5	7.5	2.5	5	7.5
Supplier 6	5	7.5	10	7.5	10	10	2.5	5	7.5	5	7.5	10	5	7.5	10
Weight	0.75	1	1	0.75	1	1	0.5	0.75	1	0.5	0.75	1	0.25	0.5	0.75

Table 4.C.4
Rating of suppliers by the second decision-maker (DM2)

DM2	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	2.5	5	7.5	2.5	5	7.5	2.5	5	7.5	5	7.5	10	2.5	5	7.5
Supplier 2	7.5	10	10	7.5	10	10	7.5	10	10	7.5	10	10	7.5	10	10
Supplier 3	7.5	10	10	5	7.5	10	7.5	10	10	5	7.5	10	7.5	10	10
Supplier 4	5	7.5	10	7.5	10	10	5	7.5	10	5	7.5	10	5	7.5	10
Supplier 5	5	7.5	10	5	7.5	10	5	7.5	10	5	7.5	10	5	7.5	10
Supplier 6	2.5	5	7.5	2.5	5	7.5	7.5	10	10	7.5	10	10	2.5	5	7.5
Weight	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.25	0.5	0.75	0.25	0.5	0.75

Table 4.C.5
Rating of suppliers by the third decision-maker (DM3)

DM3	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	5	7.5	10	2.5	5	7.5	2.5	5	7.5	2.5	5	7.5	5	7.5	10
Supplier 2	7.5	10	10	7.5	10	10	7.5	10	10	7.5	10	10	7.5	10	10
Supplier 3	7.5	10	10	5	7.5	10	7.5	10	10	2.5	5	7.5	7.5	10	10
Supplier 4	2.5	5	7.5	7.5	10	10	5	7.5	10	5	7.5	10	2.5	5	7.5
Supplier 5	0	2.5	5	2.5	5	7.5	2.5	5	7.5	2.5	5	7.5	2.5	5	7.5
Supplier 6	7.5	10	10	5	7.5	10	5	7.5	10	7.5	10	10	5	7.5	10
Weight	0.75	1	1	0.5	0.75	1	0.75	1	1	0.5	0.75	1	0.25	0.5	0.75

Table 4.C.6
Average scale related to each alternative and average weight of each criterion

Average	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	4.17	6.67	9.17	3.33	5.83	8.33	2.50	5.00	7.50	4.17	6.67	9.17	2.50	4.17	6.67
Supplier 2	7.50	10.00	10.00	7.50	10.00	10.00	6.67	9.17	10.00	7.50	10.00	10.00	6.67	9.17	10.00
Supplier 3	6.67	9.17	10.00	5.00	7.50	10.00	7.50	10.00	10.00	3.33	5.83	8.33	5.83	8.33	9.17
Supplier 4	3.33	5.83	8.33	6.67	9.17	10.00	4.17	6.67	9.17	5.00	7.50	10.00	4.17	6.67	9.17
Supplier 5	2.50	5.00	7.50	4.17	6.67	9.17	5.00	7.50	9.17	3.33	5.83	8.33	3.33	5.83	8.33
Supplier 6	5.00	7.50	9.17	5.00	7.50	9.17	5.00	7.50	9.17	6.67	9.17	10.00	4.17	6.67	9.17
Weight	0.67	0.92	1.00	0.67	0.92	1.00	0.58	0.83	1.00	0.42	0.67	0.92	0.25	0.50	0.75

Step 3: Eq. (4.51) represents the fuzzy decision matrix obtained in Step 2. Then, Eq. (4.52) is applied to calculate the normalized fuzzy decision matrix of the alternatives and the criteria. Table 4.C.7 indicates the corresponding results.

$$\tilde{S}_{ij} = \left[s_{ij} \right]_{m \times n} \tag{4.51}$$

$$\tilde{s}_{ij} = \left(\frac{l_{ij}}{u_j^{max}}, \frac{m_{ij}}{u_j^{max}}, \frac{u_{ij}}{u_j^{max}} \right) \tag{4.52}$$

Table 4.C.7
Average scale related to the alternative and average weight of each criterion

