Optimization Models for Sustainable Reverse Logistics Network Planning under Uncertainty

by

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Modèles d'optimisation pour la planification de réseaux logistiques inverses durables sous incertitudes

Julien TROCHU

RÉSUMÉ

Le terme développement durable est un terme utilisé pour désigner un développement qui intègre les trois considérations fondamentales : la dimension économique, environnementale et sociale. Un développement durable se réfère généralement à : « Un développement qui répond aux besoins du présent sans compromettre la capacité des générations futures de répondre aux leurs ». Les chaînes d'approvisionnement se trouvent aujourd'hui face au défi majeur de faire évoluer leurs pratiques traditionnelles afin d'appliquer ce concept à leurs opérations. Cette thèse vient appuyer cet effort visant à assurer la durabilité des opérations de la chaîne d'approvisionnement dans les années à venir, en proposant des modèles quantitatifs d'aide à la décision pour la conception de réseaux logistiques inverses performants.

Ma thèse, intitulée « *Modèles quantitatifs pour la conception de réseaux logistiques inverses durables sous incertitude* », souligne l'importance de développer des modèles décisionnels intégrant les incertitudes critiques inhérentes aux opérations de logistique inverses dans l'industrie. Ce travail de recherche étudie également les compromis nécessaires à la conception de réseaux logistiques inverses efficaces, tout en tenant compte de divers aspects environnementaux, améliorant ainsi les chances de progresser vers un développement durable. Dans les trois articles présentés ci-dessous, l'industrie de la construction, de la rénovation et de la démolition (CRD) est utilisée comme référence pour valider nos modèles au travers de plusieurs études de cas.

Le premier article de cette thèse présente une étude de cas détaillée qui traite des défis liés à la gestion des débris de matériaux de bois de CRD au Québec, Canada. Dans cet article, le modèle d'optimisation proposé détermine les emplacements et les capacités des centres de collecte qui assurent le tri des matériaux afin d'être en accord avec la règlementation locale sur l'enfouissement du bois. Nous formulons le problème sous la forme d'un modèle de programmation linéaire en nombres entiers mixtes (MILP), afin de minimiser le coût total du de recyclage du bois au sein du réseau de logistique inverse et de rendre son élimination moins attractive financièrement. Nous proposons une approche basée sur divers scénarios afin de redéfinir le réseau de logistique inverse actuel en fonction des incertitudes sur les emplacements des sites de collecte, la quantité et la qualité du bois collecté. Les résultats montrent que le réseau de logistique inverse optimal dans un scénario donné peut s'avérer obsolète dans d'autres scénarios, dépendamment de la réalisation des paramètres incertains. Bien que seule l'aspect économique soit considéré dans cet article, cela représente un premier pas vers des opérations de logistique inverse durables par l'optimisation des opérations de gestion des débris dans un secteur qui compte parmi les plus grands générateurs de déchets au monde.

Ainsi, dans le deuxième article et dans le but de répondre aux problèmes causés par les incertitudes, nous présentons une nouvelle formulation plus avancée qui traite simultanément un nombre élevé de scénarios. De cette manière, nous sommes capables d'optimiser nos espérances en terme de profits sur un horizon de planification multi-période. Dans ce second article, non seulement nous optimisons la conception du réseau de logistique inverse pour la gestion des débris, mais nous évaluons également l'impact de l'intégration de plateformes logistiques appelées centres de séparation à la source, que nous utilisons pour effectuer une première séparation des débris avant leur expédition vers les centres de collecte certifiés. De plus, nous réalisons une analyse de sensibilité sur le nombre de sources d'approvisionnement (générateurs de déchets) afin de comparer les zones de collecte rurales à faible densité par rapport aux zones urbaines à forte densité, où il est souvent plus complexe de réaliser des activités de collecte. La flexibilité offerte par ces plates-formes dynamiques atteint son plein potentiel dans les zones urbaines à haute densité. Les résultats suggèrent des ajustements significatifs du réseau de logistique inverse entraînant une augmentation du profit moyen espéré ainsi que de la quantité de matériaux recyclés.

Enfin, dans le troisième article, nous adaptons le modèle stochastique du précédent article en intégrant la dimension environnementale, par le biais d'une deuxième fonction objectif qui minimise la quantité de matériaux éliminés par enfouissement. Dans cette recherche, nous optimisons la conception du réseau de logistique inverse pour le recyclage des débris de bois provenant de l'industrie de CRD, sous contraintes à la fois de restrictions d'enfouissement et de contrôle des émissions par un système de plafonnement et d'échange, tel que celui en vigueur au Québec. Une fois encore, l'importance de la stratégie de séparation à la source est soulignée dans cet article, et nous établissons la relation entre l'incertitude sur la qualité du bois collecté et la difficulté de respecter les objectifs de recyclage fixés par le gouvernement. En effet, en comptabilisant les émissions libérées par les différents processus de recyclage, il s'avère que l'enfouissement des débris de bois se révèle parfois être la meilleure option selon le niveau de qualité des déchets collectés.

En résumé, le premier article permet d'établir et de quantifier l'impact des incertitudes sur l'efficacité du réseau de logistique inverse, hautement dépendante des valeurs des paramètres incertains. Sur la base de cette constatation, nous développons dans le deuxième article un modèle stochastique qui vise à établir le meilleur compromis afin de faire face à un grand nombre de scénarios simultanément. Enfin et pour finir, dans le troisième article nous adaptons ce dernier modèle à l'étude de cas sur le recyclage des débris de bois. Les émissions de gaz à effet de serre provenant des processus de recyclage du bois sont comptabilisées, et la réglementation relative aux restrictions de l'enfouissement est également appliquée.

Mots-clés : Chaîne d'approvisionnement durable, logistique inverse, conception de réseau, modèles d'aide à la décision, optimisation stochastique et multi-objectifs, industrie de CRD, gestion des déchets, recyclage du bois, réglementations environnementales.

Optimization models for sustainable reverse logistics network planning under uncertainty

Julien TROCHU

ABSTRACT

Nowadays, evolving toward sustainable operations among supply chains is a critical need for the near future and the well-being of the upcoming generations. The term sustainability commonly refers to the interactions between the economic, environmental and social dimensions of development. A sustainable development usually refers to: “A development that meets the needs of the present without compromising the ability of future generations to meet their own needs". Practitioners and academics all over the world are working toward this goal since the last three decades. Thus, this thesis comes to complement this effort toward achieving sustainability in supply chain operations.

My dissertation, entitled “*quantitative models for sustainable reverse logistics network design under uncertainty*”, focuses on the importance of developing decision-making models that include critical uncertainties inherent to the reverse logistics operations in the industry. It studies more specifically the trade-offs that are necessary to design efficient reverse logistics networks while considering various environmental aspects, thus improving our chances to take this step toward sustainability. In the three articles presented below, we will use the construction, renovation and demolition (CRD) industry as a reference to validate our models through several case studies.

The first article, titled “*Reverse logistics network redesign under uncertainty for wood waste in the CRD industry*” presents a detailed case study of the challenges related to the wood building material waste management in Quebec, Canada. In this paper, the main objective is to determine the location and the capacities of the sorting facilities to ensure compliance with the regulation and prevent the wood from being massively landfilled. We formulate the problem as a mixed-integer linear programming model (MILP) to minimize the total cost of the wood recycling processes collected from CRD sites. We start from the real collection centers' locations from the Quebec CRD industry and we propose a scenario-based approach to redesign the reverse logistics network based on various realizations of the randomness targeting the uncertain parameters. The results demonstrate that efforts toward obtaining accurate information about the supply sources' locations, the collected wood quantity and its quality would guarantee a more efficient reverse logistics network redesign. Although environmental and social considerations are not addressed in this article, it represents a first step toward sustainability by optimizing waste management operations in a sector that is among the biggest waste generators worldwide.

Thus, in the second article, titled “*A two-stage stochastic optimization model for reverse logistics network design under dynamic suppliers' locations*”, we introduce a new advanced

model formulation that addresses multiple scenarios at the same time in order to cope with uncertainty in the best manner over a multi-period planning horizon. The availability of each material collected from the supply sources and the recycling rates at the collection centers are the main sources of uncertainty considered in this study. This time, not only we optimize the reverse logistics network design, but we also evaluate the integration of logistics platforms called source-separation centers (SSC), that we use to perform source-separation of the materials before shipping them to the main collection centers. We perform a sensitivity analysis on the number of supply sources (i.e. waste generators) to compare low-density rural collection zones versus high-density urban areas, where the waste collection activities are often more challenging. Although the SSC improve the network performance in both rural and urban zones, the flexibility provided by these dynamic platforms reaches its best efficiency in the high-density urban areas. The results suggest significant RLND adjustments that lead to increase both the average expected profit and the amount of materials recycled through the reverse logistics channel.

Finally, in the third article, titled "*A carbon-constrained stochastic model for eco-efficient reverse logistics network design under environmental regulations in the CRD Industry*", we adapt the stochastic model of the previous article to include environmental considerations by adding a second objective function. In this research, we evaluate the optimal eco-efficient reverse logistics network design for the wood waste recycling from the CRD industry under both landfilling restrictions and emission control by a cap-and-trade system, such as the one effective in Quebec these days. In this paper, we emphasize the importance of the source separation strategy to address the challenge caused by the unpredictable quality of the wood collected and its impact on the efficiency of the recycling processes. Indeed, by accounting the emissions released by the various recycling processes, it turns out that the landfilling option may be the best option depending on the quality level of the collected waste. Finally, in this paper we establish the relation between the quality level uncertainty of the collected materials and the difficulty to comply with governmental recycling targets.

Overall, the scenario-based approach in the first article allows establishing the problematic of multiple uncertainties for designing an optimal reverse logistics network that performs under each scenario. Based on this finding, in the second article we develop a two-stage stochastic model in order to find the best expected RLND to cope with a large number of possible scenarios in a multi-period planning horizon. Lastly, in the third article we adapt this model to fit with the reality of the CRD industry for the wood waste recycling case study. Such adaptations imply emissions accounting from the wood recycling processes and complying with the legal framework regarding the recycling targets.

Keywords : Sustainable supply chain, reverse logistics, network design, quantitative decision-making models, stochastic and multi-objective optimization, CRD industry, waste management, wood recycling, environmental regulations.

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LIST OF ABREVIATIONS

AHP	Analytic Hierarchy Process
BOM	Bill of Materials
CC	Collection Centers
CLSC	Closed-Loop Supply Chain
CRD	Construction, Rénovation et Démolition
CSR	Corporate Social Responsibility
DSS	Decision Support System
EPA	Environmental Protection Agency
ELV	End of Life Vehicle
ETS	Emission Trading Scheme
FSC	Forward Supply Chain
GHG	Greenhouse Gases
LCA	Life Cycle Assessment
MCDM	Multi-Criteria Decision Making
MILP	Mixed Integer Linear Programming
MMC	Mixed-Material Container
MOSM	Multi-Objective Stochastic Model
MOTSSM	Multi-Objective Two-Stage Stochastic Model
PLM	Product Life Cycle Management
RL	Reverse Logistics
RLN	Reverse Logistics Network

RLND	Reverse Logistics Network Design
RoHS	Restriction on Hazardous Substance
SCND	Supply Chain Network Design
SMC	Single-Material Container
SP	Separation Platforms
SSC	Source Separation Centers
SSCM	Sustainable Supply Chain Management
WEEE	Waste on Electronic and Electrical Equipment
WM	Waste Management
WMP	Waste Management Plan

INTRODUCTION

Research context

Sustainable supply chain management has become a critical matter in nowadays society. Practitioners and academics have demonstrated an increased interest in the environmental damage caused by the supply chains activities worldwide. Indeed, the last two decades of the 20th century marked a real change regarding the awareness of the international communities of the environmental threat caused by traditional industrial practices. During the third Earth Summit of June 1992 in Rio de Janeiro, 182 states and more than a thousand organizations met and discussed measures to be adopted to preserve the environment. This unprecedented meeting contributed to the collective awareness and the start of the Sustainable development era. Today, a widely accepted definition of sustainable development is: "*a development that allows the needs of the present generation to be met without compromising the ability of future generations to meet their own*". Since the emergence of the sustainable supply chain triple bottom-line concept in the literature (Elkington, 1998), considering supply chains as entities converting raw materials into finished products to satisfy customer requirements have changed (Benita and Beamon, 1999). Figure 01 illustrates the triple-bottom-line concept.

Figure 01 The triple bottom line of sustainable development
(*adapted from Elkington, 1998*)

In fact, some of the major environmental concerns were discovered a long time ago. Among them, acid rain and atmospheric pollution were already established in 1872 (Cowling, 1982), climate change and global warming issues were noticed a few years later (Arrhenius, 1896), and the same goes for the ozone layer related problems in 1913 (Solomon, 1999). However, all these matters became of an increased interest in the late 1900s only, partly because of the evolution of the trends in the global industry. Nowadays, the rapidity of technology evolution implies an increasing variety of products with short lifecycles, thus reaching obsolescence faster than before (Hilletofth et al., 2018). As a consequence, the global market demand has increased dramatically for a wide variety of products and services in the past century (Rajeev et al., 2017). Moreover, since 2011, the emergence of what is called the « industry 4.0 » era and all the associated opportunities that will be offered to the logistics systems and industries, we can safely assume that this trend is going to remain in the following years. Indeed, we can expect to witness the emergence of supply chains that are faster and more performant than ever before (Hofmann and Rüsch, 2017). As a result, nowadays the natural resources consumption by the supply chains far exceeds the earth capacity on a long-term horizon. In the meantime, a population in constant growth and an industry in perpetual evolution in developing countries increase the risks of disruption.

The supply chains worldwide being huge resource consumers and massive polluters, they have a major role to play in the evolution toward more sustainable practices to preserve our environment for future generations. Thus, the social and environmental impacts of supply chain activities have become key targets that cannot be ignored anymore. For that purpose, in the early 1970s we see the emergence of the well-known “3R” concept (see figure 02 below). The “3R” stand for « *Reduce the waste created* », « *Reuse the products and materials that can have a future purpose* » and « *Recycle the items if you can* » (Environmental Protection Agency, EPA). However, the emergence of this new state of mind in doing business also implies new challenges for the supply chain managers around the world, moving from a profit-oriented management to a more sustainable vision of operations. From this point, we witnessed the emergence of new challenging activities that are part of many supply chains’ operations these days such as : energy consumption monitoring (Shen et al., 2017), carbon management (Chaabane et al., 2012, Rezaee et al., 2017), lifecycle assessment of products (Blass and Corbett, 2018), products' design for end of life purposes (Zhu and He, 2017; Kianpour et al., 2017), clean technology investments (Chan et al., 2018), among other numerous topic of interest. Nowadays, considering that the above-mentioned elements play a role in the decision-making process, « thinking sustainable » often leads to complex supply chains with larger structures, many assets and multiple stakeholders involved in the process.

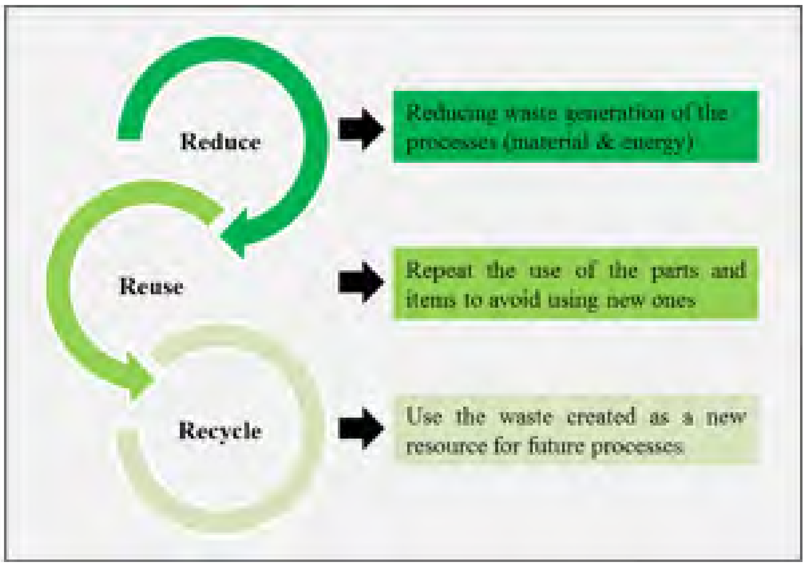

Figure 02 The 3R-hierarchy for sustainable development

Reverse logistics opportunities

Among the well-known examples of the 3R inclusion in nowadays' society, the field of reverse logistics (RL) has become a critical expertise among supply chains all over the world (Govindan et al., 2015). It is also one of the most popular field in the academic literature on sustainable supply chains (Min and Kim, 2012; Agrawal et al., 2015). The term reverse logistics refers to activities related to the management of products that have reached the end of their useful life to the consumers in any way to give them an added value (Guide and Van Wassenhove, 2009). Usually, we qualify the standard logistics activities that convert the raw materials into finished products for customers as forward supply chain (FSC). On the other hand, among the RL operations we commonly find the collection, transportation, sorting, refurbishing, recycling, reusing and also the landfilling activities (Fleischmann et al., 1997; Alshamsi and Diabat, 2017). Typically, in FSC management, the supply chain decision-making process can be divided into three (3) main categories: the strategic, tactical and operational decision levels. While the strategic decisions focus on the supply chain configuration, the tactical decisions evaluate the best ways to satisfy the demand of the customers through aggregate operation planning. The operational decisions find ways to ship the orders to meet the due dates (Chopra et Meindl, 2004). These decision levels also apply to RL planning. Strategic decisions mainly focus on the reverse logistics network design (RLND), such as facility location and capacity allocation, technology acquisition and other long-term costly decisions, while tactical decisions focus on the flow allocation between logistics units such as collection centers, recycling centers and landfills. Finally, operational issues usually focus on lot-sizing problems, vehicle routing decision or disassembly planning operations (Souza, 2013).

In this thesis, we will mainly focus on reverse logistics network design problems. Although facility location problems were introduced a long time ago (Weber, 1909), the first studies addressing network design problems in RL appeared around 20 years from now (Barros et al., 1998). From this point, we denote an increased variation in the RLND models with focus interests on various aspects of reverse logistics operations such as the collection (Kumar and Putnam, 2008), inspection and sorting (Loomba and Nakashima, 2012), disposition of the products (Mutha and Pokharel, 2009) and so on. In the articles proposed in this thesis, we will focus on the strategic RL network configuration and the tactical flow routing decisions through the reverse logistics channel. Indeed, as RLND decisions imply long-term costly strategic management that might affect the performance of the whole supply chain for the next decades, the supply chain managers should address them very carefully. Indeed, no matter how well the tactical decisions, poor choices regarding facility locations and capacity allocation will lead to a low RL network efficiency that fails to be sustainable (Daskin et al., 2005). However, although it is widely recognized that sustainable reverse logistics network design is a topic of high interest toward seeking supply chains sustainability, the decision makers are often struggling with the complexity of this process that bring many challenges

(Govindan and Bouzon, 2018). Figure 03 provides an overview of the numerous challenges faced by the supply chains managers by including RL operations in their activity.

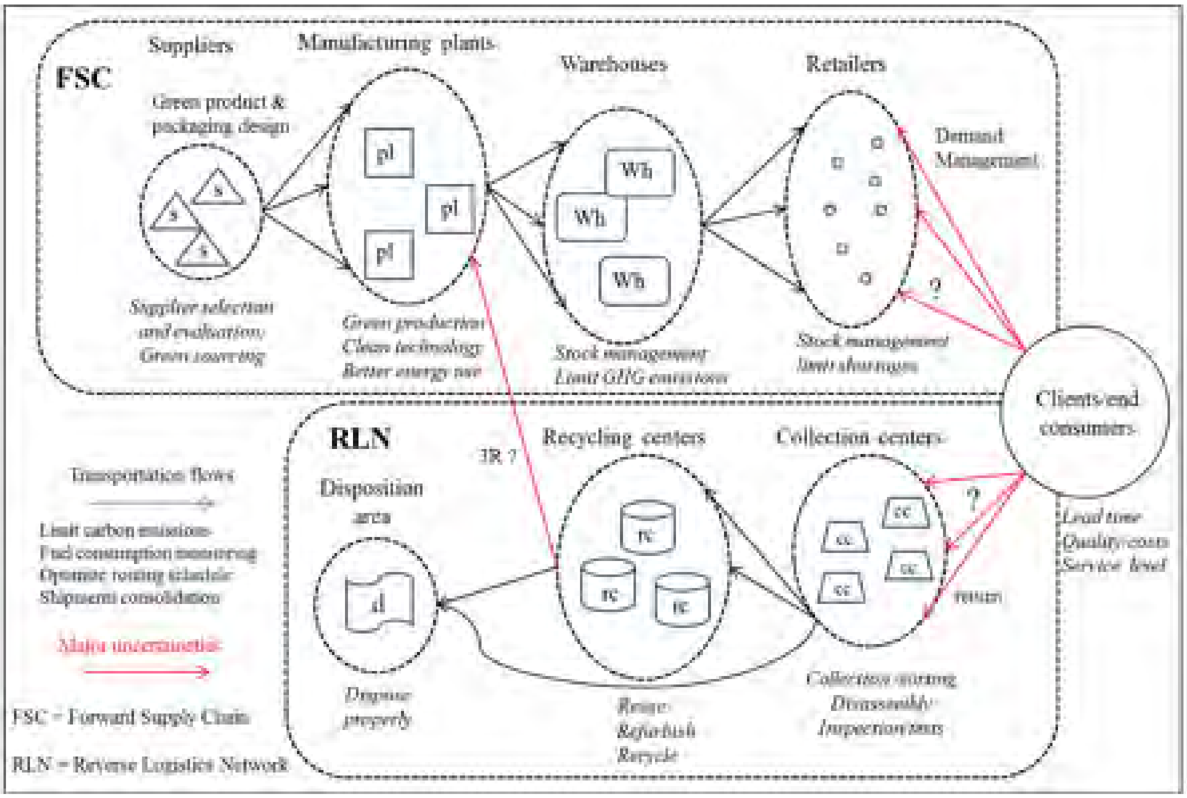

Figure 03 The complexity of CLSC management (integrated FSC & RL)

As a contribution, the research articles presented in this thesis aim to develop innovative decision-making models for sustainable supply chain management. Based on mathematical formulations, these quantitative models will help assisting the supply chain managers by providing the best decisions for RLND. We mentioned before the significance of the 3R actions toward sustainability. In this research, we will position on the last one, by developing mathematical programming models to help the decision-makers with the recycling process of the materials at the end of their useful life for the initial consumer. Lately, there is a critical need for the development of quantitative decision-making models to improve the recycling operations in industries, specifically in those being huge waste generators and represent environmental burdens for the society (Brandenburg et al., 2014).

Problem statement

The incentives are numerous to introduce reverse logistics operations into a supply chain. Nowadays, there is a growing concern among customers about "buying green" and people think in a different way than before about the environmental consequences of their actions (Gunasekaran et al., 2015). From a company perspective, the fear of reputation loss and the pressures from customers, stakeholders and governments sure encourage to take this step toward the adoption of reverse logistics operations (Seüring and Müller, 2008). However, the complexity of the associated decisions combined with a highly uncertain environment is often a turn-off, putting the companies in difficult positions in many ways. To prevent the companies from being discouraged and giving up the inclusion of reverse logistics practices into their business, the governments are enforcing more and more regulations worldwide to ensure the global transition toward a sustainable industry. Indeed, a wide variety of sectors is impacted, such as the electric and electronic equipment (Gu et al. 2016; Salhofer et al. 2017), the automotive (Wang et al. 2017), chemical industry (Wallbank et al. 2017), the durable products (Huang et al. 2017), the packaging (Arnaud, 2017), the construction industry (Trochu et al., 2018), among others. Compliance to these governmental laws and programs is one of the main reasons for the growing attention toward reverse logistics among supply chains lately. Indeed, refusing to comply implies at least penalty costs for the company (Fahimnia et al., 2015), and in the worst-case scenario the end of business activities (Koh et al., 2012).

Among the main targets of these emerging regulations, the waste management practices are receiving an increased attention these days. Thus, in the sectors that are considered as huge waste generators, supply chains are constrained to find better ways to comply with waste management policies. Among the sectors under the radar of the authorities in many countries including Canada, the construction, renovation and demolition industry (CRD) has partly motivated the research presented in this thesis (Trochu et al., 2018). More specifically, the wood building material recovery process is increasingly controlled due to its many recycling opportunities. Indeed, if the CRD sector is responsible for less than 10 % of the total annual waste quantity in countries such as Thaïland (Kofoworola and Gheewala, 2009), usually it is more common to exceed a 20 % level. For example, the CRD industry in Spain generates about 25 % of the total waste of the country (Rodriguez et al., 2015), the United States reach a 29 % level (Falk and McKeever, 2012), while Canada generates about one third of the annual national waste in this unique sector (Yeheyis et al., 2013). In practice, there is no well-defined methodology to deal with CRD waste in an effective manner internationally. Each country has different average quantities of waste generated, and according to the different geographic areas a nation might deal with various compositions and proportions for each type of building materials (General Building Contractors Association, GBCA). For example, southern countries such as Spain and Portugal use more concrete primary building structures whereas northern nations such as Finland, Sweden and Denmark are more likely to use wood building structures. With a very large territory and a lot of forest lands, the Canada is one of the countries with the highest wood building material rate inside its buildings, thus showing a particularly high quantity of wood in the CRD waste traditional composition (Yeheyis et al., 2013), as it is also the case in the province of Quebec.

However, although plenty of wood building material is collected on the CRD sites in Quebec, today the market demand for recycled wood materials exceeds the supply coming from the collection centers. One of the main reasons of this problem is that although the wood is considered a renewable resource, a large amount of this material is landfilled when leaving the CRD sites (RECYQ-QUEBEC, 2014). Unfortunately, this can be partly explained by the poor performance of the RL network in this industry, which results in difficulties being competitive with the low cost of landfilling applicable in this area (MDDELCC).

If the recycling of the wood building material is a complex process and the reverse logistics network in Quebec is not efficient, it is mainly due to the multiple uncertainties inherent to the RL operations in the CRD industry. Designing a performant RLND necessitate reliable information in order to make the best configuration decisions. In this case, we face major uncertainty regarding the amount of waste generated on the CRD sites, and by extension the amount of wood among the debris. In addition, the quality of the collected wood is also highly uncertain, which greatly impact the recycling opportunities of this material. Finally, and not the least, the reverse logistics performance in this sector is affected by the dynamic nature of its collection zones (also called supply sources in this thesis). Indeed, the reverse logistics network is often designed in a way that minimizes the transportation distances to recover the materials in order to reduce transportation costs (Kara et al., 2007) and the total transportation time (Krishnamurthy et al., 2008), which becomes a complex task when the collection zones are moving from one period to another.

Therefore, to ensure an effort toward sustainability in the CRD industry in Quebec, the local authorities are strengthening the legal framework targeting the waste management activities. This sector is facing waste elimination prevention measures and carbon emissions control in many industries, including the wood recycling processes (MDDELCC, 2016). The authorities in charge have already approved a regulation preventing the wood from being landfilled, which is expected to become effective in the near future (RECYQ-QUEBEC report, 2014). The main objective of this governmental action is to redirect all the wood building material collected from the CRD sites to certified collection centers. This way, it is expected that the amount of wood at the entrance and at the exit of these facilities will experience a strong growth in the near future, thus possibly giving an opportunity to the recycled wood products industry, while preventing the use of virgin wood materials when possible. However, the same type of legislation banning the wood material from the landfills has already been implemented in other countries before. This experience proved that the reverse logistics network for waste management has to be well-prepared to welcome such a development. Infrastructures' locations and capacity allocation to deal with an increased volume of incoming wood are concerns that must be addressed carefully. Indeed, if the network design is not suitable, it may lead to illegal dumping or some containers with wood could be landfilled in bordering countries or provinces, as it has been the case in the past in the state of Massachusetts in 2006. In order to face the upcoming regulations in the best conditions in Quebec and learn from the past mistakes, some attention should be given to designing a sustainable reverse logistics network for the wood waste material in the CRD industry.

Below, we summarize the information provided above and make the assumptions that motivate this research:

<u>*Assumption 1*</u>

Considering the huge amount of waste generated in the Canadian CRD industry, there is a need to introduce efficient RL operations that will enable this sector to face the low landfilling costs and to become more sustainable in the future.

<u>*Assumption 2*</u>

Efficiency in RL activities cannot be achieved without a suited reverse logistics network design.

<u>*Assumption 3*</u>

Because of the multiple uncertainties targeting the wood recycling process in the CRD industry, the decision-makers are facing difficulties to design and operate a performant RL network and they would clearly beneficiate some valuable insights for this purpose.

<u>*Assumption 4*</u>

Considering the increasing number of regulations and programs targeting the CRD industry, a performant RLND has become a necessity to ensure sustainability in this sector.

Thesis objectives

The main objective of this thesis is to provide the supply chain decision-makers with a set of decision support tools for sustainable reverse logstics network design and evaluation. This way, by applying the proposed models to the CRD industry case study, we propose a way for evolving toward sustainable waste management by introducing performant RL design and operations. In the meantime, these quantitative decicion-support models will help supply chains to comply with the regulations and programs of this sector in the best possible way, being a mandatory requirement.

To fulfill these objectives, we aim to answer the following research questions:

- **Q$_1$**: How are the optimal reverse logistics network configuration and performance affected by the presence of dynamic supply sources and multiple uncertainties targeting the collected wood waste volume and quality in the CRD industry ?

- **Q$_2$**: What role can play the source-separation centers and what is the impact of the source-separation strategy on the reverse logistics network configuration and performance under uncertainty in the CRD industry ?

- **Q$_3$**: What are the impact of environmental regulations on the reverse logistics network design and performance under multiple uncertainties in the CRD industry? and how does the source-separation strategy impact the compliance with the regulations ?

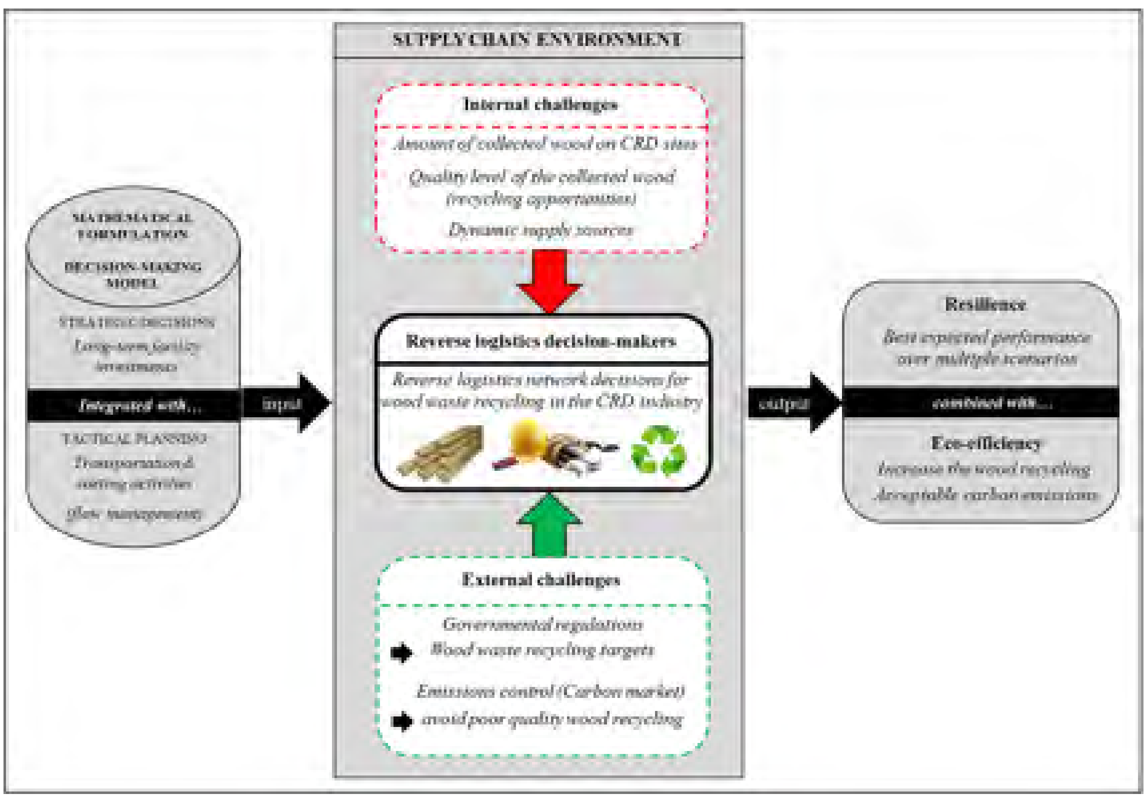

Figure 04 Thesis objectives

Proposed methodology

To address these research questions and reach the objectives of this thesis, we will follow three (3) main steps as synthesized in figure 05 below. In the first step called *problem identification*, rather than solving the problem we aim to highlight the challenge faced by the supply chain managers when dealing with the reverse logistics operations in the CRD industry. In step 2 called *the need for resilience*, we will propose a decision-making model that will offer solutions to cope with the challenges previously established in step 1. This second step ensures the RL network design efficiency under uncertainty in an economic perspective (i.e. long-term economic viability). Finally, step 3 includes the environmental dimension in the strategic decision-making process in order to provide a second aspect of sustainability: the eco-efficiency of the reverse logistics network.

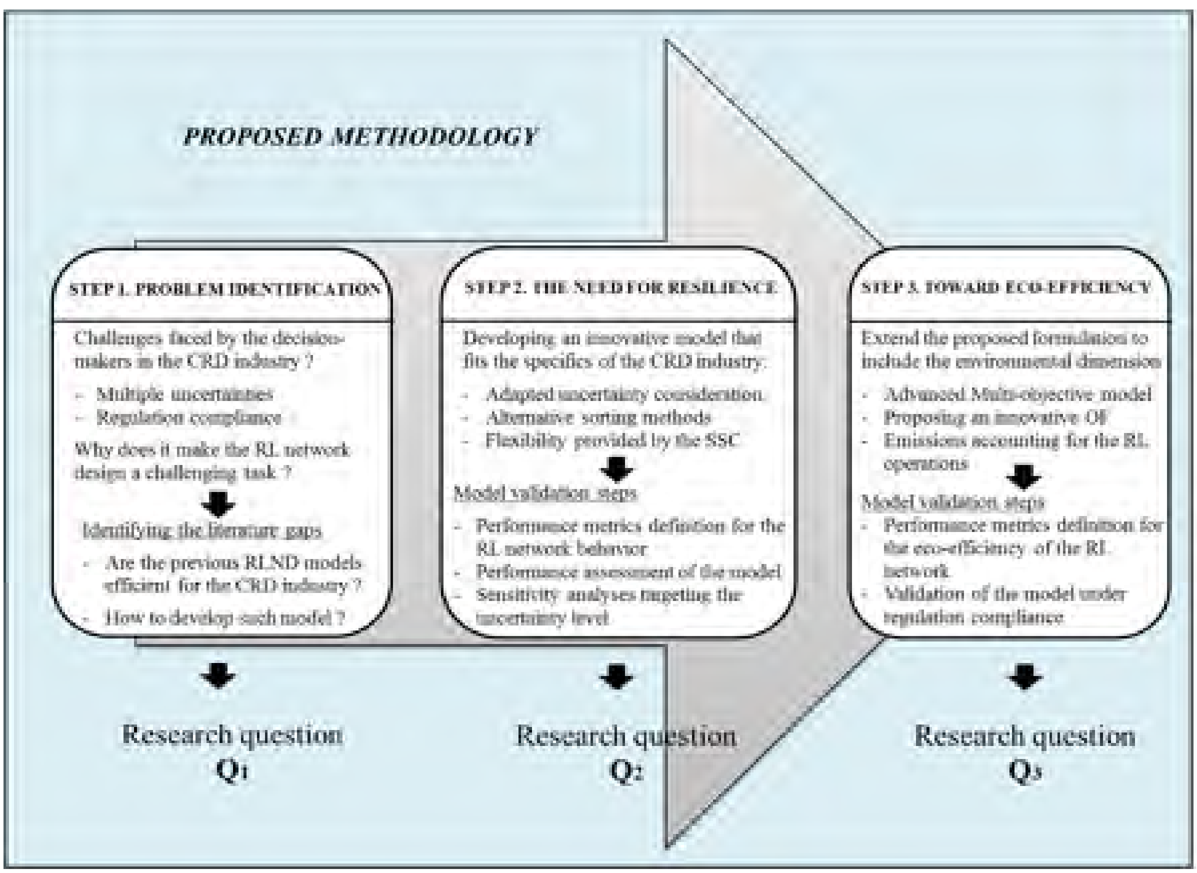

Figure 05 Methodological approach

Step 1. Problem identification

We will start by developing a scenario-based approach to evaluate and compare several RL network configurations and performances. These scenarios will present variations in key uncertain parameters that are a concern for the supply chain managers in the CRD industry. We will validate our model by performing experiments on a case study in the recycled wood CRD industry in Quebec. At this point, various performance indicators will be set to evaluate the impact of uncertainties on the optimal RL network configurations for the wood recycling process under environmental regulation. This first step represents a valuable contribution as the majority of the data used to conduct the case study was gathered from major players of the CRD recycled wood industry. Thus, the results could provide valuable insights to both supply chain decision-makers and to the legal entities that set the regulation parameters.

Step 2. The need for resilience

In this step, we will develop a model that allows setting a resilient network that will provide the best configuration for a multi-period planning horizon while considering simultaneously a large number of scenarios (i.e. randomness outcomes). We will also introduce flexibility in the RL activities by allowing an alternative sorting method: the source separation. Indeed, we will show how this alternative sorting strategy impact the efficiency of the RL operations, and the comparison will be performed for low-density rural zones versus highly populated urban areas. To achieve network resilience, a two-stage stochastic model is developed that ensures coordination between highly strategic network design decisions and tactical flow routing matters between the collection zones, the source-separation centers, the main collection centers and the building material recyclers. The main objective of this second step is to propose a solution to face uncertainty in an economically viable manner in this sector.

Step 3. Toward eco-efficiency

Finally, as an additional step toward a sustainable reverse logistics network design, we will extend the previous mathematical formulation to consider the environmental regulations that target the wood recycling process in Quebec. The main goal of this final step is to highlight the trade-offs that need to be done between the economic viability of the RL operations and the eco-efficiency of the wood recycling process. The proposed multi-objective stochastic model helps understand that the source-separation strategy shows some benefits for both economic and environmental aspects of the supply chain operations.

Thesis outline

The rest of this thesis is organized as follows. In the first chapter, we review the literature on sustainable RLND with a specific focus on quantitative models with uncertainty. This way, we will highlight the theoretical gaps that we aim to fill with our own contributions.

In chapter #2, we present a scenario-based approach to evaluate the impact of uncertainties on the RLND best decisions. We formulate the problem as a mixed-integer linear program that minimizes the total cost of the wood recycling process and we validate this model trough a case study in the Quebec CRD industry. The objective is to determine the location and the capacities of the sorting facilities to ensure compliance with the wood landfilling prevention regulation and prevent the wood from being massively landfilled. The results of this study show that the adjustment of the reverse logistics network leads to the reduction of wood recycling cost due to the improved efficiency of sorting facilities and the economy of scale achieved under the new policy.

In chapter #3, instead of addressing the scenarios one by one, we will present a two-stage stochastic programming model for reverse logistics network design under uncertainty. We solve this model with a Sampling Average Approximation procedure, being an approach allowing to deal with a significant number of scenarios simultaneously. By doing so, the model provides the optimal RLND over multiple outcomes for the random parameters in a multi-period planning horizon. However, in this paper we emphasize the importance of including the SSC to address the challenge of the dynamic supply sources and the uncertain quality of the materials. Indeed, source separation and shipments consolidation are performed at the SSC to increase the productivity level at the collection centers. We compare the efficiency of using the source-separation strategy in low-density rural collection zones versus in high-density urban areas, where the waste collection activities are often more challenging. The results indicate that the flexibility provided by the SSC improves the performance of the RL network, especially in the case of high-density urban areas.

In chapter #4, we develop a novel multi-period, multi-echelon and multi-objective two-stage stochastic model under environmental constraints for eco-efficient RLND. This last article includes the environmental dimension of sustainability as a second objective of the model. This way, we will be able to evaluate the trade-offs between the profits of recycled materials' selling versus the environmental impact of the RL operations under both landfilling and greenhouse gases emission constraints. Indeed, the case study on the wood recycling processes in the CRD industry reveals that under quality uncertainty, recycling the wood can be harmful to the environment. In addition, as we include an emission control system in this last model, recycling poor quality wood leads to additional costs that penalize the RL network efficiency. The experiments demonstrate the difficulty for the network to achieve both regulation compliance and eco-efficiency in the meantime in an uncertain environment.

Finally, concluding remarks are given at the end of this work, along with a discussion of the future potential research related to our topics.

Research contributions

Article 1 (Chapter #2). To the best of our knowledge, analyses that consider variations in the locations of the supply sources while making reverse logistics network design decisions are unavailable. Indeed, this characteristic is very specific to the CRD industry, a sector that has been neglected in terms of reverse logistics studies (Govindan and Bouzon, 2018). Moreover, a second contribution is proposed by validating the model in the Quebec CRD industry, using real data gathered from the major players of the recycled wood industry in this area.

Article 2 (Chapter #3). In the first article, we establish that the RLND is very sensitive to the uncertainty targeting the suppliers' location, the material quality and the volume of material collected. To our knowledge, no stochastic model addresses the RLND problem considering this combination of uncertainty over a multi-period horizon. By developing this model, we aim to provide valuable insights to the supply chain decision-makers in this industry that will allow them to build a resilient RLND over many possible outcomes in the future.

Article 3 (Chapter #4). In this article, we extend the formulation presented in article 2 to include a second objective function and additional constraints related to the environmental regulations. To the best of our knowledge, there is no advanced multi-objective stochastic formulation that captures the characteristics of the CRD industry for eco-efficient reverse logistics network design purposes. Moreover, traditionally objective functions (OF) are profit or cost-oriented, however, in this article we study an innovative OF that minimizes the landfilling flows to adapt to a new environmental regulation. Finally, usually the process of controlling the emissions targets the product design and procurement (Ren et al., 2015), manufacturing processes and technologies (Chaabane et al., 2012), the RL facilities in use (Kannan et al., 2012), but mainly the transportation activities (John and Sridharan, 2017). However, in this study, we account for the emissions of the customers' activities, being an entity that is often neglected in the emissions accounting process, although we believe it is relevant since we consider a supply chain collaboration perspective toward sustainability.

The work presented in this thesis has led to the publication and submission of three (3) peer-reviewed journal articles, which are presented in detail in chapters #2 (*Resources, Conservation & Recycling Journal*), chapter #3 (*Waste Management Journal*) and chapter #4 (*Journal of Cleaner Production*). In addition, our research findings and contributions were submitted, accepted and presented to seven (7) international conferences including the International Conference on Modeling, Optimization and Simulation (MOSIM), the conference on International Logistics Systems (ILS), European Conference on Operational Research (EURO), International Conference on Advanced Logistics and Transport (ICALT) and the international conference on industrial engineering (CIGI), among others.

CHAPTER 1

LITERATURE REVIEW

1.1 Fundamentals of reverse logistics in sustainable supply chains

Nowadays, it is widely acknowledged that reverse logistics has a leading role to play toward seeking sustainable supply chains. The term reverse logistics refers to operations related to the management of products that have reached the end of their useful life to the consumers in any way to give them an added value (Guide and Van Wassenhove, 2009). Reverse logistics practices have been recognized to be a powerful mean to reduce materials and products' waste at their end of life, mainly by reusing some parts, repairing, refurbishing or recycling others, and ultimately by eliminating the unusable parts in a proper way (Fleischmann et al., 1997). Thus, today reverse logistics is a critical area of expertise among supply chains. This increased popularity explains why RL is one of the most popular fields in the literature on sustainable supply chains over the past decade. Indeed, this field is constantly evolving and providing the supply chain managers with innovative decision-making models to support them in their quest of sustainability (Min and Kim, 2012; Agrawal et al., 2015; Govindan and Bouzon, 2018).

In this chapter, we will focus on the theoretical background on reverse logistics in sustainable supply chains. Although this review has not the pretention to be exhaustive, our goal is to provide a representative overview of the existing models that address RLND decision-making among supply chains. Although the first part of this review addresses reverse logistics topics in general, the second part, however, will be more focused on strategic reverse logistics network design models. The last part of this analysis provides specific emphasis on the range of applications of RL in the construction industry, as it will allow highlighting our contributions. Finally, we will conclude this review by identifying the research gaps we aim to fill with this thesis.