Normalized	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	0.42	0.67	0.92	0.33	0.58	0.83	0.25	0.50	0.75	0.42	0.67	0.92	0.25	0.42	0.67
Supplier 2	0.75	1.00	1.00	0.75	1.00	1.00	0.67	0.92	1.00	0.75	1.00	1.00	0.67	0.92	1.00
Supplier 3	0.67	0.92	1.00	0.50	0.75	1.00	0.75	1.00	1.00	0.33	0.58	0.83	0.58	0.83	0.92
Supplier 4	0.33	0.58	0.83	0.67	0.92	1.00	0.42	0.67	0.92	0.50	0.75	1.00	0.42	0.67	0.92
Supplier 5	0.25	0.50	0.75	0.42	0.67	0.92	0.50	0.75	0.92	0.33	0.58	0.83	0.33	0.58	0.83
Supplier 6	0.50	0.75	0.92	0.50	0.75	0.92	0.50	0.75	0.92	0.67	0.92	1.00	0.42	0.67	0.92

Step 4: The weighted normalized matrix (Table 4.C.8) can be reached by multiplying all TFNs existing in Table 4.C.7 by the weight row in Table 4.C.6.

Table 4.C.8
The weighted normalized matrix

W-Normalized	C1: Sustainable packaging			C2: Green transportation			C3: Environmental compliance			C4: Green process			C5: Supplier's characteristics		
Supplier 1	0.28	0.61	0.92	0.22	0.53	0.83	0.15	0.42	0.75	0.17	0.44	0.84	0.06	0.21	0.50
Supplier 2	0.50	0.92	1.00	0.50	0.92	1.00	0.39	0.76	1.00	0.31	0.67	0.92	0.17	0.46	0.75
Supplier 3	0.44	0.84	1.00	0.33	0.69	1.00	0.44	0.83	1.00	0.14	0.39	0.76	0.15	0.42	0.69
Supplier 4	0.22	0.53	0.83	0.44	0.84	1.00	0.24	0.56	0.92	0.21	0.50	0.92	0.10	0.33	0.69
Supplier 5	0.17	0.46	0.75	0.28	0.61	0.92	0.29	0.63	0.92	0.14	0.39	0.76	0.08	0.29	0.63
Supplier 6	0.33	0.69	0.92	0.33	0.69	0.92	0.29	0.63	0.92	0.28	0.61	0.92	0.10	0.33	0.69

Step 5: The fuzzy positive ideal solution $v_j^+ = (1, 1, 1)$, and the fuzzy negative ideal solution $v_j^- = (0, 0, 0)$ are defined, and the distances between ideal solutions and all TFNs are calculated (see Table 4.C.8). To this aim, Eq. (4.53), and Eq. (4.54) are applied. The results are provided in Table 4.C.9 and Table 4.C.10.

$$d_i^+ = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^+\right) \tag{4.53}$$

$$d_i^- = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^-\right) \tag{4.54}$$

where the distance between two TFNs can be calculated by Eq. (4.55).

$$d\left(\tilde{x}, \tilde{y}\right) = \sqrt{\frac{1}{3}\left[\left(x_l - y_l\right)^2 + \left(x_m - y_m\right)^2 + \left(x_u - y_u\right)^2\right]} \tag{4.55}$$

Table 4.C.9
Distance from positive ideal solution

Distance-d^+	C1: Sustainable packaging	C2: Green transportation	C3: Environmental compliance	C4: Green process	C5: Supplier's characteristics	d_i^+
$d(S_1,S^+)$	0.48	0.53	0.61	0.58	0.76	2.97
$d(S_2,S^+)$	0.29	0.29	0.38	0.44	0.59	2.00
$d(S_3,S^+)$	0.33	0.43	0.34	0.62	0.62	2.35
$d(S_4,S^+)$	0.53	0.33	0.51	0.54	0.67	2.59
$d(S_5,S^+)$	0.59	0.48	0.47	0.62	0.70	2.86
$d(S_6,S^+)$	0.43	0.43	0.47	0.48	0.67	2.47

Table 4.C.10
Distance from negative ideal solution

Distance-d^-	C1: Sustainable packaging	C2: Green transportation	C3: Environmental compliance	C4: Green process	C5: Supplier's characteristics	d_i^-
$d\ (S_1,S^-)$	0.66	0.59	0.50	0.56	0.31	2.62
$d\ (S_2,S^-)$	0.83	0.83	0.76	0.68	0.52	3.63
$d\ (S_3,S^-)$	0.80	0.73	0.79	0.50	0.47	3.29
$d\ (S_4,S^-)$	0.59	0.80	0.63	0.61	0.45	3.08
$d\ (S_5,S^-)$	0.52	0.66	0.66	0.50	0.40	2.74
$d\ (S_6,S^-)$	0.69	0.69	0.66	0.66	0.45	3.14

Step 5: Ranking each alternative is obtained through the application of the closeness coefficient (Eq. (4.56)). The supplier rankings are provided in Table 4.C.11.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{4.56}$$

Table 4.C.11
Ranking of suppliers based on environmental compliance

Supplier *s*	CC_i	Rank
Supplier 1	0.46844	6th
Supplier 2	0.64457	1st
Supplier 3	0.58367	2nd
Supplier 4	0.54325	4th
Supplier 5	0.48898	5th
Supplier 6	0.56019	3rd

The same approach is employed to rank the recovery centers and the remanufacturing plants. The green performance criteria for recovery centers are defined as the application of eco-technology, the incorporation of green transportation, and the possession of a responsible recycling certificate. While green purchasing, capacity utilization, solid and septic waste management, and green ethical approaches were determined to be the criteria for measuring environmental compliance of remanufacturing plants. The results are provided in Table 4.C.12 and Table 4.C.13, respectively.

Table 4.C.12
Ranking of recovery centers based on environmental compliance

Recovery center r	CC_i	Rank
Recovery center 1	0.6410081	2nd
Recovery center 2	0.5530874	4th
Recovery center 3	0.6231132	3rd
Recovery center 4	0.6927713	1st
Recovery center 5	0.5173172	5th

Table 4.C.13
Ranking of remanufacturing plants based on environmental compliance

Remanufacturing plant f	CC_i	Rank
Remanufacturing plant 1	0.60478	3rd
Remanufacturing plant 2	0.56903	4th
Remanufacturing plant 3	0.64199	1st
Remanufacturing plant 4	0.6178	2nd

Appendix 5

5.A. The overall framework to rank the third parties based on social responsibility and technological innovation of third parties

Sustainable development of RL networks is influenced by various factors such as the economic and environmental factors, social responsibility and technological innovation of their participants. The economic and environmental factors (i.e., Z_1 and Z_2) are quantitative parameters and can be computed accordingly. However, social responsibility and technological innovation of third parties are qualitative indicators and must be converted to a quantitative parameter before optimization. As presented by Fig. 5. 6, some qualitative criteria and sub-criteria have been selected to compare the performance of third parties (i.e., suppliers and container recovery centers) based on the social responsibility and technological innovation. In this regard, multiple criteria decision-making (MCDM) methods, such as the analytic network process (ANP), can be utilized to measure such qualitative criteria. ANP is an MCDM technique which has been adopted in many industries for the purpose of decision-making, such as in textile industry (Yüksel and Dagdeviren, 2007), investment decision for selection of power plants (Aragonés-Beltrán et al., 2014), maintenance performance indicator selection (Van Horenbeek and Pintelon, 2014), the process of software selection with using artificial neural network (Yazgan et al., 2009), for selection of interdependent information system project (Lee and Kim, 2000), healthcare sector (Nilashi et al., 2016), urban development (Malmir et al., 2016), construction project (Gunduz and Khader, 2020), battery industry (Tosarkani and Amin, 2018a), and ranking new technology-based firms (Khodayari et al., 2019). In this study, the following criteria and sub-criteria are defined to prioritize suppliers and container recovery centers.

5.A.1. Application of eco-technology in production and designing eco-friendly products

The application of eco-technology (e.g., renewable sources of energy) has been progressively considered due to reducing the environmental impact of operations. Furthermore, designing eco-friendly products (e.g., using less hazardous raw material in designing a product) can be another supplementary factor to tackle environmental issues stemming from productions. For example, Coca Cola attempts to be more sustainable by replacing the colorfully sprayed containers with a convex logo instead. This type of beverage container does not require a coloring process which may reduce the environmental impact (e.g., air and water pollution). Furthermore, a huge amount of energy can be saved in comparison with traditional containers that require many efforts to separate color from containers in the recycling process.

5.A.2. IoT implementation

IoT is defined as the robust communication among the digital and physical world which has been employed in different industries (e.g., high-tech electronics, automotive, and manufacturing) to make the operations smarter. IoT leads to higher efficiencies in production regarding completely integrated, and automated processes (Vermesan et al., 2013). In this regard, three sub-criteria (i.e., cloud-computing capabilities, digital connectivity requirements, and application of smart things such as smart machines and services) are selected to quantify the IoT implementation of third parties.