1.1.1 Incentives toward reverse logistics

Today, factors that influence RL adoption are numerous (Seüring and Müller, 2008). While it is often perceived as an initiative to look for a positive brand image of green supply chain (Srivastava, 2007), some firms actually manage to realize profits through the RL operations (Cline et al., 2015). Indeed, nowadays, there is a growing consciousness among customers toward “buying green”. A recent survey declares that more than 80% of the responders are actually considering the product “*greenness*” when making purchasing decisions (Hong and Guo, 2018). Moreover, an increasing number of customers (nearly 3 out of 4) are willing to pay higher fees or taxes for buying green (Zhao et al., 2014).

In addition from the economic incentives coming from their customers, companies are facing pressures from stakeholders (Schaltegger and Burritt, 2014; Meixell and Luoma, 2015). For example, Mathivathanan et al., (2018) proposed a framework model based on DEMATEL methodology (Decision Making Trial and Evaluation Laboratory method) to cope with multiple stakeholders’ perspectives in the Indian automotive industry. The authors claim that the evaluation of the similarities and differences between the multiple supply chain stakeholders leads to increase the chances of success to reach sustainability in supply chain management. Supply chains are also facing pressures from various environmental groups (Luthra et al., 2016). Again, quantitative methods have been developed to tackle this problem such as the structural equation model (SEM) proposed by Yang, (2018) that analyses the effects of institutional pressures on the green supply chain performance in the container shipping industry. Finally, the main source of pressure probably comes from the authorities (Rajeev et al., 2017). Indeed, an increasing number of regulations are emerging such as the extended producer responsibility framework targeting multiple product categories, for example electronics (Temur and Bolat, 2017), vehicles (Demirel et al., 2016), plastics (Bing et al., 2015), construction material waste (Trochu et al., 2018) and so on. The goal of these legislations is to force supply chains to move toward sustainable practices in their business activities.

1.1.2 Reverse logistics decision levels

The pressures coming from these various institutions are forcing supply chains either to anticipate, or at least to react and find their own way toward sustainability. Adopting RL practices among companies represent an opportunity to improve the brand image, satisfy the multiple stakeholders and comply with the legal framework (Seüring and Müller, 2008). However, there is a wide range of decisions to be made in the field of reverse logistics. As it is the case in the classical forward supply chain management, these decisions are traditionally divided into three (3) main decision levels: the strategic, tactical and operational levels. Regarding reverse logistics, strategic decisions mainly focus on the network design, such as facility location and capacity allocation decisions, the technology acquisition and other long-term costly decisions. The tactical decisions focus on the flow allocation between logistics units such as collection centers, recycling centers and landfills. Finally, operational issues focus on lot-sizing, vehicle routing or disassembly planning operations (Souza, 2013).

All three decision levels have been explored in the literature, especially in the past decade. Among the strategic models, reverse logistics network design is a field of great importance that has been addressed by many authors (Kannan et al., 2012; Soleimani and Govindan, 2014; Govindan et al., 2016; Fattahi and Govindan, 2017; Trochu et al., 2018). For a more exhaustive review of RLND models, the reader is referred to (Akçali et al., 2009; Chanintrakul et al. 2009; Sheriff, 2012; Eskandarpour et al; 2015). The RLND decisions are among the most important in order to ensure the whole supply chain sustainability. Indeed, these are long-term costly decisions that will impact the network behavior and performance over many years, even decades. No matter how well the tactical and operational levels are managed, if the network configuration is not adapted, it will affect the whole supply chain performance and the chances of success toward reaching sustainability. Except the network design problems, the other main strategic topic addressed in the models is the investment decisions into green technologies (Hu et al., 2015; Saberi et al., 2018). Some models also address network design and technology selection at the same time (Rezaee et al., 2017; Rad and Nahavandi, 2018).

We also denote a large number of models addressing tactical concerns. Among them, the very large majority are targeting the physical flows going through the network (Lieckens and Vandaele 2012; Demirel et al., 2016; Bal and Satoglu, 2018). An extended review of the tactical RL decision models is provided by Govindan et al., (2015). It is important to denote that some of the strategic models consider the network design and the tactical flow routing decisions simultaneously (Yu and Solvang, 2016; Rezaee et al., 2017; Trochu et al., 2018).

As we mentioned, network design and flow routing through the reverse logistics networks are the main decisions addressed in the strategic and tactical levels respectively. However, it is more difficult to extract a predominant topic from the literature targeting operational models. Indeed, operational decision-making models address pricing decisions between supply chain partners (Atasu et al., 2013), production rates and lot sizing for products returns (Feng et al., 2013; Sifaleras and Konstantaras, 2017; Zouadi et al., 2018), optimal order quantitites (Abdallah et al., 2012; Panagiotidou et al., 2013; Shekarian et al., 2016; Zeng and Hou, 2018), inventory related decisions (Alinovi et al. 2012; Kaya and Urek, 2016; Hiassat et al., 2017), routing decisions or trucks loading issues (Gamberini et al. 2010; Kassem and Chen, 2012; Niknejad and Petrovic, 2014; Zhalechian and Tavakkoli-Moghaddam, 2016; Qiu et al., 2018), among other topics.

1.1.3 Reverse logistics activities among supply chains

For all the decision level assessed by the models, their goal is usually to provide the supply chain managers with useful insights regarding the best reverse logistics decisions. Multiple RL activities benefit from such decision-making tools, among them one of the most popular topics in the RL literature is the management of product returns through the reverse logistics channel (Agrawal et al., 2015). Indeed, forecasting product returns has a great impact on the best reverse logistics network design and various quantitative models have been developed for this purpose, using for example simplex theory (Chen and he, 2010), flow analysis (Yu et al., 2010), analytic models (Shih et al., 2012), Bayesian estimation (Krapp et al., 2013), or fuzzy methods (Temur et al., 2014). In addition, many stochastic models consider the return of the products as an uncertain parameter so that they can deal with it in the best manner under many possible outcomes (Ayvaz et al., 2015; Jeihoonian et al., 2016; Fattahi and Govindan, 2017; Srinivasan and Khan, 2018). After the estimation of product returns and their collection in the RL channel, several RL operations can be performed. The products and parts can be reused if their quality level allows it, they can be repaired or remanufactured in case of a lower quality, or finally they may be recycled for another purpose. If no additional value can be obtained from the returned materials, their disposition is the last recourse. Thus, optimization models are developed to help with each of these operations in order to make the best decisions. Some of them cope with the reusing activities (Diabat et al., 2013; Dai and Wang, 2014; Cole et al., 2018), repairing and remanufacturing operations (Ramezani et al., 2013; Lieckens et al., 2013; Eskandarpour et al., 2014; John and Sridharan, 2017; Liao, 2018), the recycling processes (Zeballos et al., 2012; Lundkvist et al., 2013; Subulan et al., 2015; Demirel et al., 2014; Ardjmand et al., 2015; Zhang and Ding, 2017; Rahimi and Ghezavati, 2018; Trochu et al., 2018), and ultimately some models address the disposition decisions for the collected products and parts (Hazen et al., 2012; Agrawal et al., 2016; Singh and Agrawal, 2018). Again, regardless of the decision level of the above-mentioned models, it is important to note that a majority of these problems consider the transportation decisions through the RL channel.

1.2 Focus on sustainable RL network design optimization models

The previous section provided the reader with an overview of the various activities part of the RL processes among supply chains. We reviewed the quantitative models developed to help the managers making decisions to perform these operations, from either a strategic, tactical or an operational perspective. Moreover, we started by explaining the various incentives that may lead supply chains to include reverse logistics practices into their business. However, in the following section, we focus on recent quantitative optimization models for sustainable RL network design, as it falls into the category of models that we present in chapters 2, 3 and 4.

1.2.1 Deterministic reverse logistics network design models

As the interest toward RL has grown recently, we denote a significant number of academic publications that address RLND matters. Our goal here is not to provide an exhaustive review of these models, but rather to highlight some of the trends among those that were recently published. To do so, we selected what we believe to be 10 representative research papers and we analysed their content. These models were selected based on three (3) criteria: they are all reverse logistics network design models [(1)], single objective and deterministic MILP [(2)], and published in peer-reviewed journals in the last three years 2016-2017-2018 [(3)]. More advanced multi-objective and stochastic models will be reviewed in the next sections. Below, table 1.1 synthesizes the information regarding the selected content.

Table 1.1 Recent quantitative models for sustainable RLND (2016-2017-2018)

Authors (year)	Focus	Commodities	Periods	Sector	Contribution to sustainability
Demirel el al., (2016)	Recycling operations	SC	MP	Automotive	An innovative model for vehicle recycling regulation compliance in Turkey
Keirkah and Rezai (2016)	Cross-docking operations	MC	SP	General	Evaluation of cross-docking operations in the context of reverse logistics
Zandieh and Chensebli (2016)	Products collection & recovery	SC	SP	General	Development of an original metaheuristic for solving NP-hard RLND problems
Alshamsi and Diabat (2017)	Products remanufacturing	MC	MP	Household appliances	Development of an new efficient Genetic Algorithm to solve large-scale problems
Budak and Ustundag (2017)	Waste collection & disposal	MC	MP	Healthcare	Case study for waste treatment optimization in the healthcare sector in Turkey
Guo et al., (2017)	E-waste recycling	MC	MP	E-commerce	Application of combined heuristics to reduce the recycling costs of E-products in Shangaï
Kannan et al., (2017)	E-waste recycling	MC	MP	E-commerce	Analyzing the benefits of using 3PRL to minimize the cost of RLND for recycling
Li et al., (2017)	Collection & repair operations	SC	SP	General	Development of a performant algorithm for enhanced local search for large-scale RLND
John et al., (2018)	Products collection & recovery	MC	MP	Refrigerators	Innovative model for the recovery of used parts of refrigerators in India
Trochu et al., (2018)	Recycling operations	MC	SP	CRD industry	An innovative model for wood recycling under regulation compliance in Canada
SC: Single Commodity; MC: Multiple Commodities; CRD: Construction, Renovation & Demolition; RLND: Reverse Logistics Network Design; 3PRL: Third Party Reverse Logistics Providers; E-Waste: Electronic Waste; NP: Non-Polynomial					

As our first paper (later presented in chapter #2), matches the above-mentioned criteria, we decided to include it in table 1.1. Overall, MILP is the most popular modelling technique for optimizing reverse logistics network design activities. Among them, a majority presents multi-product networks while the proportion of single versus multi-period models is quite similar. Although the trend suggests that waste collection and recycling are the main topic under study (Demirel et al., 2016; Guo et al., 2017; Kannan et al., 2017; Trochu et al., 2018), a wide variety of other RL activities have been considered such as the recovery (Zandieh and Chensebli, 2016; John et al., 2018) the repairing (Li et al., 2017), the remanufacturing (Alshamsi and Diabat, 2017) and also the disposal of the products that are not reusable in any way (Budak and Ustundag, 2017).

In the past, the trend was to build generic models. Indeed, these formulations were applicable to many industries and as a result, there was a lack of quantitative models that were able to capture the characteristics of specific sectors (Brandenburg et al., 2014). However, as suggested in table 1.1, lately we witnessed an increased number of optimization models applied to specific sectors. One of the main reasons for this evolution is the growing number of environmental regulations and programs targeting supply chains in many countries. Thus, because the requirements of these legislations are targeting specific sectors and commodities, there is a need for the models to adapt and be more industry-related in the meantime. As we can see in table 1.1, increasing recycling rates of products under regulation is an increasingly popular contribution of the research papers toward sustainability (Demirel et al., 2016).

1.2.2 RL network design under uncertainty: a focus on stochastic models

Uncertainty being a major concern in RL optimization, an increasing number of models are considering it in order to be more realistic. Although there are various approaches for uncertainty modeling such as fuzzy methods (Govindan et al., 2016; Soleimani et al., 2017) or robust optimization (Entezaminia et al., 2017; Haddadsisakht and Ryan, 2018), this section essentially reviews stochastic optimization models applied to sustainable RLND problems, as the research presented in chapters 3 and 4 fall into this category.

Stochastic optimization models are usually divided into two (2) different approaches. The first one is known as the two-stage stochastic modeling, which uses two types of decision variables. The first type is fixed before observing the uncertainty outcome and is called first-stage decision variables, while the second type is released only after the realization of the randomness and known as second-stage decision variables or recourse actions (Birge and Louveaux, 1997). Multi-stage stochastic programming modeling with recourse is a formulation that extends the two-stage stochastic models by allowing the revision of the decisions at each stage, based on the realization of the uncertainty. In multi-stage stochastic models, the focus is on the decisions to be made today considering current resources, future outcomes and possible corrective actions in the future (Kall and Wallace 1994, Kall and Mayer 2005). In this section, we will focus on recent contributions that use stochastic models for RLND using the two-stage or the multi-stage stochastic approaches.

A major concern or RLND is the uncertainties related to the market demand for new and recycled products and/or the quantity of goods returned by the consumers that will be treated through the reverse logistics channel (Baptista et al., 2012; Zeballos et al., 2014; Srinivasan and Khan, 2018). This trend inevitably leads to consider critical issues such as uncertainty in the pricing of the new or recycled products and parts (Soleimani and Govindan, 2014; Fattahi and Govindan, 2016; Yu and Solvang, 2017) and the capacity of the reverse logistics supply chain to process the potential returned flows (Chouinard et al., 2008; Ramezani et al., 2013). Although there is a growing concern about developing innovative stochastic models that include a wider variety of unknown parameters, few studies focused on the uncertainty in the quality of the products and materials collected through the RL channel (Kara and Onut, 2010; El-Sayed et al., 2010; Zeballos et al., 2012). For instance, Ayvaz et al. (2015) are one of the first studies that developed a generic two-stage stochastic RLND formulation that includes the unknown returned product quantity, the uncertain sorting ratio at the collection facilities and the uncertain transportation costs between the nodes of the network. However, information about the material waste quality is a critical element in many sectors in order to manage RL activities properly. This is especially true in the CRD industry, where the returned materials are often suffering extensive damage (Sobotka and Czaja, 2015).

More recently, the design of sustainable reverse logistics networks has become a significant challenge. Therefore, new stochastic models have been developed that consider uncertainty regarding social and environmental parameters such as greenhouse gases (GHG) emissions levels (Pishvaee et al., 2012) and carbon tax rates (Haddadsisakht and Ryan, 2018). The model of Yu and Solvang (2016) takes into consideration both economic performance and environmental impacts in the decision-making process. The environmental impacts are evaluated in terms of carbon emissions and the optimal solutions are generated for a case study in the WEEE industry. Another work from Yu and Solvang (2017) also consider uncertainty targeting the profits and government subsidies for repairing and recycling the products in the RL channel.

1.2.3 Multi-objective reverse logistics network design models

Instead of simply including environmental and social parameters in the mathematical formulations, some efforts toward sustainability are also made by considering additional objective functions. This way, it allows giving more importance to the environmental or social criteria if required by the supply chain decision-makers. During the past decade, a growing attention has been payed to multi-objective optimization models. In practice, decision-making in RL involves several objectives that can be in conflict with one another. In such problems, the multi-objective approach is used to balance the trade-off among the different conflicting objectives. In multi-objective optimization, the optimal trade-off between the objective functions is called the “Pareto optimal solution”, also called the efficient solution. It actually represents the set of solutions that cannot be improved without decreasing the performance of at least one of the objectives of the model (Mavrotas, 2009).

Multi-objective optimization has been used in recent research problems in order to include more than the only economic dimension of sustainability. For example, network design problems have been addressed while considering both costs and GHG emission minimization objectives (Chaabane et al., 2012). The work of Devika et al., (2014) even compared solutions to a multi-objective CLSC network design problem integrating the three dimensions of sustainability. Yu and Solvang (2016) present a multi-objective MILP that selects facility locations for treatment, recycling and disposal sites. The model also makes decisions regarding the technology choice for hazardous waste treatment and transportation flows. Two objective functions are presented, minimizing both the costs of the network operations and the risk of the local residents regarding hazardous waste treatment. Another multi-objective MILP in the area of hazardous waste management is developed by Yilmaz et al., (2017) that minimizes the cost of transportation, while minimizing the risks on both the public health and the environment. Soleimani et al., (2017) considered profit optimization, reduction of the lost working days due to occupational accidents, and maximizing the responsiveness to customer demand. Based on these, the proposed CLSC network design model makes decisions regarding product, components and raw material recycling through the RL channel. In the electronic sector, Tosarkani and Amin (2018) propose a multi-objective model to maximize the total profit, green practices, and on-time delivery while minimizing the rate of defect in the RL channel. Finally, in the home appliance sector, Zarbakhshnia et al., (2019) present a multi-objective model, which first objective is to minimize the operation costs, processes, transportation, and fixed costs. The second objective is to minimize the amount of emissions, and a third objective function optimizes the number of machines required in the production line.

1.2.4 Advanced multi-objective stochastic formulations

Even though a lot of progress has been made developing RLND models during the last two decades, very few of them address multiple objectives and uncertainty at the same time. Indeed, while the first quantitative models for reverse logistics network design problems emerged in the 1990s (Fleischmann et al., 1997), more advanced formulations such as multi-objective stochastic models (MOSM) are still recent. Among the first research to propose such models, Amin and Zhang (2012) developed a MOSM for strategic decisions regarding plants and collection centers' locations for product recovery, and tactical flow decisions. The objective functions minimize the total cost while maximizing the use of friendly materials and clean technologies at plants. In this work, the ε-constraint and the weighted-sums methods are compared. The demand and return of the products in the RL channel are considered as uncertain parameters. The proposed example in the copier remanufacturing industry shows the superiority of the ε-constraint method.

While most of the consider the demand parameter as the main source of randomness, there are still few of them that consider uncertainty related to the quality issues (Vahdani and Mohammadi, 2015; Azadeh et al., 2016) while it is an aspect that can impact the feasibility of the network design decisions (Trochu et al., 2018). In addition, although the large majority of the models are cost or profit-oriented, recently some authors felt the need to address different types of goals such as maximization of on-time delivery or waiting time minimization (Amin and Zhang, 2012), maximization of the service level (Feito-Cespon et al., 2017), risk minimization (Zeballos et al., 2016) and GHG emissions minimization (Ameknassi et al., 2016; Yuexin and Yunwei, 2017). Very recently, Fatollahi-Fard and Hajiaghaei-Keshteli, (2018) developed a MOSM that considers a cost-minimization function and a social objective function quantifying the risk of work injuries and job opportunities.

In addition, the model developed in Tosarkani and Amin (2019) apply a MOSM for optimizing the CLSC network design in a case study in the region of Winnipeg in Canada. Different scenarios are proposed to maximize the profits, while maximizing the environmental compliance of suppliers, plants, and battery recovery centers in the meantime.
Finally, models including the three dimensions of sustainability are emerging. The work of (Feitó-Cespón et al., 2017) integrates economic, environmental and social objectives to support the strategic facility location decisions, the material flow and the transportation mode selection. The environmental impact objective is assessed through the LCA methodology using the Eco-indicator 99 approach. In addition, the research of Rahimi and Ghezavati (2018) presents a model including three simultaneous objectives, being the profits and the social impact maximization along with the environmental effect minimization. In this paper, the network design problem has a stochastic demand for the recycled products and for the rate on investment. In order to cope with the uncertainty, the authors consider a risk averse two-stage stochastic formulation, where the conditional value at risk (CVaR) is measured.

1.3 Reverse logistics in the construction industry

After providing the basic concepts of RL activities, we focused on the quantitative RLND models and highlighted their critical importance toward pursuing sustainability in supply chain operations. However, in the next section, we will bring specific attention to the main topics addressed in the CRD waste management literature. Although waste management is part of the RL activities, we will highlight the lack of studies that consider a logistics perspective in this sector, being one of the gaps filled by the models developed in this thesis.

1.3.1 Legal framework: a sector under the radar of the authorities

As the CRD companies worldwide are increasingly controlled, many of them are trying to improve the recovery rates of building materials. The reasons for this are very similar to the traditional incentives toward RL adoption among companies as mentioned in section 1.1.1. According to a survey conducted on 74 building companies in Spain, those reasons are mainly costs reduction (55%), increasing the firms' competitiveness (65%), sustainability commitment (70%), trying to improve the companies' image (75%). Finally, over 80% of the respondents mention their goal is to comply with environmental regulations (Gangolells et al., 2014).

Indeed, the CRD industry has its own legal framework. Mainly, we denote a few recurrent regulations in this industry internationally. The most popular scheme is the requirement of a minimum recycling rate after leaving the CRD sites. It is the case for example in the European Union, targeting a 70% recovery level to building contractors (Pacheco-Torgal, 2014). To get the approval of the authorities, the contractors have to prepare a recycling plan specifying how building material waste is going to be recovered (European Union Waste Framework Directive, EU-WFD). In addition, many countries have their own legislations regarding specific recycling policies. Among the recurrent programs that aim to reduce the CRD waste, we denote an increasing popularity for the banishment of some specific materials from landfilling, such as asphalt, brick, pavement, gypsum and wood. Sometimes, building materials are still landfilled incurring a simple tax, but lately the trend is to strictly forbid these practices. Finally, more and more countries are starting to encourage the reuse of CRD waste in new building constructions through the development of some recycled product standardizations. It was the case for the use of recycled concrete made with a mix of waste aggregates in Finland (2011) and in Germany (2012). Although the recycled aggregates are mainly used for concrete production (Silva et al., 2014), it is also an option for other matters such as geotechnical applications (Cardoso et al., 2016), mortars (Katz and Kulisch, 2017), paved bike lanes (Tavira et al., 2018) and so on. Although lately there is a discussion regarding the possibility to impose recycled building material rates into the new building constructions. However, to the best of our knowledge this type of policy has not been legally implemented yet (Galvez-Martos et al., 2018). To conclude, the CRD sector is facing its own challenges in terms of reverse logistics requirements and regulations. Unfortunately, the next sections will show that it has been neglected in terms of RLND modelling efforts.

1.3.2 Estimation of the waste quantity generated

A few topics are recurrent in the literature on CRD waste management. One of them refers to the efforts that are made for waste quantity estimations. Indeed, one of the particularities of this sector is that it is very difficult to anticipate the amount of building material waste in advance. Among the papers addressing this problem, Solis-Guzman et al., (2009) used a hundred real CRD projects to develop a model calculating three key coefficients. Thus, they estimated the expected packaging volume left on site, the demolished volume, and the volume of debris generated. The developed formulas were applied to two (2) real case studies in Spain to prove the efficiency of this model. Later, Lage et al., (2010) managed to estimate the expected waste quantity of a specific geographic area by studying real data on the surface of new buildings, renovation and demolition sites. The authors used their work to estimate the waste generation per surface for several building materials and anticipate the quantities and proportions of CRD debris in the region of Galicia for the year 2011. Only for the construction sites this time, Katz and Baum (2011) monitored several building constructions and developed a predictive model allowing calculating the waste accumulation during the process. This work underlines an interesting correlation between the duration of the project and the amount of waste generated. Indeed, the authors found that for large building constructions (7000 m^2 and more), the waste quantity generated was growing exponentially in the time. Al-Sari et al., (2012) also focused on construction projects only and used a regression model evaluating correlation between waste generation and sustainability commitment of the CRD managers in Palestine. In addition, along with the behaviour of the contractor, the surface area of the construction site was proved a determinant factor while estimating the expected amount of debris generated. Finally, a very recent work from Li et al. (2016) proposed a quantitative construction waste estimation model using the mass balance principle, work breakdown structure, wastage levels of different building materials and so on. The authors claim that this model allows improving the accuracy of construction waste generation estimation. Ram and Kalidindi (2017) determined waste generation rates through a regression analysis in order to estimate the CRD waste generated in the Indian city of Chennai based on 45 case studies. The authors claim their estimation method could be useful for the local authorities to estimate CRD waste in case of a lack of available data on site. Finally, Saez et al., (2018) state that the waste quantity estimation techniques for building renovation can be quite different than in the case of new constructions. Thus, the authors used two (2) pilot sites to collect the necessary data to estimate waste generation ratios and highlight the differences between material types among the waste generated.

1.3.3 Evaluating the recovery opportunities for the collected material waste

A second topic of interest is the recovery process and the recycling opportunities of building materials. Indeed, collecting real data from building companies in Spain, Mercante et al., (2012) studied the life cycle of CRD waste including storage in containers, recovery process and landfilling. Based on different impact category factors, the authors showed that the environmental impact of the CRD waste is severely affected by 3 activities in particular: transportation, sorting, and landfilling. Yuan and Shen (2013) analyses different waste management strategies by applying S.W.O.T (Strength, Weakness, Opportunity and Threat) methodology in a case study in China. Based on data mainly collected from governmental reports, literature review and group meetings, this work aims to provide construction stakeholders with a better understanding of the opportunities and threats of the immature market for recycled products in this specific geographic zone. Udawatta et al., (2015) published a case study in Australia. Based on interviews and surveys of building contractors in the region, the authors present a mixed qualitative and quantitative approach minimizing on-site waste generation. Several factors such as the providing of waste management guidelines, building supervision and innovation in recovery decisions suggest that two (2) parameters have a great influence on waste generation: the technology used and the managers' attitude toward sustainability. Di Maria et al. (2016) used a new methodology based on image analysis technique to evaluate the size range of CRD aggregates entering the sorting centers. This method was tested in a sorting plant and allowed achieving recovery rates up to 85% for the recycled aggregates. This recovery rate revealed to be above the quality achievable with manual sieving or laser diffraction. As there are still promising recycling and recovery opportunities to be discovered in the future for building material waste, this field is in constant evolution in the literature (Jin et al., 2017; Tavira et al., 2018).

1.3.4 Facility location assessment

Among the research addressing facility locations in the CRD industry, Banias et al., (2010) used multi-criteria analysis to evaluate the optimal location for the facilities. The proposed approach takes into consideration the three dimensions of sustainability: economic, environmental and social. As part of the data set was estimated by the authors, a sensitivity analysis is performed on the key indicators: the financial viability, the environmental quality and the acceptance of the local citizens. The proposed framework is applied to a case study in Greece. Another multi-criteria analysis is proposed by Dosal et al., (2012) in the region of Cantabria in Spain. The goal of this work is to help local building contractors to comply with the European EU-WFD imposing 70% recovery rates for the waste leaving the CRD sites. Once again, the authors chose to consider the three dimensions of sustainable development to make a decision regarding the potential locations of the recycling units. The conclusion of this paper underlines the importance of considering uncertainties while making a location decision due to the very high investments required to operate such an infrastructure. Also in Europe, Coelho and de Brito (2013) present a CRD waste recycling plant optimal location problem in Portugal. Still under the EU-WFD framework, this work studies the location and the design of a recycling facility considering the expected building material proportions at the entrance. The building material types considered are concrete aggregates, wood, glass, plastics, paper and cardboards, iron, steel, and insulating materials. The optimal location decision method uses the average transportation distances and waste quantities involved according to the population density of the geographic zone.

Although not focused on facility location, the work of Rodriguez et al., (2015) studies the RL network for CRD waste management in Spain. This work promotes the use of recycled aggregates into new building constructions. However, the authors performed very thorough analyzes on the characteristics making recycling plants more performant. What emerges from the conclusion of this work is the importance to classify CRD waste into quality categories, the maximum reasonable transportation distance from a recycling facility of around 30 km, and the need for more governmental implication and incentives to help the recycling industry to develop in this country. Finally, a MILP model is proposed by de Andrade et al., (2018) to assess the best RLND and minimize the costs for waste management in the CRD industry. With a specific focus on the recycling plants, a case study in the Lisbon Metropolitan Area shows that the landfilling still remains an attractive option compared to highly technological recycling plants that are not economically viable.

1.4 Discussion on the research gaps

The construction, renovation and demolition industry is responsible for nearly 10% of total water use, 40% of the global energy consumption, 40% of raw materials extraction, thus representing around 32% of the world resources consumption and 35% of the global industrial waste generation (Construction Materials Recycling Association, 2005). Moreover, the CRD sector accounts for almost 25% of total virgin wood use, which makes it a major player in terms of potential environmental damage (GBCA, 2009).

The implementation of sustainable waste management practices is, indeed, a hotspot for this industry. However, although a performant reverse logistics network design is essential to the success of sustainable waste management operations, the CRD industry has not been payed enough attention yet in this domain compared to sectors such as automotive, electrics and electronics, food, or packaging's among others (Souza, 2013; Agrawal et al., 2015). Indeed, from a general perspective, there is a lack of quantitative models that address the specific needs of industries being an environmental burden for the society (Brandenburg et al., 2014).

As the CRD industry is among the biggest waste generators in many countries, some important efforts have been made to estimate the amount of waste generated and the recovery opportunities for the collected CRD materials. Thus, it is legitimate to evaluate the network configuration that will provide the best performance in terms of waste collection, process, transportation and distribution. However, we deplore a lack of advanced mathematical formulations that take into consideration the specificities of this sector in order to make the best decisions toward RL network design and performance. The supply chain decision-makers could really use such formulations that capture the key uncertainties, challenges and constraints of this sector. By filling these gaps, these decision-support models could also provide useful insight to the authorities about the potential risks of setting environmental targets that are too ambitious and could endanger the sustainability of the reverse logistics operations.

CHAPTER 2

REVERSE LOGISTICS NETWORK REDESIGN UNDER UNCERTAINTY FOR WOOD WASTE IN THE CRD INDUSTRY

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Abstract

This paper addresses the reverse logistics network (RLN) design problem under environmental policies targeting recycled wood materials from the construction, renovation and demolition (CRD) industry. The main objective is to determine the location and the capacities of the sorting facilities to ensure compliance with the new regulation and prevent the wood from being massively landfilled. We formulated the problem as a mixed-integer linear programming model (MILP) to minimize the total cost of the wood recycling process collected from CRD sites. The main contribution lies in the consideration of important uncertain factors such as supply sources locations, the available quantity of recycled wood at the collection sites, and the various quality grades of the collected wood. A scenario-based analysis is conducted to evaluate the impact of uncertainties on the RLN design. In addition, the proposed MILP model has been applied for a case study in the CRD industry within the province of Quebec, Canada. The results of this study show the adjustment of the reverse logistics network leads to the reduction of wood recycling cost due to the improved efficiency of sorting facilities and the economy of scale achieved under the new policy. Moreover, sorting facilities are now located near the CRD collection points and not close to landfilling site as for the actual situation. Finally, the study demonstrates that efforts to obtain accurate information about the supply sources locations and the expected wood quantity recovered from sorting facilities will guarantee a more efficient RLN redesign.

2.1 Introduction

Nowadays, environmental regulations are emerging in many countries worldwide. The European Union Waste Framework Directive (EU-WFD) imposes a minimum of 70% collection of material waste in the construction industry (Supino et al., 2016). Turkey has recently seen the enforcement of the Waste on Electrical and Electronics Equipment (WEEE) regulation on its territory (Amin et al, 2017) and India is facing an increasing number of air and water pollution legislations (Greenstone and Hanna, 2014). Indeed, this is probably the most efficient solution to achieve more sustainable operations and force managers to take action to reduce the damage to the environment and avoid social problems caused by supply chain activities (Seüring and Müller, 2008). Waste management and recycling activities are usually connected with environmental regulations and many countries are putting a lot of effort into improving their efficiency in this area. Thus, we notice the emergence of many closed-loop supply chains (CLSC) in the past few years. The objective of CLSC is to combine the classical forward logistics flows with reverse logistics (RL) activities, which are becoming very popular fields among practitioners and academics, both of whom are trying to find better strategies to be in compliance with waste management policies.

This research addresses the specific problem of the management of wood waste by the construction, renovation, and demolition (CRD) industry. CRD is the first industrial waste generator in Canada, being responsible for a third of the total national waste generation (RECYQ-QUEBEC, 2012). Wood is frequently used as a building material in many countries, and more specifically in cold environments due to the advantages that are provided such as modularity, energy efficiency, etc. This is why countries such as Sweden, Denmark or Canada present a very high rate of usage of wood materials in their buildings (Sathre, 2014). In addition, with a very large territory and a lot of forest land, Canada is one of the countries with the highest rate of wood material inside its buildings (Yeheyis et al., 2013). Thus, wood is the first building material in terms of waste generated during the construction, renovation and demolition processes, often exceeding 30% of the total debris collected (Yeheyis et al., 2013). The recycled wood sector is facing some important challenges in

Quebec. Today, more than 60% of wood generated at CRD sites is landfilled, partly because the recycling process is more expensive than the landfilling cost (RECYQ-QUEBEC, 2012).

Efficient RL networks have a major role to play in increasing the recovery rate of the recycled wood from the CRD industry. Indeed, in order to manage the wood recycling process in an efficient manner, we should be able to adequately locate the sorting facilities and decide on their annual treatment capacity. Dealing with transportation activities and building material flow between the collection sites and sorting facilities is usually a difficult task. It is even more complex in the CRD industry because of uncertainties in the reverse supply chain network. First, the location of the supply sources is variable over time, which means that they are different from one year to another making it complicated to locate the sorting facilities to minimize transportation distances. Secondly, the amount of wood material collected is highly unpredictable. Thus, the treatment capacity decision that must be allocated to each sorting facility to process the recycled wood is also a concern. Finally, according to the construction decisions that were made decades ago during the design stage of the buildings, the quality level of the collected wood on the CRD sites is highly unpredictable. The uncertainty of the location, quantity and quality level of wood generated in the CRD industry makes the recycled wood RL network design problem challenging.

Thus, the main objective of this research is to build a quantitative model for RL network redesign under an environmental policy that targets the recycled wood material from the CRD industry. To the best of our knowledge, this is the first study that addresses this specific problem targeting the CRD industry in this geographical area from a reverse logistics perspective. This research could be beneficial for the local authorities providing some useful insights about the expected impact of the environmental policy targeting the recycled wood material from the CRD industry, thus possibly preventing illegal dumping and border landfilling under the regulation.

To reach this goal, we propose a MILP formulation that allows making decisions at a strategic facility level such as 1) Should an existing sorting facility be closed or not? 2)

Should we expand the treatment capacity of an existing facility? and 3) Should we relocate some of the existing facilities to decrease transportation distances in the RL network? Also, our model considers the RL tactical flow decisions between logistics units. The contribution of this work lies in two particularities. First, the model is able to capture both dynamic change in supply sources locations and also the variations in the quality levels of the collected wood materials. A scenario-based approach is proposed in this study to assess the potential impacts of these sources of uncertainty by selecting relevant discrete values of the uncertain parameters. The applicability of the model is illustrated with a case study in the province of Quebec, Canada.

The remainder of this paper is structured as follows. Section 2.2 presents the relevant literature review in the reverse logistics field. Section 2.3 presents in detail the mathematical formulation of the proposed model. Section 2.4 introduces the case study for the recycled wood from the CRD industry in the province of Quebec. Section 2.5 discusses some managerial insights based on the main findings. Finally, conclusions and future research perspectives are derived in Section 2.6.

2.2 Literature review

We have recently noted an increased number of research papers addressing RL problems and several literature reviews were also published in this field: Pokharel and Mutha (2009), Agrawal et al. (2015), Govindan et al. (2015). The first studies addressing network design problems in RL appeared less than 20 years ago (Barros et al., 1998). From this point, we denote an increased variation in the RLN design models with collection centers and refurbishing facilities' location with multiple products consideration. Kara and Onut (2010) proposed a stochastic programming model to select a long-term strategy under uncertainties regarding the facility locations and the optimal flow in an RL network design problem with an application in the paper industry. Lieckens and Vandaele (2012) developed a mixed-integer nonlinear program (MINLP) considering uncertainties on the collected quantities and quality of the products parts in order to make decisions about collection facility location.

Lickens et al. (2013) also proposed a MINLP that helps make decisions on reverse facility locations, capacity allocation and flow between the network nodes. The study of Toso and Alem (2014) investigates both deterministic and stochastic capacitated facility location model considering discrete time intervals. Another stochastic programming model is presented in Dai et al. (2014) that investigates the impact of uncertain collected quantity and secondary market demand for the returned products. A genetic algorithm is used to decide on collection point locations and flow decisions in the RL network. Later, Jeihoonian et al. (2016) also considered the unknown amount of returned products in a multi-stage stochastic model in order to locate the collection facilities in the reverse network. A scenario clustering decomposition is proposed to solve the multi-period model and its utility is illustrated in the sector of large household appliances. Fattahi and Govindan (2016) used a two-stage stochastic formulation to address the uncertainty related to new products demand and potential returns of used products. The proposed model is solved using a novel simulated annealing algorithm for large-sized problems. Finally, Nakatani et al. (2017) propose a robust multi-period formulation to address the optimal flow decisions in the context of uncertain demand and material prices. Table 2.1 shows that facility location and flow are the most common decision variables. Moreover, capacity expansion decisions are not very common in RL and CLSC models. The main sources of uncertainties are the demand and the collected quantity of the returned products in the RL network. Very few papers address quality issues of collected products. However, to the best of our knowledge, studies that consider variation in the supply sources locations while making reverse network design decisions are unavailable. Indeed, this characteristic is very specific to the CRD industry. It is difficult to predict where the building materials collection points will be located in the future. Such feature has a real impact on the RLN design decision. Indeed, transportation distances play a major role on the recovery rate of building materials as the building contractors will not accept to travel too far to the nearest sorting facility. Finally, we denote a significant number of decision models that are applied to industrial case studies, sometimes for a specific sector or from a more general perspective, without targeting a particular product category. In Table 2.2, we reviewed 104 papers in the RL and CLSC fields by industrial sector.

Table 2.1 Recent RL and CLSC decision models considering uncertainties (2007-2017)

	Model formulation	**Uncertain parameters**			**Decision variables of the model**			**Planning horizon**		**Type of data set**		**Proposed case study**
		SSL	CV	MQ	FL	CE	FD	SP	MP	FD	CS	Industry
Salema et al. (2007)	MILP		×		×		×	×		×		–
Chouinard et al. (2008)	2 stage ST		×		×		×	×			×	Medical
Pishavee et al. (2009)	ST program		×	×	×		×	×		×		–
Lee et al. (2010)	2 stage ST		×		×		×	×			×	Electronics
Kara and Onut (2010)	2 stage ST		×		×		×	×			×	Paper
Gomes et al. (2011)	MILP		×		×		×		×		×	Electronics
Gomes et al. (2011)	2 stage ST		×	×	×		×		×	×		–
Pishavee et al. (2011)	Robust		×		×		×	×		×		–
Lieckens et al. (2012)	MINLP		×	×	×	×	×		×		×	
Cardoso et al. (2013)	MILP		Else		×		×		×		×	–
Lieckens et al. (2013)	MINLP		Else		×		×		×		×	Manufacturing
Toso and Ahem (2014)	ST program		×		×		×		×		×	Residential
Dai and Wang (2014)	ST program		×		×		×	×		×		–
Zeballos et al. (2014)	Multi-stage ST		Else		×		×		×	×		–
Subulan et al. (2015)	Fuzzy		Else		×		×		×		×	Automotive
Jeihoonian et al. (2016)	Multi-stage ST		×	×	×		×		×		×	Electronics
Sun and Chen (2016)	Robust		×	×	×		×	×			×	Electronics
Nakatani et al. (2017)	Robust		Else		×		×		×	×		Plastics
Amin and Baki (2017)	Fuzzy		Else		×		×	×			×	Electronics
Amin et al. (2017)	MILP		×		×		×	×			×	Automotive
Proposed model	MILP	×	×	×	×	×	×	×			×	CRD

SSL: Supply Sources Location; CV: Collected Volume; MQ: Material Quality; FL: Facility Location; CE: Capacity Expansion; FD: Flow Decisions; SP: Single Period; MP: Multi-Period; FD: Fictive Data; CS: Case Study; ST: Stochastic

Table 2.2 RL and CLSC papers by sectors (2007 – 2017)

Sector	Proportion	Published papers
General	29,8%	Zikopoulos and Tagaras (2007) Lieckens and Vandaele (2007) Salema et al. (2007) Zhu et al. (2008) Francas and Minner (2009) Xiaofeng and Tijun (2009) Pishvaee et al. (2009) Salema et al. (2010) Pishvaee and Torabi (2010) Wongthatsanekorn et al. (2010) Chen and He (2010) Gomes et al. (2011) Pishvaee et al. (2011) Cardoso et al. (2013) Dai and Wang (2014) Zeballos et al. (2014) Amin and Zhang (2012) Diabat et al. (2013) Huang and Su (2013) Ramezani et al. (2013) Vahdani et al. (2013) Lieckens et al. (2013) Gu and Tagaras (2014) Niknejad and Petrovic (2014) Eskandarpour et al. (2014) Demirel et al. (2014) Wei et al. (2015) Tan and Chanchaichujit (2016) Zhalechian et al. (2016) Esmaeili et al. (2017) Battini et al. (2017)
Electronics	19,2%	Hammond and Beullens (2007) Lee and Dong (2008) Kumar et Putnam, (2008) Lau and Wang (2009) Xiaofeng and Tijun (2009) Tsai and Hung (2009) Janse et al. (2010) Gomes et al. (2011) Lieckens and Vandaele (2012) Rahman and Subramanian (2012) Daim et al (2012) Chiou et al. (2012) Kissling et al. (2012) Krapp et al. (2013) Kilic et al. (2015) Ayvaz et al. (2015) Jeihoonian et al. (2016) Guarnieri et al. (2016) Sun and Chen (2017) Amin and Baki (2017)
Manufacturing	13,5%	Xanthopoulos and Iakovou, (2009) Atasu et al. (2010) Kapetanopoulou and Tagaras (2011) Sharma et al. (2011) Millet (2011) Drake et al. (2012) Rahman and Subramanian (2012) Lieckens et al. (2013) Jaber et al. (2013) Mittal and Sangwan (2014) Abdulrahman et al. (2014) Galvez et al. (2015) Otay et al. (2016) Bazan et al. (2017)
Materials	10,6%	Kara and Onut (2010) Zeballos et al. (2012) Kannan et al. (2012) Giannetti et al. (2013) Lundkvist et al. (2013) Schweiger and Sahamie (2013) Bing et al. (2014) Bing et al. (2015) Kumar et al. (2016) Alshamsi et al. (2017) Nakatani et al. (2017)
Automotive	7,7%	Gerrard and Kandlikar (2007) Zhu et al. (2007) González-Torre et al. (2010) Gołebiewski et al. (2013) Mahmoudzadeh et al. (2013) Demirel et al. (2014) Subulan et al. (2015) Amin et al. (2017)
E-waste	4,8%	Gomes et al. (2008) Kannan et al. (2009) Dat et al. (2012) Liu et al. (2014) Agrawal et al. (2014)
Agri-food	3,8%	Hasani et al. (2012) Kim et al. (2014) Accorsi et al. (2016) Banasik et al. (2017)
Cell phones	2,9%	Hanafi et al. (2007) Mitra (2007) Geyer and Blass (2010)
Packagings	1,9%	Silva et al. (2013) Edgar et al. (2014)
Hazardous	1,9%	Ardjmand et al. (2015) Shojaeipour et al. (2015)
Containers	1,9%	Francesco et al. (2009) Meng and Wang (2011)
Paper	~ 1%	Zhou and Zhou (2010)
Construction	~ 1%	Sinha et al. (2009)

2.3 Model development

2.3.1 Assumptions

In order to build a model adapted to the reality of the wood building-material recycling supply chain, we consider a RL network that includes the main actors of this industry. First, we assume that a set of CRD sites, also referred to as collection sites or supply sources are available. Collection activities are performed at these nodes. Mixed building-material waste is collected into containers and loaded onto trucks. Then, there is a choice to make between two possibilities: the landfilling or the recycling option. The materials moved to the landfills have reached the end of their useful life and are ultimately disposed. On the other hand, each container shipped to a sorting facility increases the opportunity to extract wood to be sold and used by final customers: the wood material recyclers. In this work, we assume that capacities and locations of existing sorting facilities are known in advance, as well as the location for the new potential sorting facilities and the recyclers demand for each grade (g_i) of recycled wood. The main assumptions regarding the building-material containers are synthesized in Figure 2.1 below.