5.A.3. Environmental compliance

To prioritize suppliers and beverage recovery centers, their environmental compliance should be considered as an overriding indicator. In this study, three sub-criteria (e.g., packaging from recoverable materials, regulatory compliance audit and ISO 14001 certificate, solid and septic waste management) have been taken into account to measure the environmental compliance of third parties. For example, some types of materials (e.g., papers, cardboard, and glasses) can be recovered and used for the purpose of packaging many times. In this regard, environmental compliance of third parties contributes to reducing the adverse impact of their operations on the environment.

5.A.4. Third party characteristics

Nowadays, customers are considering the social characteristics (e.g., social contributions, labour practices, and decent work) of third parties on their community in addition to their environmental compliance. For example, opening new facilities can create job opportunities contributing to enrich the economy of society. Furthermore, there are some efforts (e.g., labour code and human rights, training, and education) leading to create a safe, diverse workplace. In this regard, employee safety and training must be a priority for the employer. To rank the third parties regarding the social responsibility and technological innovation, seven steps are employed as follows:

Step 1: Pairwise comparisons are implemented regardless of interdependency among the criteria. The triangular linguistic values employed for comparison are indicated in Table 5.A.1 and Fig. 11. The results of comparisons for suppliers and beverage recovery centers are provided in Table 5.A.2.

Step 2: A relationship may exist among different criteria. In this regard, the pairwise comparisons should be conducted while it is assumed that there is the inner dependency among criteria. The results of the interdependent ranking of criteria are provided in Table 5.A.3. For more information, you can refer to Chang (1996).

Step 3: Weight of criteria is estimated by multiplication of two matrices of W_1 and W_2 obtained in Steps 1 and 2.

Step 4: The pairwise comparisons are also conducted for the sub-criterion. The results are indicated in Table 5.A.4.

Step 5: The overall ranking of each sub-criterion is estimated by multiplication of results obtained in Steps 3 and 4.

Step 6: The overall rankings of suppliers and beverage container recovery centers regarding each sub-criterion have been calculated by pairwise comparisons, and the results provided in Tables 5.A.5 and 5.A.6.

Step 7: As illustrated in Table 5.A.7 and 5.A.8, the final ranking of third parties are calculated by multiplication of W_3 and W_4 for suppliers, and W_3 and W_5 for beverage container recovery centers.

Table 5.A.1
Lingustic scales for importance

Linguistic scales for comparison	Triangular fuzzy scales	Reciprocal value of triangular fuzzy scales
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important (EI)	(0.5, 1, 1.5)	(0.67, 1, 2)
Weakly more important (WMI)	(1, 1.5, 2)	(0.5, 0.67, 1)
Strongly more important (SMI)	(1.5, 2, 2.5)	(0.4, 0.5, 0.67)
Very strongly more important (VSMI)	(2, 2.5, 3)	(0.33, 0.4, 0.5)
Absolutely more important (AMI)	(2.5, 3, 3.5)	(0.29, 0.33, 0.4)

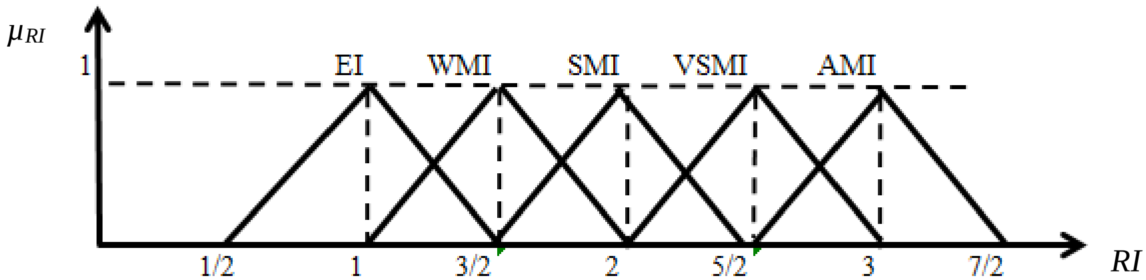

Fig. 5.A.1. Triangular linguistic values for comparison

Table 5.A.2
Pairwise comparisons of criteria associated with suppliers and beverage recovery centers