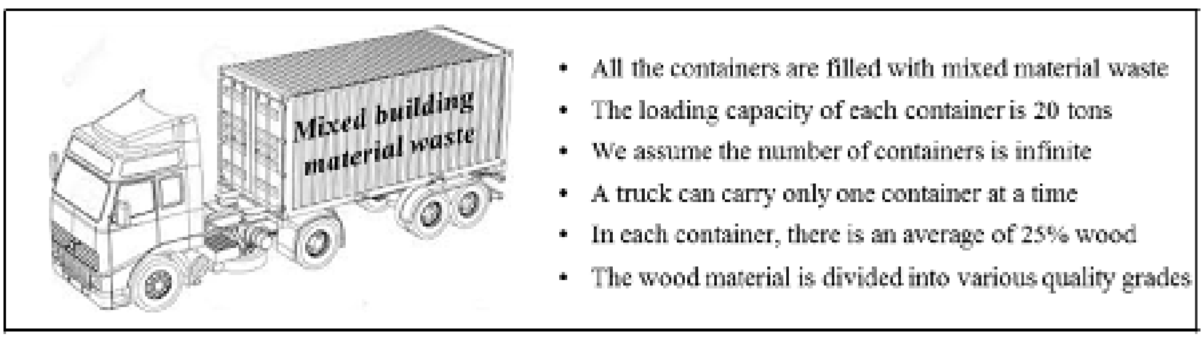

Figure 2.1 Main assumptions regarding the containers collected at CRD sites

2.3.2 Mathematical formulation

We formulated the RL network design problem of recycled wood from the CRD industry as a mixed-integer linear program (MILP). The proposed formulation helps in making decisions regarding the sorting centers operation, facilities relocation, capacity expansion and material flow decisions between the network nodes under the environmental policy. The structure of the RL network is illustrated in Figure 2.2.

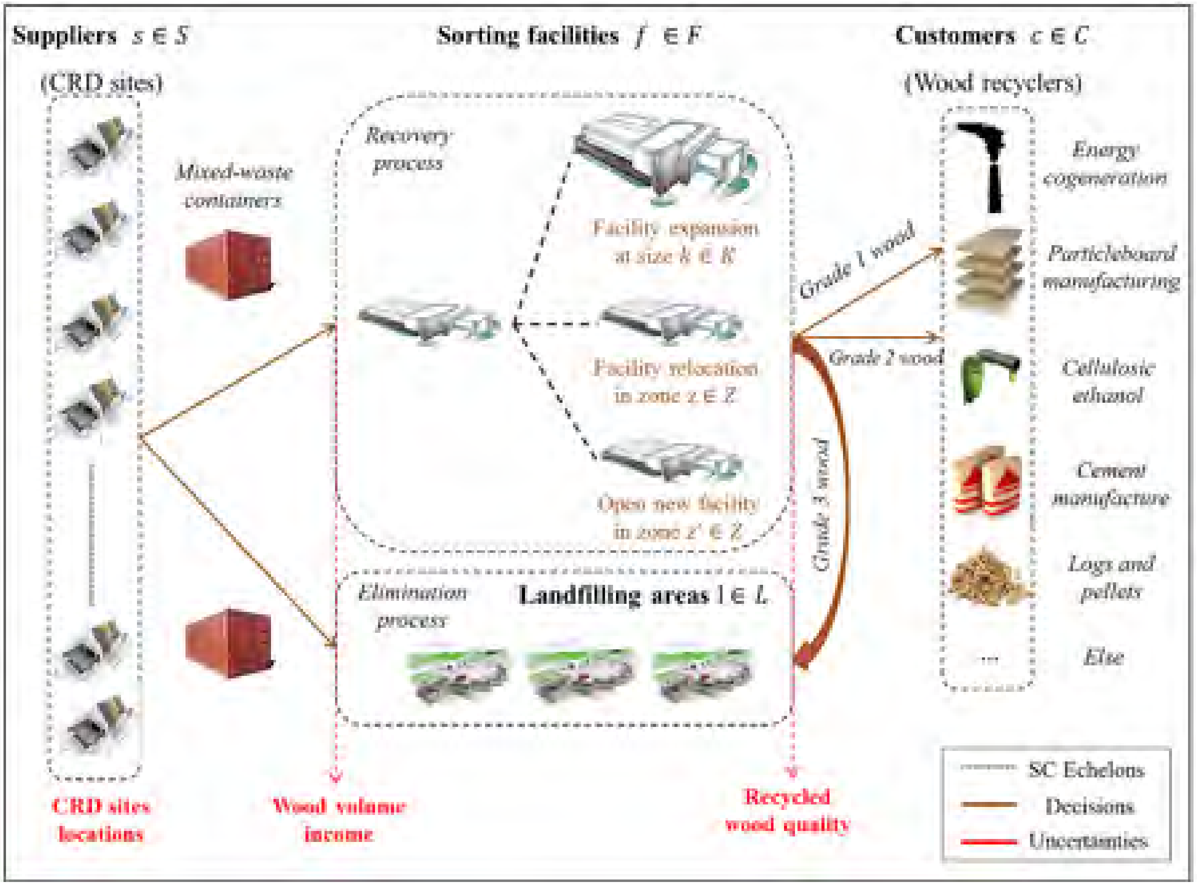

Figure 2.2 RL network for the recycled wood material from the CRD industry

The sets, parameters, decisions variables, objective function and the constraints of the model are listed below. The nodes of the network $\{i, j\}$ represent any CRD site, sorting facility, landfilling area and the demand markets of wood recyclers.

Sets

$i, j \quad \in N$ Nodes of the network

$s \in S \quad \subset N$ Set of supply sources

$f \quad \in F \quad \subset N$ Set of existing sorting facilities

$f' \quad \in F \quad \subset N$ Set of potential sorting facilities

$k \in K$ Set of possible existing facility sizes

$k' \in K$ Set of available sizes for expanded sorting facilities

$l \in L \quad \subset N$ Set of landfilling areas

$c \in C \quad \subset N$ Set of customers (i.e. building material recyclers)

$m \in M$ Set of collected materials

$g \in G$ Set of various quality grades for the materials

$z \in Z$ Set of geographic zones

$u \in U$ Set of scenarios

Parameters

t_{ij} = Transportation cost for shipping one metric ton of materials between node $i\epsilon N$ and node $j\epsilon N$

ξ_{ij} = Transportation distances between node $i\epsilon N$ and node $j\epsilon N$

ω = Loading capacity of the trucks

d_{mgc} = Annual demand for material $m\in M$ of grade $g\in G$ at customer $c\in C$

h_{fk} = Annual treatment capacity at sorting facility $f\in F$ of size $k\in K$

h'_{fk} = Added capacity in case sorting facility $f\in F$ of initial size $k\in K$ is expanding

r_m = Recycling rate at sorting facilities for material type $m\in M$

c_m^L = Unit landfilling cost for one ton of material $m\in M$ at a landfilling area

c_m^R = Unit recycling cost for one ton of material $m\in M$ at the sorting facilities

Ω_{fk} = Fixed annual operating cost for an existing sorting facility $f\in F$ of size $k\in K$

$\Omega_{f'k'}$ = Fixed annual operating cost for a potential sorting facility $f'\in F$ of size $k'\in K$

$\delta_{fkk'}$ = Expansion cost of sorting facility from size $k \in K$ to size $k' \in K$

π_{fkz} = Opening cost for sorting facility $f \in F$ of size $k \in K$ in geographical zone $z \in Z$

Ψ_m = Target proportion of material type $m \in M$ that must be sent to sorting facilities

$LS_u\ (x_u, y_u)$ = Coordinates of the supply sources of the network in scenario $u \in U$

V_{mgsu} = Quantity of material $m \in M$ of quality grade $g \in G$ collected at supply source $s \in S$ in scenario $u \in U$

Q_{mgu} = Proportion of quality grade $g \in G$ in one ton of collected material $m \in M$ at supply sources in scenario $u \in U$

Decision variables

X_{mgsfu} = Flow of material of type $m \in M$ of quality grade $g \in G$ transported from supply source $s \in S$ to sorting facility $f \in F$ in scenario $u \in U$

X_{mgslu} = Flow of material of type $m \in M$ of quality grade $g \in G$ transported from supply source $s \in S$ to landfilling area $l \in L$ in scenario $u \in$

X_{mgfcu} = Flow of material of type $m \in M$ of quality grade $g \in G$ transported from sorting facility $f \in F$ to customer $c \in C$ in scenario $u \in U$

X_{mgflu} = Flow of material of type $m \in M$ of quality grade $g \in G$ transported from sorting facility $f \in F$ to landfilling area $l \in L$ in scenario $u \in U$

N_{su} = Number of trucks required to perform collection activities on supply site $s \in S$ in scenario $u \in U$

$$\beta_{fku} = \begin{cases} 1 & \text{if sorting facility } f \in F \text{ of size } k \in K \text{ is operating in scenario } u \in U \\ 0 & \text{if not} \end{cases}$$

$$\alpha_{fkk'u} = \begin{cases} 1 & \text{if sorting facility } f \in F \text{ should expand its treatment capacity} \\ & \text{to size } k' \in K \text{ in scenario } u \in U \\ 0 & \text{if not} \end{cases}$$

$$\theta_{f'kzu} \;=\; \begin{cases} 1 & \text{if a new sorting facility } f' \in F \text{ of size } k \in K \text{ should open in} \\ & \text{geographical zone } z \in Z \text{ in scenario } u \in U \\ 0 & \text{if not} \end{cases}$$

Objective function

The objective function minimizes the total reverse supply chain operation cost as follows:

Min = Transportation costs + Recycling costs + landfilling costs + operating costs + expansion costs + opening costs

$$\begin{aligned} Min \; & \sum_{m\in M}\sum_{g\in G}\sum_{i\in I}\sum_{j\in J} t_{ij}\;\xi_{ij}\,X_{mgiju} + \sum_{m\in M}\sum_{g\in G}\sum_{s\in S} c_m^R\left[\sum_{f\in F} X_{mgsfu} + \sum_{f'\in F} X_{mgsf'u}\right] \\ & + \sum_{m\in M}\sum_{g\in G}\sum_{l\in L} c_m^L\left[\sum_{s\in S} X_{mgslu} + \sum_{f\in F} X_{mgflu} + \sum_{f'\in F} X_{mgsf'u}\right] \\ & + \sum_{f\in F}\sum_{k\in K}\sum_{k'\in K}\left[\Omega_{fk} + \sum_{z\in Z}(\pi_{fkz} + \Omega_{f'k'})\,\theta_{fkzu} + \delta_{fkk'u}\,\alpha_{fk'u}\right] \end{aligned} \tag{2.1}$$

Subject to the following constraints

Demand satisfaction

$$\sum_{f\in F} X_{mgfcu} \le d_{mgc} \qquad \forall u \in U, \forall m \in M, \forall g \in G \;, \forall c \in C \tag{2.2}$$

Flow conservation at the supply sources

$$V_{mgsu} = \sum_{f\in F} X_{mgsfu} + \sum_{l\in L} X_{mgslu} \qquad \forall u \in U, \forall m \in M, \forall g \in G \;, \forall s \in S \tag{2.3}$$

Environmental policy target

$$\sum_{f\in F} X_{mgsfu} \ge \;\Psi_m\, V_{mgsu} \qquad \forall u \in U, \forall m \in M, \forall g \in G \;, \forall s \in S \tag{2.4}$$

Flow conservation at sorting facilities

$$\sum_{s\in S} X_{mgsfu} = \sum_{c\in C} X_{mgfcu} + \sum_{l\in L} X_{mgflu} \quad \forall u \in U, \forall m \in M, \forall g \in G \ , \forall f \in F \quad (2.5)$$

Flow conservation at potential sorting facilities

$$\sum_{s\in S} X_{mgsf'u} = \sum_{c\in C} X_{mgf'cu} + \sum_{l\in L} X_{mgf'lu} \quad \forall u \in U, \forall m \in M, \forall g \in G \ , \forall f' \in F \quad (2.6)$$

Achievable recycling rates at sorting facilities

$$\sum_{s\in S} X_{mgsfu} . r_m \geq \sum_{c\in C} X_{mgfcu} \quad \forall u \in U, \forall m \in M, \forall g \in G \ , \forall f \in F \quad (2.7)$$

Achievable recycling rates at potential sorting facilities

$$\sum_{s\in S} X_{mgsf'u} . r_m \geq \sum_{c\in C} X_{mgf'cu} \quad \forall u \in U, \forall m \in M, \forall g \in G \ , \forall f' \in F \quad (2.8)$$

Treatment capacity at sorting facilities

$$\sum_{m\in M} \sum_{g\in G} \sum_{s\in S} X_{mgsfu} \leq \ h_{fk} \, \beta_{fku} + \ h'_{fk} \, \alpha_{fk'u} \quad \forall u \in U, \forall k, k' \in K \ , \forall f \in F \quad (2.9)$$

Treatment capacity at potential sorting facilities

$$\sum_{m\in M} \sum_{g\in G} \sum_{s\in S} X_{mgsf'u} \leq \ h_{f'k} \, \theta_{f'kzu} \quad \forall u \in U, \forall z \in Z, \forall f' \in F \ , \forall k \in K \quad (2.10)$$

Trucks loading capacity

$$\sum_{m\in M} \sum_{g\in G} V_{mgsu} \ \leq \ \omega \, N_{su} \quad \forall u \in U, \forall s \in S \quad (2.11)$$

Integrity and binary constraints

$$X_{mgiju} \in \mathbb{R}^{+} \text{ Where } \mathbb{R}^{+}=\{x \in \mathbb{R}, x \geq 0\},\ \forall m \in M, \forall g \in G\ \ \forall i \epsilon N, \forall j \epsilon N, \forall u \in U \quad (2.12)$$

$$N_{su} \in \mathbb{N} \quad \text{Where } \mathbb{N} = \{x \in \mathbb{R}, x\ \ integer\}, \qquad \forall s \in S, \forall u \in U \qquad (2.13)$$

$$\beta_{fku}, \alpha_{fkk'u}, \theta_{f'kzu} \in \{0,1\} \quad \forall u \in U, \forall f \epsilon F, \forall k, k' \epsilon K, \forall z \in Z \qquad (2.14)$$

The objective function in (2.1) minimizes the total cost. The latter includes the transportation costs, the recycling and landfilling costs, and facility-related costs for operation, expansion and new openings. Finally, the additional cost incurred in case of poor quality materials is also included. Constraint (2.2) ensures that customer demand is not exceeded for each material type and quality grade. Constraint (2.3) guarantees that all the materials are collected from the supply sources to be either landfilled or shipped to a sorting facility, while constraint (2.4) imposes the compliance with the government policy target in terms of material flow shipped to certify sorting infrastructure. Constraints (2.5) and (2.6) ensure that all the materials leaving a sorting facility (existing or new) are either landfilled or shipped to a customer while respecting the recycling rates mentioned in constraints (2.7) and (2.8). Constraints (2.9) and (2.10) guarantee the treatment capacities of the sorting and the potential new sorting facilities are not exceeded. Constraint (2.11) limits the amount of collected materials that can be loaded on a truck. Finally, constraints (2.12) to (2.14) ensure flow decision variables positivity or integrity and that the operating, expanding and opening decisions are binary variables.

2.4 Case study description and data collection

The province of Quebec is the largest Canadian province with a territory of 1,667,441 km^2. Moreover, there are a relatively small number of inhabitants, barely exceeding 8 million people, thus implying a very low average density population of around 5 inhabitants per km^2. Although the average population density seems very low, it is however unequally distributed and almost 52% of the inhabitants are concentrated in 3 regions out of 17 (see Figure 2.3).

For example, the north of Quebec is characterised by a density of 0.1 inhabitant per km^2 while a city like Montreal has 5,500 inhabitants per km^2 (Statistical Institute of Quebec, 2014). These characteristics make the redesign of the RL network for the recycled wood that can efficiently serve the entire territory a real challenge.

For the purpose of this study, we used several sources of data for the recycled wood industry in Quebec: Statistical Institute of Quebec, RECYQ-QUEBEC and historical data provided by wood recyclers. These data were used to estimate the annual quantity of CRD waste generated in the province and the proportions of each grade of recycled wood. With an average of 0.65 tons of waste generated per inhabitant per year, the average of building-material waste to be collected on the CRD sites in the province of Quebec is estimated to reach 5.3 million annually. As the historical data about the exact number and locations of CRD sites are not available, we divided the amount of waste generated into 203 collection sites taking into account the population density of each region. Table 2.3 gives more details about the characteristics and the geographical configuration of the different regions.

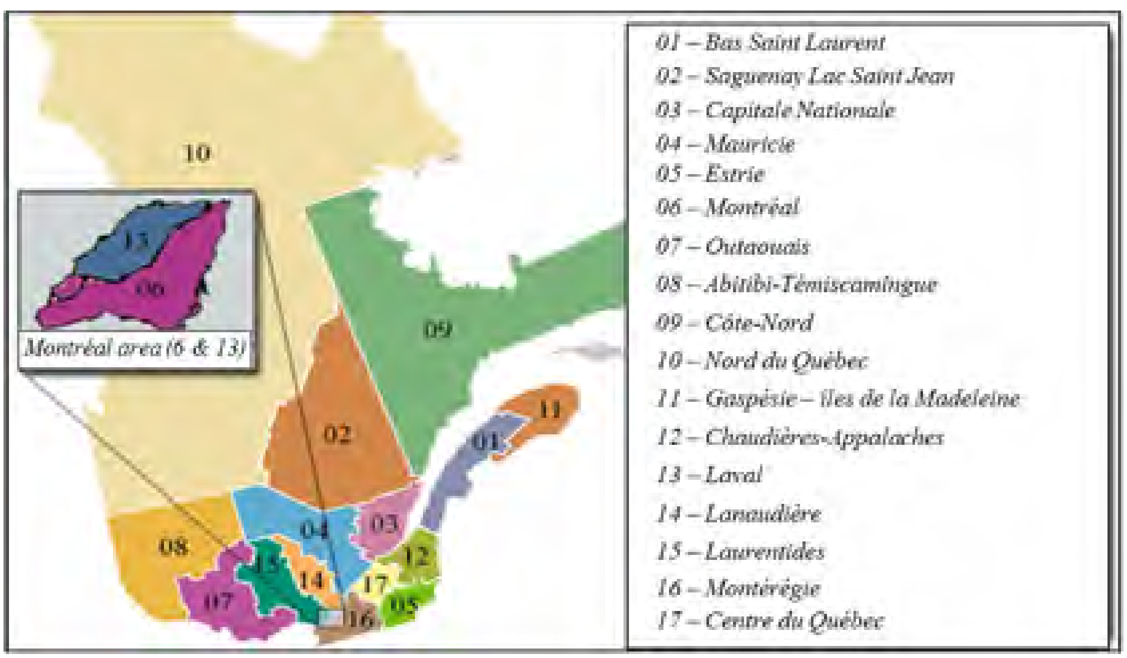

Figure 2.3 Repartition of Quebec provinces into regions

Table 2.3 Annual estimated CRD waste generation by administrative region in Quebec

Administrative region	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Population (K-inhabitants)	200	277	732	267	320	1 988	383	148	95
CRD waste generated (K-tons)	130	180	476	174	208	1 292	249	96	62
Number of CRD sites per region	4	5	15	5	6	61	7	3	2
Administrative region	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**Total**
Population (K-inhabitants)	44	92	420	421	492	586	1 508	240	**8 213**
CRD waste generated (K-tons)	29	60	273	274	320	381	980	156	**5 338**
Number of CRD sites per region	1	3	8	8	10	12	46	7	**203**

We identify 38 sorting centers dealing with CRD building-material waste today in Quebec (as listed in Appendix I). The treatment capacity varies from 10,000 to 400,000 tons per year. Moreover, in order to redesign the RL network, we assume that each sorting facility is able to increase its annual treatment capacity (i.e. capacity expansion) by a factor of 2. Also, 51 potential locations are selected for opening new sorting facilities based on the population density of each region. Each new sorting facility has three possible treatment capacities, either of 20,000 tons, 50,000 tons or 100,000 tons per year. We also considered 36 registered certified landfill sites. We assume that sorting facilities receive mixed-waste containers from the building contractors. After that, wood has to be extracted from these containers before being redirected to the recyclers. We consider that every landfill site has an infinite capacity for a one-year planning horizon. Thus, the proposed RL network is composed of 343 nodes including collection sites, sorting facilities, landfilling areas and finally the recyclers of building materials (customers). For the transportation of waste collected at CRD, we assume that containers have a capacity of 20 tons each, and the cost structure is defined in a way that the shipping cost is correlated with the travelling distance and vehicle load.

Three quality levels (grades) of collected wood are considered in this study. “Grade 1” is free of contaminants with a very high demand. “Grade 2” is slightly contaminated, sometimes simply by contact with other building materials (painting, chemical treatment against moisture, insects) or simply by time degradation. Grade 2 accounts for 65% to 70% of the total wood quantity. Finally, “Grade 3” is highly contaminated, sometimes with dangerous substances which are potentially harmful to the environment and/or for human health. This type wood is likely to be landfilled all the time. In this case study, the annual demand for grade 1 and grade 2 is shared between 15 recyclers (customers) according to the proportions shown in Table 2.4 (3R-MCDQ, 2013). Among the recycled wood products, only the particleboard manufacturing requires grade 1. Grade 2 wood is good enough for the remaining customers.

Table 2.4 Annual market demand for recycled wood material in Quebec

Industrial activity	Energy cogeneration	Particleboard manufacturing	Cellulosic Ethanol	Cement manufacture	Logs and pellets	Else
Recycled wood use (tons)	595 000	287 000	120 000	62 000	57 000	≤11 500
Market proportion	52 %	25 %	11 %	6 %	5 %	≤ 1 %

2.5 Experimental evaluation and managerial insights

In order to deal with the reality of the wood recycling process, the experimental evaluation considers the reverse logistics redesign under wood waste-management constraint and the importance of uncertain parameters by adopting a scenario-based approach (Soleimani et al., 2016). Indeed, the strategic decisions to be made regarding the RLND are very dependent on numerous parameters, and some of them are highly unpredictable: the location of the collection sites, the availability of recycled materials (i.e. the supplied quantity) and finally the quality level of collected wood for recycling. In order to evaluate the impact of these uncertainties, we built multiple scenarios considering three (3) discrete values for each of these parameters based on historical data analysis.

Let's consider LS_1 (x_1, y_1), LS_2 (x_2, y_2) and LS_3 (x_3, y_3) three different locations for the set of supply sources $s \in S$. Let's define also V^{low}, V^{avg}, and V^{high} the possible values for the total quantity of CRD building-material waste collected annually. As mentioned previously, an average of 5.3 million tons (V^{avg}) of building-material waste is generated in Quebec annually. We suppose that this value can vary more or less 20% and we use these values for the realisations of V^{low} and V^{high}. Finally, we define Q^{low}, Q^{avg}, and Q^{high} as the potential quality levels for the collected wood. The difference between the various quality levels is related to the rates of Grades 1, 2 and 3 of recycled wood inside the container. Considering the different combinations, we obtain 27 scenarios as depicted in Appendix II. Scenario 1 (SC1) uses the combination of the mean values for the quality and volume parameters (Q^{avg}, V^{avg}) and the first set of supply sources LS_1. To evaluate the impact of environmental legislations, we conduct the experiments with the following methodological steps:

- **Step 1. Baseline scenario**. As a first step, we run the optimization model to obtain the optimal reverse logistics network without any waste management policy constraint (Constraint 3 is not active).

- **Step 2**. **Scenario 1.** For this scenario, we run the optimization but constraint 3 is active (70% of recycled wood shipped to sorting centers). We use the first set of supply sources LS_1 and the mean values of uncertain parameters V and Q are used to obtain the new reverse logistics network design (fixed network).

- **Step 3**. **SC2 to SC27.** Solving all the scenarios without any change in the reverse logistics configuration obtained in SC1.

- **Step 4**. **SC2* to SC27*.** Solving to optimality all the remaining scenarios allowing the adjustment of RLN design decisions obtained in SC1.

- **Step 5. Experiments and insights**. At this level, the objective is to evaluate the impact of the uncertain parameters on RLND optimal decisions and analyse the managerial insights.

2.5.1 Redesign of the current reverse logistics network

As a baseline scenario, the behaviour of the Quebec network before applying the waste management policy is evaluated. The results show that the overall utilisation rate of sorting facilities barely exceeds half of their global treatment capacities (58%). The landfilling activities represent a huge proportion of the collected wood because the recycling process is not competitive compared to the “low” landfilling cost. These results are very representative of the current situation of the recycled wood industry in the province of Quebec where some sorting facilities are closed for some periods within a year. Indeed, a significant quantity of mixed waste containers from CRD sites is not shipped to the sorting centers. Moreover, 175,000 tons of collected wood are recycled. Thus the service level for the wood recyclers is very low, with 16.8% for grade 2 and 12.2% for grade 1. In this scenario, the model suggests that only 28 sorting centers among the 38 available are operating and neither expansion nor new sorting facility openings are required.

As the annual demand for recycled wood material is estimated to be around 1.15 million tons in Quebec (3R-MCDQ, 2013), almost 15% of this quantity is provided from the Quebec CRD sites. Thus, the majority of the recycled wood used by the recyclers is imported from the US. The remaining demand is satisfied by using virgin wood fibre and implies a significant increase in procurement costs (about three times the price paid for the recycled wood material at the exit of the sorting centers). In the second phase, and in order to comply with the waste management regulation, we run the decision model and we observe many adjustments compared to the network obtained for the baseline. The optimal network for scenario 1 (SC1), named “fixed network” for the rest of the study, is now composed of 38 sorting centers. Many sorting facilities (26 sites) have expanded their capacities and five (5) new facilities are added in strategic locations in order to minimize transportation distances. These adjustments require an investment of 35 M$. The main features of the baseline scenario and SC1 are illustrated by Table 2.5. The reader is referred to appendix III for additional graphical content.

Table 2.5 Baseline scenario versus scenario 1 (fixed network)

Activity	**Criteria**	**Baseline scenario**	**Scenario 1 (fixed network)**
Sorting facilities	Expansion (new opening)	-	26 (5)
	Number of sorting centers	28 from 38	38
	Facility investments (M$)	21.2	56.2
	Sorting facility use	58%	96.5%
	Avg. distance to recycle	116 km	75.4 km
	Wood recycling cost ($)	17,780,000 ($101.6/ton)	74,493,086 ($85.2/ton)
Customers	Recycled wood (tons)	175,166	874,332
	Service level – Grade 1	12.2%	54%
	Service level – Grade 2	16.8%	84.7%
Landfills	Landfilling (tons)	1,426,234	727 068
	Number of sites used	33 from 36	26 from 36
	Average distance to landfills	27.9 km	38.9 km
RL network	Total Cost ($)	268,699,279	359,830,582

The first observation from Table 2.5 is that the adjustment of the reverse logistics network leads to the reduction of wood recycling cost from $101.6/ton in the baseline scenario to $85.2/ton. This value considers facility processing costs and average distance traveled by the containers in the RL network. The reduction achieved is mainly due to the improved efficiency of sorting facilities (usage of 96.5 %) and the economy of scale achieved in scenario 1. As the quantity treated by sorting centers increases, the fixed costs are spread out between the larger quantities of wood recycled. Also, the new RLN allows the relocation of sorting centers in order to reduce the average distance to travel in order to treat CRD waste at the recyclers. Finally, many landfilling sites are not used with scenario 1 and the average distance to travel for CRD waste increases. Thus, under the environmental policy, the sorting facilities are located near the CRD collection points and not close to landfilling site as for the baseline scenario.

2.5.2 Reverse logistics configuration under collection sites location change

In SC1, we used the first set of supply sources location LS_1 (x_1, y_1) and we obtained the RL network named "fixed network". Since these locations might change from one period to another, we evaluate the possible changes in the RL network under uncertainty. On average, the total travelling distance for recycled wood increases when the CRD sites locations change. Initially, the trucks travelled an average of 75.4 km to recycle one ton of wood building material against 91.6 km for LS_2 and 88.1 km for LS_3 (see appendix IV). Although the second location presents the worst results in terms of average recycling distances, it is however the best one regarding the landfilling options with an average of 34.4 km travelled. These distances increase up to 35.7 km and 42.3 km for the first and the third locations respectively. The increase in the average transportation distances could be explained mainly due to two reasons. First, sorting facilities are not well located regarding the CRD collection points, and forced to move containers over long distances to reach the nearest sorting facility. Usually, such configuration is suitable when landfilling of CRD waste is the privileged option. However, the environmental policy prevents such behaviour and obliges the contractors to move CRD waste containers to sorting centers. The second reason is that sorting centers receive different quantities of grade 1 and grade 2. As grade 1 wood demand is difficult to fulfil, it may be supplied from more distant facilities than in the first scenario.

Also, it is important to mention that for the baseline scenario, it was an advantage to locate sorting centers very close to the landfilling sites considering the significant amount of building materials to eliminate (see Table 2.5). However, under the environmental policy, it is less costly when the sorting centers are located near the CRD. Indeed, as 70% of the building material waste collected must be shipped to a certified sorting facility, in this case, there is a need to adjust the network design in order to minimize the related travelling distances in scenario 1. The overall transportation cost using the data set of LS_1 (x_1, y_1) is \$41,926,882. This cost increases by 18.2% using LS_2 (x_2, y_2) locations named SC10 and by 21.2% with LS_3 (x_3, y_3) locations named SC19. The total reverse logistics cost increases by 4.9% in SC10 and by 6% in SC19 when compared with scenario 1. Table 2.6 illustrates the impact of changing the CRD site locations in terms of travelling distances between the supply sources and the sorting centers.

Table 2.6 Potential impact of a change in collection sites locations

CRD Location set	**LS_1**	LS_2		LS_3	
Criteria	**SC1**	SC10	SC10*	SC19	SC19*
Distance travelled for recycling (km)	**75.4**	91.6	70.2	88.1	76.7
Distance travelled for landfilling (km)	**34.4**	35.7	31.8	42.3	36.5
Transportation cost ($) (Δ %)	**41,926,882** **-**	49,557,574 (+ 18.2 %)	37,520,366 (- 10.5%)	50,815,380 (+ 21.2 %)	44,755,851 (+ 6.7 %)
Number of expanded sorting centers	**26**	-	25	-	29
New openings	**5**	-	5	-	3
Total cost ($)	**359,830,582**	377,709,715	353,511,880	381,722,441	364,772,979

In a second phase, SC10 and SC19 were solved to optimality offering the possibility to make adjustments within the RL network: capacity expansion and opening new sorting facilities. These two scenarios are named SC10* and SC19*. The optimized network using LS_2 data set leads to a configuration of twenty-five (25) expansions and new opening for five (5) sorting centers. Finally, using data set of LS_3, the model suggests twenty-nine (29) expansions and three (3) new openings. It is interesting to denote that in SC10*, the optimized network configuration allows achieving a better result than the one obtained in SC1. Indeed, the slight decrease in the average distances travelled for recycling and landfilling reduces the total transportation cost from 8.9% compared to scenario 1. However, SC19* shows a slight increase in both recycling and landfilling distances compared to SC1, thus leading to a total transportation cost increase of 6.7%. This is mainly due to the fact that only 3 sorting centers are opening instead of 5 under the fixed network. Overall, this analysis underlines the advantages of allowing RL redesign under CRD sites location changes when compared with

SC10 and SC19. The potential total cost reduction for the RL network is 6.8% with SC10*and 4.6% for SC19*. Indeed, the policy makers could use such model to relocate or expand strategically some sorting facilities closer to supply sources in order to minimize the transportation distances and make the building materials landfilling option less attractive.

2.5.3 Reverse logistics configuration under recycled wood quality uncertainty

The quality of the recycled wood collected on the CRD sites plays an important role in fulfilling the needs of the recyclers. On the one hand, it is difficult to estimate the quality level of the wood to be recycled in the collection centers in advance. On the other hand, poor quality lots imply lower recycling rates at the sorting facilities and ultimately also a lower service level for the wood recyclers. Thus, the main goal of this section is to evaluate the impact of the recycled wood quality uncertainty on the overall RL network behaviour and performance. To do so, we used the first set of supply sources location (LS_1) and an average collected quantity at CRD sites, and we compared the average, high and low-quality scenarios (i.e. SC1, SC2 and SC3 respectively). Then, in a second time, we analyse the results of scenarios SC2* and SC3* in order to highlight the loss of performance caused by using a fixed network for the various quality realisations. The results of these experiments are illustrated in Table 2.7. The performance of the network is expressed in terms of network configuration, overall facility use, recycling and landfilling proportion and average distances, recyclers' service level, and all the related costs.

First, we note that in case of high-quality scenario, the number of opening sorting centers increases from 5 in the fixed network to 8 facilities in SC2*. Indeed, as there is a significant increase of good quality wood suitable for recycling, it is well-advised to open a few sorting centers in strategic areas in order to minimize the transportation distances to reach the closest facility from the CRD sites. If grade 2 wood service level is not impacted a lot when comparing SC1 and SC2, the fixed network can however only fulfil 55% of the demand in SC3. This value can be increased to 69.8% with the optimized network as proposed in SC3*. In a second time, we can see that grade 1 recycled wood service level is highly influenced by the predefined network design. Indeed, allowing the change in the RL network leads to the fulfilment of 81.1% of the grade 1 demand instead of 65.2% in SC2* and SC2 respectively. However, in the case of low-quality scenario, the service level achieves 28.4% for grade 1 with scenario SC3* instead of 19.1% with SC3. It is also important to mention that for scenario 1, twenty-six (26) landfills are active, while only twenty-one (21) are active in SC2*. The number of active landfills achieves thirty (30) sites with SC3* due to the significant amount of poor quality wood waste, and which is not usable.

The total RL network cost increases by 8.3% from SC1 to SC2 which is mainly due to the fact that recycling is more expensive than landfilling. Finally, an optimized RL network allows improving the total cost from 5.2% in the case of high-quality scenario from SC2 to SC2*, but this improvement is reduced to 2% in the case of poor quality scenario from SC3 to SC3*. Thus, an effort toward improving the quality level and better estimation will lead to an improvement in the RLN design process and to a better control in the investment and opening decisions. Plus, in terms of network facilities investments and average recycling cost per ton of wood building-material, redesigning the RLN allows some economies of scale that would be revealed significant on a longer planning horizon.

Table 2.7 Potential impact of a change in collection sites locations

Activity	Criteria	Avg. Quality	High Quality		Low Quality	
		SC1 (fixed network)	**SC2**	**SC2***	**SC3**	**SC3***
Sorting facilities	Expansion (opening)	26 (5)	-	25 (8)	-	23 (4)
	Number of sorting centers	38	-	38	-	38
	Sorting facility use	96.5%	98.2%	94.7%	94.9%	89.9%
	Recycled wood (tons)	874,332	905,199	959,980	732,589	795,685
	Wood recycling cost (M$) / Avg. cost per ton	74,5 ($85.2/ton)	77,1 ($85.2/ton)	75,5 ($78.6/ton)	62,4 ($85.2/ton)	72,8 ($91.5/ton)
	Avg. distance to recycle one metric ton (km)	75.4	75.4	59	75.4	91.3
Customers	Service level Grade 1	54%	65.2%	81.1%	19.1%	28,4%
	Service level Grade 2	84.7%	89.9%	89.9%	55%	69.8%
Landfills	Landfilling (tons)	727 068	696,201	641,420	868,811	805,715
	Number of sites used	26/36	-	21/36	-	30/36
	Average distance to landfills (km)	38.9	38.9	43.6	38.9	34.4
RL Network	Total Cost (M$)	359,8	389,7	370,6	357,0	349,7
	Facility investments (M$)	56.2	56.2	61.5	56.2	49.9

2.5.4 RLND under joint waste quantities and collection sites locations change

The quantity of the building material collected at the CRD sites is one of the most influential parameters on the RL configuration (expansion, new openings). Plus, the variability in the collected quantity impacts greatly the recycled wood service level offered to the recyclers. Only the scenarios with high quantity realisations allow satisfying entirely the demand of the recyclers. While low volume scenarios provide around 1.2 million tons of recycled wood from the collection sites, high volume scenarios exceed 2.1 million tons supply which means that the recycling rate increases but also the landfilling quantity increases in the meantime. Table 2.8 presents the sorting facility expansion decisions, new openings and the associated initial investments required to adjust the RLN design. Plus, it provides the total network capacity and the variation compared to the fixed network from scenario 1. The scenarios depicted in this table are respectively SC4*, SC13* and SC22* (different locations with low volume collected); SC1* (fixed network), SC10* and SC19* (different locations with average volume collected); SC7* SC16* and SC25* (different locations with high volume collected). All the scenarios proposed in this table consider an average quality realisation.

The optimization model suggests 11 to 13 expansions plus 1 or 2 new facility openings with a 20,000 ton-capacity in the case of low collected quantity scenarios. For an average quantity scenario, between 25 to 29 expansions and 3 to 5 openings are recommended. In this case, only the new sorting centers 13 and 47 have 100,000-ton treatment capacity and the remaining are 20,000-ton facilities. Finally, a complete reconfiguration is required in case we face the high quantity scenarios with 29 to 31 expansions and 10 to 14 openings with a majority of facilities with 100,000-ton treatment capacity. Depending on the scenario the investment cost required for network optimal configuration varies from 10.5 M$ up to 68.7 M$. However, the required investments are not proportional to the additional capacity of the network. Indeed, it is less expensive to expand some existing sorting facilities than to build new ones. Thus, as the increasing quantity of debris collected also implies additional sorting center openings, if the collected waste at the CRD sites increases, the average investment required per ton of material increases in the meantime. We also denote that the RL network increases its capacity on average from 28.4% from low quantity to average quantity scenarios, and from 24.7% from average quantity scenarios to high ones. In the case of low volume scenarios, the optimization allows saving around 30% capacity compared to the fixed network. However, high volume scenarios require an increase in the overall treatment capacity from 27.9% to 35.5% from the fixed network in order to guarantee regulatory compliance. Depending on the collected quantity at the CRD sites, the optimal RL network suggests between 11 and 31 sorting facility expansions and between 2 and 14 new openings. Thus, we denote a very significant difference with the fixed network proposing 26 expansions and 5 openings.

Table 2.8 Optimal RLND according to the CRD sites locations and waste quantity

SSL	SF.E	SF.O	CAP	CV/FN	T.INV	U.RC
Low collected quantity scenarios						
LS1	11	2	2 755 000 t	(-) 28,4	11,2 M$	92,3 $/t
LS2	13	1	2 703 500 t	(-) 29,7	11,1 M$	96,7 $/t
LS3	11	2	2 685 000 t	(-) 30,2	10,5 M$	93,5 $/t
Average collected quantity scenarios						
LS1	26	5	3 845 000 t	N/A	34,7 M$	85,2 $/t
LS2	25	5	3 995 000 t	(+) 3,9	36,1 M$	87,1 $/t
LS3	29	3	3 770 000 t	(-) 2,1	32,2 M$	89,4 $/t
High collected quantity scenarios						
LS1	30	13	5 105 000 t	(+) 32,7	67 M$	72,4 $/t
LS2	29	14	5 210 000 t	(+) 35,5	68,7 M$	69,5 $/t
LS3	31	10	4 920 000 t	(+) 27,9	65,8 M$	76,9 $/t

SSL: Supply Sources Location; SF.E: Sorting Facility Expansions; SF.O: Sorting Facility Openings; CAP: Network Capacity; CV/FN: Capacity Variation compared to the Fixed Network; T.INV: Total Investment; U.RC: Unit Recycling cost per 1 metric ton of wood

In summary, in order to guarantee a more efficient RLN redesign in the CRD industry, there is a real need to get more accurate information about the supply sources locations and the expected wood quantity recovered from sorting facilities.

2.6 Conclusion

This paper addresses the reverse logistics network redesign for wood waste in the CRD industry under the environmental policy, based on a case study conducted on recycled wood building-materials in Quebec, Canada. The key decisions are the relocation and capacity investment of sorting facilities. A MILP model has been developed in order to analyse the direct impact of different key uncertain parameters on RL network design decisions under the waste management policy. The objective is to minimize the total cost under such restrictions. Although existing sorting facilities were not used at their full capacity in the baseline scenario, results from this study show clearly that the enforcement of environmental policy will lead to increase in the RL network efficiency and reduce the cost of recycling. Indeed, using the proposed model, the decision makers could ensure maintaining a wood recycling cost under the cost of virgin wood fibre procurement, estimated at around 120$ per ton. Moreover, under the uncertainty of parameters, the different RLN configurations are quite different. A precise estimation of the location and the available quantities of wood in future CRD collection sites will lead to efficient investment and relocation decisions that will reduce transportation costs and decrease landfilling activities. Efforts towards the improvement of the quality level of the collected wood (sorting at CRD sites, reducing material contamination in the construction process, etc.) will increase the service level for customers and avoid importing recycled wood or use of virgin wood. In the model assumptions, we assume demand for each grade of recycled wood is known in advance. The concept of wood quality grades was used to classify demand of the different recyclers. The uncertainty in demand is also a parameter that might be included in future research especially with the development of new opportunities to use recycled wood in new emerging industrial activities regardless of the quality level.

With the proposed case study in the province of Quebec, these results provide valuable insights on the importance of implementing efficient reverse logistics network as an incentive to reducing landfilling from the CRD industry. Practically, this paper provides a decision support for policy makers involved in CRD waste recycling management. It offers some useful logistics insights before setting new regulations that could be an issue for the recycled wood industry and non-sustainable in terms of environmental impacts. Although the paper focused on a case study for wood recycling from CRD in the province of Quebec, Canada, the application of this model is not limited to this country. Also, the model can be applied to a reverse supply chain for waste recycling in general.

In this work, we present various optimal RLN designs according to the uncertainty outcomes. However, in practice, the decision makers will have to choose a unique network configuration for the coming years that will efficiently handle various supply sources locations, waste collected quantities, and quality of the building materials. Although the scenario-based approach is efficient to handle uncertainty in the decision model, it is based essentially on the discrete realisation of uncertainty, which considerably reduces the number of tractable scenarios. As a future research direction, we suggest the development of a stochastic programming version of this model to avoid this limitation and propose the best supply chain configuration for a longer planning horizon. For the coming years, trends related to the uncertain parameters may be estimated using historical CRD data (Kalcher et al., 2016). Finally, it would be of major interest to include an environmental evaluation after policy implementation in the decision model as a future work.

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CHAPTER 3

A TWO-STAGE STOCHASTIC OPTIMIZATION MODEL FOR REVERSE LOGISTICS NETWORK DESIGN UNDER DYNAMIC SUPPLIERS' LOCATIONS

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Abstract

In this paper, we present a two-stage stochastic programming model for reverse logistics network design (RLND) under uncertainty with dynamic supply sources' locations. The primary goal of this optimization model is to maximize the expected profit generated by selling the materials collected from the supply sources to the secondary markets for recycling in order to make the landfilling option less attractive. The decision model identifies the best strategies to operate and adjust the processing capacity of the existing collection centers, while opening new ones with the appropriate size and suitable location. However, in comparison with the previous stochastic optimization models in this area, which mainly focus on the expected optimal value, this paper emphasizes the importance of source separation centers to address the challenge of the dynamic supply sources. Indeed, source separation and shipments consolidation of collected materials are performed at the SSC to increase the productivity level at the collection centers. The availability of each material collected from the supply sources and the recycling rates at the CC are the primary sources of uncertainty considered in this study. We adopt the Sample Average Approximation (SAA) procedure to solve the stochastic model and perform sensitivity analyses on the number of supply sources, the sample size and the level of uncertainty targeting the random parameters. The variation in the number of supply sources is mainly used to compare low-density rural collection zones versus high-density urban areas, where the waste collection activities are often more challenging. Managerial implications are discussed through a case study in the

construction, renovation and demolition industry (CRD) in the province of Quebec, Canada. Although the SSC improve the network performance in both rural and urban zones, the flexibility provided by these dynamic platforms reaches its best efficiency in the case of high-density urban areas. The results suggest significant RLND adjustments that lead to increase the average profit by 17.6% and recycle around 29% of additional building materials.