	C_1			C_2			C_3			C_4			W_1
C_1: Application of eco-technology in production and designing eco-friendly products	1	1	1	1	1.5	2	1	1.5	2	1.5	2	2.5	0.36
C_2: IoT implementation	0.5	0.67	1	1	1	1	1	1.5	2	2	2.5	3	0.34
C_3: Sustainable approach	0.5	0.67	1	0.5	0.67	1	1	1	1	0.5	1	1.5	0.17
C_4: Third party characteristics	0.4	0.5	0.67	0.33	0.4	0.5	0.67	1	2	1	1	1	0.14

Table 5.A.3
Results of ranking the criteria while it is assumed that there is the inner dependency among them

W_2	C_1	C_2	C_3	C_4	W_1	Weight of criteria
C_1: Application of eco-technology in production and designing eco-friendly products	1	0.39	0.38	0.15	0.36	0.29
C_2: IoT implementation	0.34	1	0.36	0.45	0.34	0.29
C_3: Sustainable approach	0.28	0.45	1.00	0.41	0.17	0.24
C_4: Third party characteristics	0.38	0.16	0.26	1	0.14	0.18

Table 5.A.4
The overall ranking of each sub-criterion associated with suppliers and beverage recovery centers

Criteria	Weight of criteria calculated in Step 3	Sub-criteria	Weight of each sub-criterion calculated in Step 4	W_3: The overall ranking of each sub-criterion (Step 5)
C_1: Application of eco-technology in production and designing eco-friendly products	0.29	Sc_1: Utilizing eco-technology in production (renewable source of energy, producing less carbon	0.684	0.197
		Sc_2: Application of less hazardous raw material in producing products	0.316	0.091
C_2: IoT implementation C_3: Sustainable approach	0.29	Sc_3: Cloud-computing capabilities	0.305	0.089
		Sc_4: Digital connectivity requirements	0.454	0.132
		Sc_5: Application of smart things such as smart machines and services	0.241	0.070
C_3: Sustainable approach	0.24	Sc_6: Packaging from recoverable materials	0.685	0.163
		Sc_7: Regulatory compliance audit and ISO 14001 certificate	0.224	0.053
		Sc_8: Solid and septic waste management	0.091	0.022
C_4: Third party characteristics	0.18	Sc_9: Social contributions	0.50	0.092
		Sc_{10}: Labour practices and decent work	0.50	0.092

Table 5.A.5
The overall ranking of suppliers regarding each sub-criterion

W_4	Ranking of each supplier regarding each sub-criterion									
	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}
Supplier 1	0.098	0.034	0.021	0.081	0.108	0.023	0.065	0.060	0.023	0.020
Supplier 2	0.040	0.142	0.064	0.038	0.068	0.022	0.050	0.102	0.022	0.062
Supplier 3	0.444	0.398	0.401	0.447	0.458	0.605	0.428	0.533	0.605	0.548
Supplier 4	0.323	0.320	0.337	0.296	0.257	0.262	0.294	0.239	0.262	0.349
Supplier 5	0.095	0.106	0.178	0.138	0.109	0.089	0.162	0.065	0.089	0.021

Table 5.A.6
The overall ranking of recovery centers regarding each sub-criterion

W_5	Ranking of each supplier regarding each sub-criterion									
	Sc_1	Sc_2	Sc_3	Sc_4	Sc_5	Sc_6	Sc_7	Sc_8	Sc_9	Sc_{10}
Recovery center 1	0.440	0.401	0.317	0.394	0.384	0.379	0.432	0.351	0.394	0.354
Recovery center 2	0.224	0.196	0.270	0.203	0.149	0.159	0.227	0.312	0.118	0.304
Recovery center 3	0.168	0.255	0.194	0.250	0.165	0.180	0.210	0.190	0.199	0.206
Recovery center 4	0.050	0.048	0.189	0.036	0.148	0.162	0.040	0.022	0.151	0.066
Recovery center 5	0.074	0.064	0.009	0.065	0.067	0.023	0.001	0.046	0.083	0.048
Recovery center 6	0.045	0.036	0.021	0.052	0.086	0.095	0.091	0.079	0.055	0.023

Table 5.A.7
Ranking of suppliers

ANP Result	
Supplier 1	0.06
Supplier 2	0.05
Supplier 3	0.49
Supplier 4	0.30
Supplier 5	0.10