3.1 Introduction

Waste management and reverse logistics (RL) have become areas of particular interest in the supply chain literature over the past decades (Agrawal et al., 2015). Nowadays, industries worldwide are making efforts to implement RL practices among their supply chains (Mangla et al., 2016; Bing et al., 2016). The term reverse logistics refers to the management of products that have reached the end of their useful life for the consumers in order to give them an added value (Guide and Van Wassenhove, 2009). Converting raw materials into finished products and deliver to customers is known as forward supply chain (FSC). On the other hand, the collection, sorting, recycling, reusing and landfilling processes are part of the reverse logistics (RL) supply chain operations (Fleischmann et al., 1997, Alshamsi and Diabat, 2017). To deal with uncertainty, stochastic models for RLND can generate a network that will perform well in the future under different expected scenarios (Salema et al., 2007). Indeed, if the uncertainty is not considered at the design stage, the chances are very high to face demand shortages and service levels decrease that will affect the overall supply chain performance and profitability. To avoid such issues, the goal of this research is to propose a new generic RLND model that considers key uncertain parameters that are recurrent in several industries dealing with the challenges of RL activities. In addition, we aim to consider the uncertainty related to suppliers' location, a problem particularly faced by the construction, renovation, and demolition (CRD) industry (Trochu et al., 2018). For instance, we will consider three types of uncertainty in this study: the "volume" of collected material at the supply sources, the "quality" of the materials received at the collection centers (CC), and the "dynamic location of the suppliers" that are moving over time. Indeed, suppliers' location has a direct impact on the RL network configuration (Schmitt and Snyder, 2012). To cope with this problem, the decisions to be made target the utilization and possible capacity expansion of the existing CC (allowed during each period), and also the opening and location of new CC along with their capacity allocation. In addition, setting dynamic (or mobile) source separation centers (SSC) is also a potential option considered in this research. Source separation centers are dynamic and flexible facilities (not permanent) that can be opened or closed in order to be relocated closer to the supply sources and deal with waste separation near to the sources of waste (suppliers). Indeed, separation of recyclables at source is more efficient than the recovery of recyclables from mixed waste, as source separation produces cleaner materials of higher quality for recycling (Bennagen et al., 2002; Owusu et al., 2013). We assume that SSC relocation is possible due to the low cost of operating these facilities, as they do not require too much infrastructure and equipment (Moh, 2017). Moreover, using the SSC, transportation improvements can be achieved through shipments' consolidation of the appropriate materials before being redirected to the recycling centers (Kheirkhah and Rezaei, 2016). By separating good quality materials from poor quality or hazardous ones at an early stage of the recycling process, we manage to increase the recycling rates and improve the quality of the materials transported to the CC (Quebec Association of CRD materials recyclers, 2014). Finally, shipments' consolidation with the SSC strategy reduces the congestion that might be caused by the transportation activities around the CRD sites located in the city. In practice, source separation centers can be operated by the municipalities to encourage materials recycling and prevent waste elimination on their territory due to the low cost of landfilling (Kinobe et al., 2015).

In a previous study, we established that the RLND is very sensitive to the uncertainty targeting the suppliers' location, the material quality and the volume of material collected (Trochu et al., 2018). However, to the best of our knowledge, no stochastic model addresses the RLND problem considering these criteria over a multi-period horizon, which is essential in this case given the dynamic behavior related to the suppliers' locations. By developing the proposed quantitative model, we aim to answer the following research questions:

- What is the optimal RLND for material recycling under dynamic suppliers' locations and uncertainties in the volume and the quality of the collected materials?

- What role can the SSC play and what are their impacts on the RLND performance under the uncertainties of the quantity and the quality of collected materials?

The structure of this paper is as follows. Section 2 reviews the literature on RLND models under uncertainty. In section 3, we present the formulation of the model and the solution procedure. Section 4 synthesizes our experiments and main results while providing the reader with useful managerial insight regarding the SSC by conducting sensitivity analyses. Finally, conclusions and future research directions are discussed in section 5.

3.2 Literature review

Stochastic models can be classified into two (2) different approaches. The first one is known as the two-stage stochastic modeling, which uses two types of decision variables. The first type is fixed before observing the uncertainty outcome and is called first-stage decision variables, while the second type is released only after the realization of the randomness and known as second-stage decision variables or recourse actions (Birge and Louveaux, 1997). Multi-stage stochastic programming modeling with recourse is a formulation that extends the two-stage stochastic models by allowing the revision of the decisions at each stage, based on the realization of the uncertainty. In multi-stage stochastic models, the focus is on the decisions to be made today considering current resources, future outcomes and possible corrective actions in the future (Kall and Wallace 1994, Kall and Mayer 2005). In this section, we will summarize recent studies that use stochastic models for RLND using the two-stage or the multi-stage stochastic approaches. The reader is referred to Pokharel and Mutha (2009), Govindan et al. (2015) and Agrawal et al. (2015) for a more exhaustive review of RLND models. The primary concern for RLND is the uncertainties related to the market demand for new and recycled products and/or the quantity of goods returned by the consumers that will be treated through the reverse logistics channel (Listes, 2007; Lee and

Dong, 2008; Baptista et al., 2012; Zeballos et al., 2014; Srinivasan and Khan, 2018). This trend inevitably leads to consider some critical issues such as uncertainty in the pricing of the new or recycled products and parts (Soleimani and Govindan, 2014; Fattahi and Govindan, 2016; Yu and Solvang, 2017) and the capacity of the reverse logistics supply chain to process the potential returned flows (Chouinard et al., 2008; Ramezani et al., 2013).

More recently, the design of sustainable reverse logistics networks has become a significant challenge. Therefore, new stochastic models have been proposed to take into consideration the uncertainty regarding environmental parameters such as greenhouse gases (GHG) emissions levels (Pishvaee et al., 2012) and carbon tax rates (Haddadsisakht and Ryan, 2018). Although there is a growing concern about developing innovative stochastic models that include a wider variety of unknown parameters, few studies focused on the uncertainty in the quality of the products and materials collected through the RL channel (Kara and Onut, 2010; El-Sayed et al., 2010; Zeballos et al., 2012). For instance, Ayvaz et al. (2015) are one of the first studies that developed a generic two-stage stochastic RLND formulation that includes the unknown returned product quantity, the uncertain sorting ratio at the collection facilities and the uncertain transportation costs between network nodes. However, information about the material waste quality is a crucial element in the CRD industry in order to manage reverse logistics activities properly (Sobotka and Czaja, 2015). Thus, there is a need for further consideration of this aspect in quantitative models in the field of reverse logistics, being one of the contributions of this article. Table 3.1 synthesizes some additional information on two-stage and multi-stage stochastic programming models for RLND. To the best of our knowledge, no stochastic model includes SSC location decisions to cope with the uncertain quantity and quality of the collected materials coming from dynamic supply sources over time. Moreover, there is a lack of quantitative reverse logistics models that present some applications in industries that represent a huge environmental burden for the society, being the case of the CRD industry (Brandenburg et al., 2014; Chileshe et al., 2018. In this study, the originality of the model lies in the dynamic locations of the collection points (suppliers) for the collected materials. This situation is a mainly a challenge for the CRD industry where the collection sites locations are changing continuously over time.

Indeed, it has been established in previous studies that waste management efficiency is impacted by the locations of the waste collection zones, especially in high-density urbanized areas (Ghiani et al., 2015). Moreover, in this research, we introduce the SSC that contributes to transportation consolidation and better source separation (sorting) of the materials. Thus, we consider a direct correlation between the RL network design decisions and the recycling rates at the collection centers.

Table 3.1 Review of two-stage & multi-stage stochastic optimization models for RLND

Stochastic models for RLND	Model type		Horizon		Commodities		Factors of uncertainty	Model application/ Type of industry
Authors of the publication	two stage	Multi stage	Single period	Multi period	Single	Multi		
Salema et al. (2007)	x		x			x	Products demand and return quantities	General
Listes (2007)	x		x		x		Demand at the markets and product returns	Electronic equipmen
Chouinard et al. (2008)	x		x			x	Recovery, processing, and demand volumes	Medical (wheelchair)
Lee and Dong (2008)	x		x		x		Products demand and return quantities	General
Kara and Onut (2010)	x		x		x		Product demand, quantity, and quality of returns	Paper recycling
El-Sayed et al. (2010)		x		x	x		Demand, returns, and quality of the product	General
Baptista et al. (2012)	x			x		x	Demand and returns of the customers	Glass industry
Zeballos et al. (2012)	x			x		x	Quantity and quality of the returned products	Glass industry
Sazvar et al. (2013)	x			x	x		The uncertain demand for the products	Pharmaceutical secto
Ramezani et al. (2013)	x		x			x	Production costs, operating costs, collection costs, disposal costs, demands, and return rates	General
Soleimani and Govindan (2014)	x			x		x	Products demand and pricing	General
Roghanian et al. (2014)		x	x			x	The demand for products and parts of manufacturing and recycling centers	General
Zeballos et al. (2014)		x		x		x	Products supply and demand quantities	General
Ayvaz et al. (2015)	x				x	x	Products returned quantity, sorting ratio, and transportation costs	Electric & electronic equipment
Jeihoonian et al. (2016a)		x	x		x		Quality of the returned flows	Durable products
Jeihoonian et al. (2016b)	x		x			x	Uncertain return quantities	Durable products
Fattahi and Govindan (2016)	x			x		x	Products demand and returns	General

3.3 Model description

In the following section, we will present the mathematical formulation including the notations such as the sets, parameters, objective function as well as the constraints of the model. Let T be the set of periods and S be the set of dynamic supply sources of the model. Thus, we consider a binary matrix φ_{st}, with values equal to 1 if supply source $s \in S$ is visited during the period $t \in T$, and 0 if not. We assume that each collection point is available only once (the materials are collected in one single period) during the planning horizon. In this study, the locations $[(x_1, y_1), \dots, (x_s, y_s)]$ of the supply sources are randomly generated, and we apply the following steps to build the matrix φ_{st}:

- **Step 1**: We generate random coordinates (x_s, y_s) in the Euclidian plan for each of the supply sources.

- **Step 2**: For each collection point generated in step 1, we generate a random value between 0 and 1 and assign these values to the supply sources. All supply sources with a value between 0 and 0.2 are collected in period 1, those between 0.2 and 0.4 are collected in period 2, and so on until period 5 for the values between 0.8 and 1.

- **Step 3**: Based on step 2, we build the binary matrix φ_{st}. Therefore, each supply source is operating only once in the planning horizon.

Figure 3.1 illustrates the methodological steps for random generation of the dynamic supply sources with an illustrative example using 50 collection points and 5 periods. The materials collected from the supply sources are sorted, processed, and finally sold to the secondary markets. We assume that the demand for recycled materials is known and stationary over time. Indeed, before reaching the final markets, the materials must be shipped either to an existing or potential (to be open in predefined site) collection center $f \in F$. The processing facilities are responsible for materials sorting and recovery before being shipped to the markets. However, we consider that the quality of the materials collected at the suppliers is unpredictable and affects the recycling rates at the collection centers. Thus, this parameter (i.e., recycling rates at CC) is uncertain in the model formulation. In order to cope with the challenge of supply sources locations (SSL), we allow the opening of SSC on a set of predefined locations. These logistics units are used for source separation of mixed materials and trucks consolidation that allows shipping single-material containers (SMC) to the collection centers. If mixed-material containers (MMC) are sent to SSC before reaching the CCs, then we assume that we can achieve better recycling rates. Thus, by introducing the SSC, we consider that a correlation exists between the source separation of the collected materials at the SSC and the achievable recycling rates at collection centers. This reasoning is based on the following facts. First, we assume that source separation of the materials will avoid poor mix and limit the degradation of the materials' quality sent to the CC. Secondly, we suppose that the operations at CCs are more efficient with the treatment of SMC rather than with MMC (Quebec building material recyclers, personal communication, 2016).

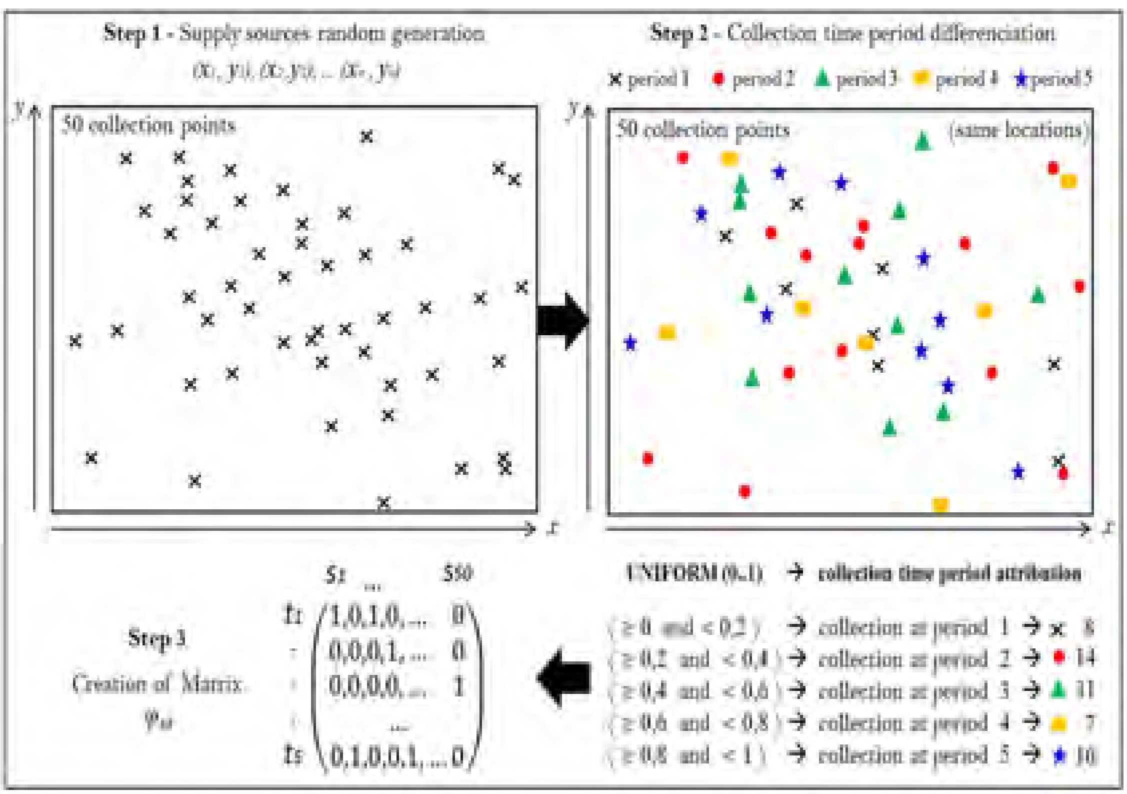

Figure 3.1 Methodology for SSL random generation (example with S=50 and T=5)

Thus, let's consider r_{mtu} and $\tilde{r}_{mtu}$ the recycling rates we can achieve at the collection centers in case the materials are shipped directly from the supply sources (dealing with MMC) or if they have been processed at the source separation centers (thus dealing with SMC) respectively. Both uncertainties on the recycling rates (i.e. r_{mtu} and $\tilde{r}_{mtu}$) are randomly generated in each scenario and follow uniform distributions such as $r_{mtu} \in [\alpha\,;\beta]$ and $\tilde{r}_{mtu} \in [\tilde{\alpha}\,;\tilde{\beta}]$ with $\alpha < \tilde{\alpha}$ and $\beta < \tilde{\beta}$. Also, in addition to the quality of the materials received at the collection centers, we assume that uncertainty has an impact on the volume collected from the supply sources. We denote v_{mstu} the volume of each material $m \in M$ collected at the supply source $s \in S$ during each period $t \in T$ in the scenario $u \in U$. We assume that v_mstu is normally distributed such as $v_{mstu} \sim N\ (\mu\,, \sigma^2)$. The proposed reverse logistics network structure is illustrated in figure 3.2.

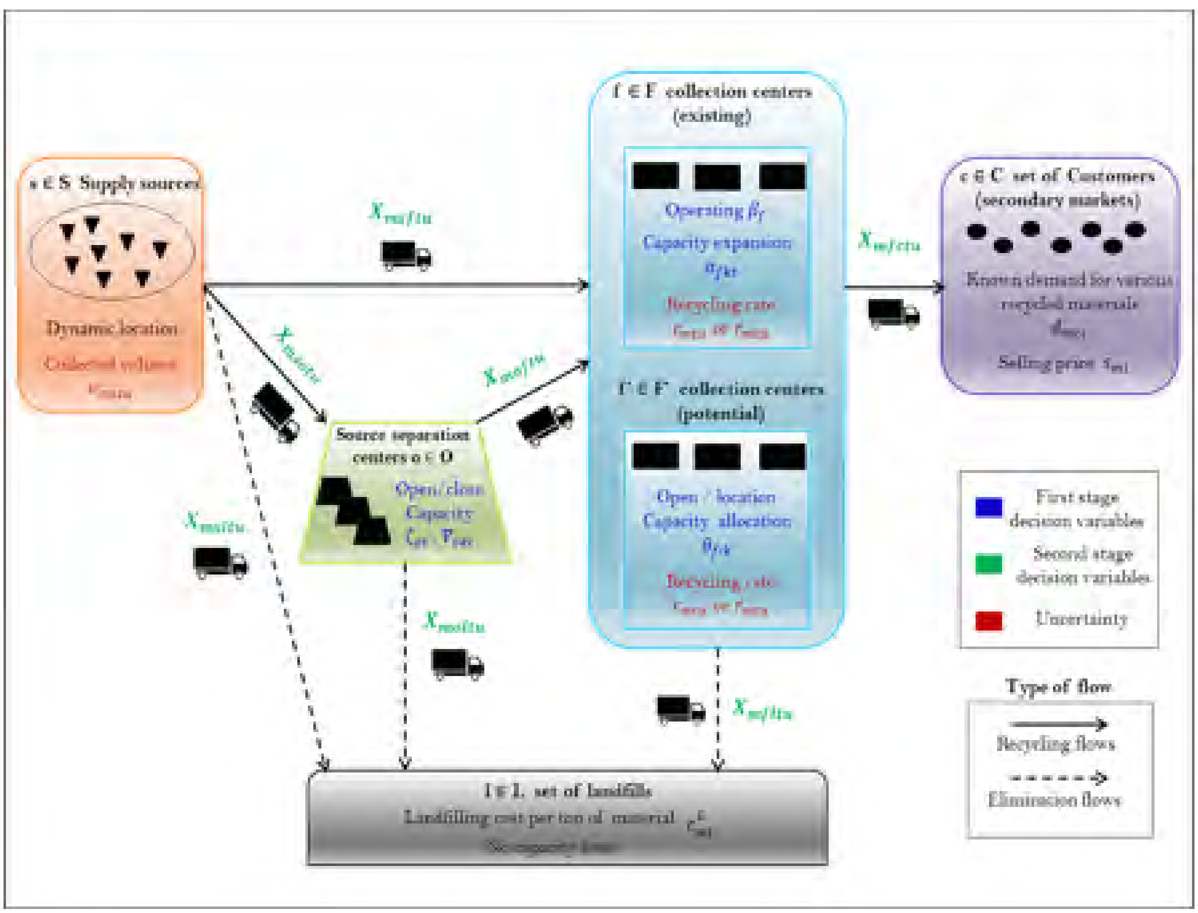

Figure 3.2 A Generic framework for RLND under dynamic suppliers' locations

3.3.1 Model notations

Sets

$i, j \quad \in N$ Nodes of the network

$s \in S \quad \subset N$ Set of supply sources

$o \in O \quad \subset N$ Set of potential source separation centers

$k \in K^O$ Set of potential source separation centers capacities

$f \in F = F^E + F^P$ Set of collection centers

$F^E \subset F$ Set of existing collection centers

$F^P \subset F$ Set of potential collection centers

$k \in K^E$ Set of additional capacities for collection centers expansions

$k \in K^P$ Set of opening collection centers capacities

$l \in L \quad \subset N$ Set of landfilling areas

$c \in C \quad \subset N$ Set of customers

$z \in Z$ Available truck sizes (small and large)

$m \in M$ Set of collected materials

$t \in T$ Set of time periods

$u \in U$ Set of scenarios

Parameters

$p_u =$ Probability of scenario $u \in U$

$t_{ij} =$ Transportation cost for shipping one metric ton of materials between origin node $i \in N$ and destination node $j \in N$

$\xi_{ij} =$ Transportation distances between origin node $i \in N$ and destination node $j \in N$

$\omega_z =$ Loading capacity of a truck with a size $z \in Z$

$d_{mct} =$ Demand for material $m \in M$ at customer $c \in C$ at period $t \in T$

$d_{mt} =$ Selling price of one unit (1 metric ton) of material $m \in M$ at period $t \in T$

g_{ft} = Annual processing capacity at collection center $f \in F$ at period $t \in T$

h_{fk}^{E} = Additional capacity if collection center $f \in F^{E}$ is expanding to capacity $k \in K^{E}$

h_{fk}^{P} = Available capacity in case of new collection center $f \in F^{P}$ is open with a size $k \in K^{P}$

h_{okt}^{O} = Available capacity in case of source separation center $o \in O$ is open with a size $k \in K^{O}$ at period $t \in T$

ψ = Minimum filling rate at a source separation center in order to keep it open

r^{min} = Minimum mandatory recycling rate to achieve (recyclers' service level)

c_{mt}^{L} = Landfilling cost of one ton of material $m \in M$ at a landfilling area at period $t \in T$

c_{mt}^{R} = Recycling cost of one ton of mixed material $m \in M$ at the collection center at period $t \in T$

$\tilde{c}_{mt}^{R}$ = Recycling cost of one ton of single material $m \in M$ at the collection center at period $t \in T$

Ω_{f} = Fixed operating cost for an existing collection center $f \in F$ during the planning horizon

δ_{fk} = Expansion cost of existing collection center $f \in F^{E}$ to size $k \in K^{E}$

π_{fk} = Opening cost for potential collection center $f \in F^{P}$ of size $k \in K^{P}$

σ_{ok} = Fixed setting cost for source separation center $o \in O$ of size $k \in K^{O}$

λ_{ot} = Variable unit operating cost for source separation center $o \in O$ at period $t \in T$

η_{ot} = Closing cost for source separation center $o \in O$ at period $t \in T$

$$\varphi_{st} = \begin{cases} 1 & \text{if supply source } s \in S \text{ is operating at period } t \in T \\ 0 & \text{if not} \end{cases}$$

Uncertain parameters

r_{mtu} = Recycling rate at the collection center for material type $m \in M$ at period $t \in T$ in scenario $u \in U$ without source separation

$\tilde{r}_{mtu}$ = Recycling rate at the collection center for material type $m \in M$ at period $t \in T$ in scenario $u \in U$ with source separation

v_{mstu} = Supply capacity of material $m \in M$ collected at supply source $s \in S$ at period $t \in T$ in scenario $u \in U$

Decision variables

First stage variables

$$\beta_f = \begin{cases} 1 & \text{if sorting center } f \in F \text{ is operating during the planning horizon} \\ 0 & \text{if not} \end{cases}$$

$$\alpha_{fkt} = \begin{cases} 1 & \text{if CC } f \in F^E \text{ should be expanded to size } k \in K^E \text{ at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$\theta_{fk} = \begin{cases} 1 & \text{if a new collection center } f \in F^P \text{ of size } k \in K^P \text{ should be opened} \\ 0 & \text{if not} \end{cases}$$

$$\nabla_{okt} = \begin{cases} 1 & \text{if a SSC } o \in O \text{ of size } k \in K^O \text{ should be opened at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$\zeta_{ot} = \begin{cases} 1 & \text{if a source separation centers o} \in \text{O should be closed at period t} \in \text{T} \\ 0 & \text{if not} \end{cases}$$

Second stage variables

X_{mijtu} =Flow of material type $m \in M$ transported from origin node $i \epsilon N$ to destination node $j \in J$ at period $t \in T$ in scenario $u \in U$

N_{stu} =Number of required trucks to perform collection activities on supply site $s \in S$ at period $t \in T$ in scenario $u \in U$

N_{otu} = Number of required trucks to perform consolidation activities at source-separation centers $o \in O$ at period $t \in T$ in scenario $u \in U$

3.3.2 Objective function – Maximizing the profits

$$
\begin{aligned}
Z = \sum_{u \in U} p_u \left[\sum_{m \in M} \sum_{c \in C} \sum_{t \in T} \sum_{f \in F^E \cup F^P} d_{mt} \, X_{mfctu} \right] - \sum_{f \in F^E \cup F^P} \Omega_f \sum_{k \in K^E \cup K^P} \left(\sum_{t \in T} \delta_{fk} \alpha_{fkt} + \pi_{fk} \theta_{fk} \right) \\
- \sum_{o \in O} \sum_{t \in T} \sum_{k \in K^O} (\sigma_{ok} \nabla_{okt} + \eta_{ot} \, \zeta_{ot}) \\
- \sum_{u \in U} p_u \left[\sum_{m \in M} \sum_{t \in T} c^R_{mt} \left(\sum_{f \in F^E \cup F^P} \sum_{s \in S} X_{msftu} \right) \right. \\
+ \sum_{m \in M} \sum_{t \in T} \tilde{c}^R_{mt} \left(\sum_{f \in F^E \cup F^P} \sum_{o \in O} X_{moftu} \right) \\
+ \sum_{m \in M} \sum_{t \in T} c^L_{mt} \sum_{l \in L} \left(\sum_{s \in S} X_{msltu} + \sum_{f \in F^E \cup F^P} X_{mfltu} + \sum_{o \in O} X_{moltu} \right) \\
\left. + \sum_{o \in O} \sum_{t \in T} \lambda_{ot} \sum_{m \in M} \sum_{s \in S} X_{msotu} + \sum_{i \in I} \sum_{j \in J} t_{ij} \, \xi_{ij} \sum_{m \in M} \sum_{t \in T} X_{mijtu} \right]
\end{aligned} \quad (3.1)
$$

The first part of the objective function represents the expected profit made by selling the recycled materials to the secondary markets. The second part involves the first stage decision variables of the model, related to existing and potential collection center opening and operating decisions. Finally, the last part of the objective function represents the expected costs related to :1) the recycling activities at collection centers depending on the container type (i.e. mixed versus single materials), 2) the landfilling costs of the remaining materials, 3) the opening, operating and closing costs of the source separation centers and lastly 4) the expected transportation costs over the entire planning horizon. The goal is to maximize the expected value generated by selling the recycled materials to the secondary markets while considering the recycling rates at collection centers and the quantity of collected materials at supply sources as uncertain parameters. The next part of this section further details the constraints of this two-stage stochastic model.