Table 5.A.8
Ranking of recovery centers

ANP Result	
Recovery center 1	0.39
Recovery center 2	0.21
Recovery center 3	0.20
Recovery center 4	0.10
Recovery center 5	0.05
Recovery center 6	0.05

5.B. Values of the parameters

Table 5.B.1
Values of the parameters

I = 3	E_s = 1,000	e_i = 0.10
S = 5	B_r = 4,000	H_i = 15
R = 7	A_c = 1,500	K_i = 1
D = 10	F_d = 1,500	k_{ri} = $(50{,}000)_{7*3}$
M = 22	O_i = 0.097	l_{di} = $(10{,}000)_{10*3}$
C = 6	J_i = 10	f_{ci} = $(25{,}000)_{6*3}$
T = 2	G_i = 10	p_{si} = $(30{,}000)_{5*3}$
	g = 1,200	u = 400

Table 5.B.2
Values of the TFNs

E_s = (750, 1,000, 1,250)	$e_{i\omega}$ = (0.05, 0.10, 0.15)
B_r = (3,000, 4,000, 5,000)	H_i = (11.25, 15, 18.75)
A_c = (1,125, 1,500, 1,875)	K_i= (0.75, 1, 1.25)
F_d = (1,125, 1,500, 1,875)	G_i = (7.5 ,10, 12.5)
O_i = (0.072, 0.097, 0.121)	u = (300, 400, 500)
J_i = (7.5 ,10, 12.5)	g = (900, 1,200, 1,500)

Appendix 6

6.A. Chance constraint

$P\left(d' \leq A'\ddot{x}\right) \geq 1-\alpha$ means that such a chance constraint must be satisfied with a probability of at least $1-\alpha$. Eq. (6.A.1) can be written in case of $d' \sim N\left(\dot{\mu}, \dot{\sigma}^2\right)$.

$$P\left(\frac{d'-\dot{\mu}}{\dot{\sigma}} \leq \frac{A'\ddot{x}-\dot{\mu}}{\dot{\sigma}}\right) \geq 1-\alpha \qquad \text{Eq. (6.A.1)}$$

Eq. (6.A.1) can be converted to Eq. (6.A.2), since $\Phi\left(\dot{z}_\alpha\right)$ equals to $1-\alpha$ (Banks et al., 2005). Where $\dot{z}_\alpha$ is the value of the standard normal variable, and $\Phi\left(\dot{z}_\alpha\right)$ is the cumulative distribution function (cdf) for the standard normal distribution. The cdf of $\dot{z}_\alpha$ is given by $\Phi\left(\dot{z}_\alpha\right) = \int_{-\infty}^{\dot{z}_\alpha} \frac{1}{\sqrt{2\pi}} e^{\frac{-\dot{z}^2}{2}} d\dot{z}$.

$$\Phi\left(\frac{A'\ddot{x}-\dot{\mu}}{\dot{\sigma}}\right) \geq \Phi\left(\dot{z}_\alpha\right) \qquad \text{Eq. (6.A.2)}$$

Eq. (6.A.2) will be satisfied only if $\frac{A'\ddot{x}-\dot{\mu}}{\dot{\sigma}} \geq \dot{z}_\alpha$, or $A'\ddot{x} \geq \dot{\sigma}\dot{z}_\alpha + \dot{\mu}$.

6.B. Values of the parameters

Table 6.B.1
The values of parameters in the mathematical model

L = 5	e_l = Uniform [1.5 to 3.5]	j_q = Uniform [30 to 50]	Γ_o = Uniform [0.45 to 0.75]
M = 6	f_m = Uniform [3 to 4]	k_r = Uniform [1.88 to 6.24]	w = 15
N = 3	g_n = Uniform [2.5 to 5]	ω_t = Uniform [0.10 to 0.40]	x = 20
O = 2	ht = Uniform [0.10 to 0.12]	β_t = 0.05	y = 45
P = 2	i_p = Uniform [6 to 25]	$\zeta_t = \theta_t$ = 0.25	CW_{lt} = 150,000
Q = 4	$A_l = F_o = G_p$ = 100,000	υ_t = 0.70	CD_{rt} = 50,000
R = 7	B_q = 500,000	γ_t = 0.4	CU_{qt} = 70,000
T = 2	C_r = 40,000	F_o = 30,000	CB_{mt} = 25,000
S = 68	E_m = 10,000	G_p = 50,000	CF_{ot} = 65,000
u = 50	CT = 7	ς_o = Uniform [0.05 to 0.1]	CO_{pt} = 15,000

6.C. Optimal solutions of RFCCM for 100 data sets

Table 6.C.1

Optimal solutions of RFCCM for 100 data sets (φ = 10%)

No.	Consumed fracturing fluids	Total costs	No.	Consumed fracturing fluids	Total costs
1	47,971.86	6,597,150.02	51	43,580.11	6,055,881.48
2	40,716.87	5,709,853.25	52	67,382.26	9,308,954.98
3	39,422.52	5,553,429.69	53	48,592.69	6,672,424.41
4	57,372.52	7,842,280.25	54	43,484.13	6,044,282.10
5	61,049.40	8,450,876.39	55	63,431.31	8,810,348.48
6	65,923.27	9,124,831.70	56	52,461.26	7,141,481.93
7	43,759.16	6,077,520.03	57	46,815.96	6,456,999.48
8	63,973.54	8,878,777.44	58	48,037.99	6,605,169.37
9	52,804.41	7,183,088.18	59	43,718.32	6,072,584.43
10	52,594.66	7,157,656.41	60	37,868.37	5,365,606.38
11	50,130.57	6,858,890.47	61	35,997.23	5,139,475.40
12	62,583.34	8,642,323.15	62	45,635.78	6,304,314.48
13	54,626.60	7,505,531.36	63	65,880.56	9,119,441.73
14	41,237.66	5,772,792.96	64	46,839.91	6,459,904.58
15	61,649.26	8,525,744.49	65	44,148.76	6,124,603.96
16	49,201.81	6,746,278.98	66	51,166.67	6,984,515.50
17	65,033.78	9,012,580.08	67	40,871.31	5,728,517.63
18	48,768.35	6,693,724.04	68	56,463.94	7,730,856.37
19	58,461.45	7,985,908.64	69	67,557.32	9,331,048.67
20	48,420.36	6,651,530.96	70	68,710.24	9,476,546.18
21	58,169.79	7,940,054.68	71	39,143.93	5,519,761.54
22	59,053.07	8,159,221.28	72	60,135.52	8,336,817.59
23	64,855.93	8,990,135.57	73	50,936.17	6,956,566.63
24	55,505.22	7,613,282.27	74	58,364.64	7,973,972.30
25	52,118.15	7,099,879.32	75	38,104.95	5,394,198.75
26	47,947.08	6,594,146.71	76	41,756.73	5,835,523.60
27	35,557.70	5,086,357.33	77	30,208.31	4,435,249.23
28	51,360.71	7,008,041.25	78	63,824.93	8,860,022.99
29	44,640.81	6,184,069.18	79	48,465.76	6,657,034.40
30	64,490.93	8,944,072.88	80	33,828.48	4,868,692.12
31	50,180.08	6,864,893.46	81	54,465.49	7,485,773.38
32	59,547.42	8,220,919.72	82	39,787.04	5,597,482.66
33	51,919.10	7,075,746.12	83	48,842.29	6,702,687.91
34	55,735.11	7,641,475.18	84	37,021.41	5,263,249.58
35	50,691.47	6,926,897.25	85	46,744.52	6,448,337.53
36	42,946.76	5,979,341.08	86	55,057.92	7,558,425.72
37	40,395.16	5,670,973.96	87	52,963.09	7,202,326.59
38	57,304.15	7,833,895.59	88	56,486.22	7,733,588.71
39	63,349.15	8,799,979.96	89	40,216.99	5,649,442.97
40	49,131.55	6,737,761.31	90	45,117.77	6,241,711.95
41	54,587.15	7,500,692.12	91	43,188.37	6,008,540.13
42	50,138.21	6,859,816.80	92	52,883.97	7,192,734.66
43	54,587.10	7,500,685.99	93	46,966.36	6,475,236.39
44	34,663.87	4,968,713.35	94	63,131.44	8,772,505.14
45	44,909.99	6,216,600.11	95	42,832.23	5,965,498.70
46	45,473.80	6,284,737.67	96	50,648.86	6,921,730.87
47	37,369.35	5,305,298.82	97	47,662.74	6,559,669.85
48	51,065.96	6,972,304.62	98	46,021.93	6,350,980.27
49	45,884.11	6,334,325.65	99	42,390.11	5,912,067.62
50	64,876.67	8,992,751.67	100	45,365.00	6,271,590.18

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