3.3.3 Constraints of the model

Demand satisfaction

$$r^{min}\, d_{mct} \leq \sum_{f \in F^E \cup F^P} X_{mfctu} \leq d_{mct} \qquad \forall m \in M, \forall c \in C, \forall t \in T, \forall u \in U \qquad (3.2)$$

Flow conservation at the supply sources

$$v_{mstu} \cdot \varphi_{st} = \sum_{f \in F^E \cup F^P} X_{msftu} + \sum_{l \in L} X_{msltu} + \sum_{o \in O} X_{msotu} \qquad \forall m \in M, \forall s \in S, \forall t \in T, \forall u \in U \qquad (3.3)$$

Flow conservation at collection centers

$$\sum_{s \in S} X_{msftu} + \sum_{o \in O} X_{moftu} = \sum_{c \in C} X_{mfctu} + \sum_{l \in L} X_{mfltu} \qquad \forall m \in M, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \qquad (3.4)$$

Flow conservation at potential source separation centers

$$\sum_{s\in S} X_{msotu} = \sum_{f\in F^E \cup F^P} X_{moftu} + \sum_{l\in L} X_{moltu} \quad \forall m \in M, \forall o \in O, \forall t \in T, \forall u \in U \tag{3.5}$$

Achievable recycling rates at collection centers without source-separation

$$\left(\sum_{s\in S} X_{msftu}\right) r_{mtu} \geq \sum_{c\in C} X_{mfctu} \quad \forall m \in M, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \tag{3.6}$$

Achievable recycling rates at collection centers with source separation

$$\left(\sum_{o\in O} X_{moftu}\right) \tilde{r}_{mtu} \geq \sum_{c\in C} X_{mfctu} \quad \forall m \in M, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \tag{3.7}$$

Treatment capacity at the existing collection centers

$$\sum_{m\in M}\sum_{s\in S} X_{msftu} + \sum_{m\in M}\sum_{o\in O} X_{moftu} \leq g_{ft}\,\beta_f + h^E_{fk}\,\alpha_{fkt} \qquad \forall k \in K^E, \forall f \in F^E, \forall t \in T, \forall u \in U \tag{3.8}$$

Treatment capacity at potential collection centers

$$\sum_{m\in M}\sum_{s\in S} X_{msftu} + \sum_{m\in M}\sum_{o\in O} X_{moftu} \leq h^P_{fk}\,\theta_{fk} \quad \forall k \in K^P, \forall f \in F^P, \forall t \in T, \forall u \in U \tag{3.9}$$

Treatment capacity at potential source separation centers

$$\sum_{m\in M}\sum_{s\in S} X_{msotu} \leq h^O_{okt}\,\nabla_{okt} \qquad \forall k \in K^O, \forall o \in O, \forall t \in T, \forall u \in U \tag{3.10}$$

Throughput flow at potential source separation centers (minimum filling rate)

$$(h^O_{okt}\,\psi)\nabla_{okt} \leq \sum_{m\in M}\sum_{s\in S} X_{msotu} \leq h^O_{okt}\,\nabla_{okt} \quad \forall o \in O, \forall k \in K^O, \forall t \in T \tag{3.11}$$

Source separation centers opening and closing constraints

$$\zeta_{ot} + \sum_{k \in K^O} \nabla_{okt} \le 1 \qquad \forall o \in O \;, \forall t \in T \tag{3.12}$$

Collection centers expansions are limited to 1 per facility

$$\sum_{k \in K} \sum_{t \in T} \alpha_{fkt} \le 1 \qquad , \forall f \in F \tag{3.13}$$

Trucks loading capacity at supply sources

$$\sum_{m \in M} v_{mstu} \le \sum_{z \in Z} \omega_z \; N_{stu} \quad \forall s \in S, \forall t \in T, \forall u \in U \tag{3.14}$$

Trucks loading capacity at source separation centers

$$\sum_{m \in M} \sum_{s \in S} X_{msotu} \le \sum_{z \in Z} \omega_z \; N_{otu} \quad \forall o \in O, \forall t \in T, \forall u \in U \tag{3.15}$$

Integer and binary constraints

$$X_{mijtu} \in \mathbb{R}^+ \text{ Where } \mathbb{R}^+ = \{x \in \mathbb{R}, x \ge 0\}, \quad \forall m \in M, \forall i \epsilon I, \forall j \epsilon J, \forall t \in T, \forall u \in U \tag{3.16}$$

$$N_{stu}, N_{otu} \in \mathbb{N}\,, \quad \forall m \in M, \forall i \epsilon I, \forall j \epsilon J, \forall t \in T, \forall u \in U \tag{3.17}$$

$$\beta_f,\; \alpha_{fk}, \theta_{fk,}\; \varphi_{st}\;, \nabla_{okt}\;, \zeta_{ot} \;\; \in \{0,1\} \qquad \forall f \in F^E \cup F^P, \forall k \in K^E \cup K^P,$$

$$\forall o \epsilon O, \forall s \epsilon S, \forall t \epsilon T, \forall u \epsilon U \tag{3.18}$$

The first constraint (3.2) ensures that we ship the recycled materials from the collection centers to the secondary market only if this is profitable. Indeed, we have no obligation to fulfill the totality of the recyclers' demand. However, there is a minimum mandatory recycling rate that we need to meet for environmental reasons, mainly to avoid massive landfilling on the territory. The second constraint (3.3) regulates the flow of materials leaving the supply sources either by shipping them to an existing or a new CC, a SSC or a landfilling area. Constraints (3.4) and (3.5) ensure the incoming flows at CC are redirected either to secondary markets or landfills and that the incoming flow at SSC is shipped either to CC or landfills. Constraints (3.6) and (3.7) set the maximum recycling rates at both existing and potential CC per material for single and mixed containers. This constraint sets the recycling limitations due to quality issues of the materials. Constraints (3.8) to (3.10) are the CC, potential CC, and potential SSC capacity constraints. Constraint (3.11) sets the capacity of the SSC and the minimum utilization rates. Constraint (3.12) is related to the binary variables for opening and closing the SSC. Constraint (3.13) limits the number of expansions for the CC during the planning horizon. Constraints (3.14) and (3.15) establish the truck requirements to perform the collection activities at suppliers and consolidation at the SSC. Finally, (3.16) - (3.18) are the integer and binary constraints for the decision variables.

3.3.4 Solution procedure

As both the uncertain collected volume of materials and the recycling rates follow continuous distributions, we have to deal with a potentially very large number of outcomes in this problem. Thus, we perform a SAA procedure for solving it, a well-known method to consider a large number of scenarios (Kleywegt et al., 2002). The sampling average approximation (SAA) is a well-known approach to solve stochastic optimization problems. The efficiency of this methodology applied to supply chain network design has been proven by many researchers (Chouinard et al. 2008; Ayvaz et al. 2015). Using this technique based on Monte Carlo simulations, we aim to approximate the expected objective function of the stochastic problem by an SAA derived from a random sample. Afterward, we solve the problem repeatedly obtained with various samples to get statistical estimates of the optimality gaps (see appendix V). This sampling technique presents advantages such as good convergence and benefits regarding numerical implementation, but mainly it allows considering a higher number of scenarios than many resolution methods (Santoso et al. 2005).

The sampling average approximation procedure

Let us consider the following well-known compact two-stage stochastic formulation:

$$min\, f(y) = c^T y + \mathbb{E}\ [Q(y,\xi)] \tag{3.19}$$

Where vector c^Trepresents the supply chain network investment costs, $y \in \{0,1\}$ represents the binary variables for the facility settings, $\xi\ (q,d,s,M)$ is a random cost vector, and $Q(y,\xi)$ is the optimal value of the following problem:

$$min\, q^T x + h^T z \tag{3.20}$$

$$s.t.\ \ Nx = 0, \tag{3.21}$$

$$Dx + z \geq d, \tag{3.22}$$

$$Sx \leq s, \tag{3.23}$$

$$Rx \leq My, \tag{3.24}$$

$$x \in \mathbb{R}^+, \tag{3.25}$$

Vector q corresponds to the processing and transportation costs of the model and x to the flow in the network. The matrices N, D, and S are used to define the supply chain network classical flow conservation, demand and supply constraints respectively. Also, R is the matrix for the processing requirements at each node while M is the matrix setting the nodes capacities in the network. Note that any particular realization of random vector $\xi\ (q,d,s,M)$ is called a scenario of the uncertain parameters and that the probability distribution of ξ is supposed to be known. Typically, the vector y represents the network configuration decision (i.e. first stage variables). The cost element $h^T z$ and the variable z respectively in (3.20) and (3.22) represent the penalty incurred in the two-stage model. Depending on the nature of the stochastic formulation, the nature of the penalty costs is variable (for example, penalties due to lost sales, additional delays, re-allocation of resources and so on).

Thus, (3.19) - (3.25) is a typical compact two-stage formulation whose objective is to minimize the configuration investments $c^T y$ and the expectation of the future operating costs represented by $\mathbb{E}\,[Q(y,\xi)]$. As it is well established that $\mathbb{E}\,[Q(y,\xi)]$ is a convex non-linear function of y (Santoso et al. 2005), the problem presented in (3.19) is often difficult to solve, especially in case of continuous distribution of $Q(y,\xi)$. For this reason, the aim of the SAA methodology is helping with the evaluation of $\mathbb{E}\,[Q(y,\xi)]$ by generating *N* scenarios of a random vector $\xi^1,\dots,\xi^N$ in order to build an approximation of the following function:

$$N^{-1}\sum_{n=1}^{N} Q(y,\xi^n) \tag{3.26}$$

Thus, that means the problem: $min\, f(y) = c^T y + \mathbb{E}\,[Q(y,\xi)]$ described in (3.19) will, in fact, be approximated by the following one:

$$min_y\left\{\hat{f}_N(y) = c^T y + \frac{1}{N}\sum_{n=1}^{N} Q(y,\xi^n)\right\} \tag{3.27}$$

To reach this goal, we need to solve the problem (3.27) multiple times by generating independent samples. These are the main steps of the SAA procedure in practice:

Step 1. Generate *M* independent samples of size *N*: $(\xi_1^1,\dots,\xi_M^N)$, and solve the SAA problem in (3.27) for each sample generated. We use the notations v_N^m and $\hat{y}_N^m$ (with m = 1,...,*M*) for the optimal objective value and the optimal solution of this problem respectively.

Step 2. We compute**:**

$$\bar{v}_{N,M} = \frac{1}{M}\sum_{m=1}^{M} v_N^m \text{ and } \sigma^2_{\bar{v}_{N,M}} = \frac{1}{(M-1)M}\sum_{m=1}^{M}(v_N^m - \bar{v}_{N,M})^2 \tag{3.28}$$

As it is known that $E[\,v_N] \le v^*$, with $E[\,v_N]$ being the expected value of v_N and v^* being the optimal value of the problem (Norkin et al., 1998; Mak et al., 1999), then we have $E\left[\bar{v}_{N,M}\right] \le v^*$ which implies $\bar{v}_{N,M}$ is a lower bound (LB) for optimal value v^* with $\sigma^2_{\bar{v}_{N,M}}$ as an estimated variance.

Step 3. We select a feasible solution of the initial problem in (3.27) that we call $\bar{y}$, and we use it to obtain an estimation of the objective value $f(\bar{y})$ such as:

$$\widetilde{f_{N'}}(\bar{y}) = c^T\bar{y} + \frac{1}{N'}\sum_{n=1}^{N'} Q(\bar{y}, \xi^n) \tag{3.29}$$

Here, the randomly generated sample $\xi^1, \ldots, \xi^{N'}$ of size N' is independent of the initial sample that has been used to find the solution $\bar{y}$. Typically the SAA procedure suggests that $N' >> N$. It is well-known that $\bar{y}$ being a feasible solution to (3.27), then $f(\bar{y}) \geq \upsilon^*$ (Santoso et al. 2005). Thus, this time $\widetilde{f_{N'}}(\bar{y})$ represents an upper bound (UB) for the optimal solution υ^* and the sample variance can be estimated by:

$$\sigma_{N'}^2(\bar{y}) = \frac{1}{(N'-1)N'}\sum_{n=1}^{N'}\left(c^T\bar{y} + Q(\bar{y}, \xi^n) - \widetilde{f_{N'}}(\bar{y})\right)^2 \tag{3.30}$$

Later in appendix V, we provide lower and upper bounds confidence intervals. Thus, we have four values (2 for each bound) called the lower-lower bound (LLB), lower-upper bound (LUB), upper-lower bound (ULB) and finally, the upper-upper bound (UUB).

Step 4. Using steps 2 and 3, we can compute an estimate of the optimality gap (OG) of solution $\bar{y}$ using (3.28) and (3.29) such as:

$$OG_{N,M,N'}(\bar{y}) = \widetilde{f_{N'}}(\bar{y}) - \bar{\upsilon}_{N,M} \tag{3.31}$$

We estimate the variance of this gap by:

$$\sigma_{gap}^2 = \sigma_{N'}^2(\bar{y}) + \sigma_{\bar{\upsilon}_{N,M}}^2 \tag{3.32}$$

Finally, assuming that $z_\alpha = (1-\alpha)\Phi^{-1}$ represents the cumulative distribution of the standard normal distribution we calculate the confidence interval for the OG as follows:

$$\widetilde{f_{N'}}(\bar{y}) - \bar{\upsilon}_{N,M} + z_\alpha \sqrt{\sigma^2_{N'}(\bar{y}) + \sigma^2_{\bar{\upsilon}_{N,M}}} \tag{3.33}$$

In order to obtain a good quality solution, we repeat this procedure until the estimated OG is reasonable by increasing the sample size *N*. The next section will present the main findings of this research by applying the SAA to our two-stage stochastic model.

3.4 A case study in the construction, renovation and demolition (CRD) industry

In this section, we present an application of the proposed model for the design of the reverse logistics network in the CRD industry in the Canadian province of Quebec. This sector is known to be one of the biggest industrial waste generators and sometimes represent up to 40% of the total industrial waste of a country (General building contractor association, 2012). Moreover, the amount and the quality of the materials collected at the CRD sites are often highly uncertain, especially in the case of a demolition process where the materials usually incur significant damages (Jeffrey, 2011). In this sector, it is also challenging to obtain a precise estimation regarding the future location of the CRD sites (i.e., the supply sources). Indeed, if the construction and renovation projects can last several years at the same place, the same building, however, cannot be demolished twice, which implies changing locations for many waste collection sites from one year to another. These characteristics make the design of an efficient network a challenging task. If the reverse logistics network is designed to perform under a specific data set at period $t \in T$, it is likely that this same configuration is not as efficient under the new characteristics of the next time periods *(t+1, t+2 … t+n)*.

The elements mentioned above making the proposed model suitable for this application. Thus, we use our stochastic formulation to cope with uncertainty in this environment and provide the optimal RLND for recycling the materials from the CRD industry in Quebec, Canada. Indeed, this province currently faces some issues with the low landfilling costs that make this option too attractive compared to the recycling process. Thus, in order to avoid excessive landfilling on the territory, we aim to optimize waste management operations. The primary data used to conduct our experiments are summarized in Table 3.2.

Table 3.2 Main data used in the CRD industry case study

Number supply sources (*S*)	10,50,100,250	Average total supply (weight)	4 million tons
Number existing CC	8	Recycling rate (r_{mtu})	[45 % ; 75 %]
Number potential CC	5	Recycling rate ($\tilde{r}_{mtu}$)	[65 % ; 95 %]
Number of SSC	7	Container (weight)	20 tons, 40 tons
Number landfills	8	SSC filling rate (min)	$\Psi = 50$ %
Number of secondary markets	5	Number of batches	$M = 20$
Number of material types	3	Sample size	N = 10,30,60,90
Time Periods	5	Confidence interval	$\alpha = 95\%$

3.4.1 Reverse logistics network configuration under uncertainty

As shown in table 3.2, the number of supply sources (*S*) and the sample sizes (*N*) vary in our experiments. Indeed, we will see that given the combination (*S, N*) of the scenario, the optimal RLND can change significantly, and so does the overall reverse logistics network performance. A small number of supply sources with a large volume of collected materials is usually the case of rural areas or countryside with the low density of construction sites. However, in the urban area with high population density and infrastructure, the number of CRD sites is higher than in the rural zones but the waste generated at each site is also relatively smaller. Thus, while the experiments with 10 and 50 supply sources reflect the behavior of low-density rural areas, the instances with 100 and 250 supply sources, however, represent higher-density urban zones. For the case study in Quebec Province, the comparison between these two configurations is of particular interest due to the unequally populated regions, going from 0.1 in the North of Quebec, up to 5500 inhabitants per square kilometer in a dense city like Montreal (statistical institute of Quebec, 2014).

The main results obtained for each combination (*S, N*) are summarized in Table 3.3. The preliminary analyses show that both the number of collection points and the sample size of the problem are critical parameters. Indeed, in low-density rural areas with a few collection points and a large amount of materials per site, we manage to obtain a higher expected profit by using and expanding some of the existing CC, and also by opening strategically two (2) new CC in locations that minimize the distances for the collection activities. Moreover, we notice that the scenarios with a low number of supply sources are those with the lowest SSC utilization rates (<40%). However, when the number of CRD sites is increasing to 100 or 250 collection points, the average utilization rate of the SSC increases up to 89% and 94% respectively. Indeed, the SSC are extensively used to cope with the high number of dynamic collection points that increase the average distance to move the recycled materials in urban areas (>20% distance increase). Therefore, it is more profitable to invest in new CC closer to the collection sites rather than expanding existing ones that are not appropriately located.

Table 3.3 Summary of the optimal RLND features according to (*S,N*) Variations

Supply sources	Sample size N	Existing collection centers (CC)		Potential CC	SSC	Secondary markets (recyclers)		Avg. FI	Avg. EP
		Operating	Expansions	Opening	usage rate	TRQM	Avg. TD		
10	10	7/8	3/8	2/5	34%	2,21 Mt	59,5 km	37.5 M$	59,1 M$
	30	6/8	3/8	2/5	37%	2,22 Mt			
	60	6/8	4/8	2/5	39%	2,25 Mt			
	90	6/8	4/8	2/5	39%	2,29 Mt			
50	10	5/8	3/8	3/5	55%	2,29 Mt	71,7 km	54.1 M$	37.9 M$
	30	6/8	4/8	4/5	60%	2,33 Mt			
	60	6/8	4/8	3/5	64%	2,38 Mt			
	90	6/8	5/8	4/5	66%	2,44 Mt			
100	10	4/8	4/8	4/5	78%	2,59 Mt	81,4 km	72.2 M$	28,7 M$
	30	5/8	5/8	4/5	82%	2,61 Mt			
	60	5/8	5/8	4/5	85%	2,78 Mt			
	90	5/8	5/8	5/5	85%	2,86 Mt			
250	10	4/8	4/8	4/5	73%	2,41 Mt	88,9 km	96.6 M$	22,8 M$
	30	4/8	4/8	4/5	81%	2,71 Mt			
	60	4/8	5/8	5/5	91%	2,89 Mt			
	90	5/8	5/8	5/5	94%	3,03 Mt			

S : Supply sources; N : Sample Size; TRQM: Total Recycled Quantity of Materials; Avg. TD: Average transportation distance for recycling; Avg. FI: Avg. Facilities Investments; Avg. EP: Average Expected Profit

In addition, we observe that depending on the number of supply sources considered, increasing the sample size does not lead to similar improvements. For example, the comparison between scenarios (S, N) = (10, 10) and (S, N) = (10, 90) shows very close results both in terms of RLND and supply chain performance. For instance, with 10 supply sources, a sample size of N = 10 is enough to obtain a valuable solution. However, the more we increase the number of supply sources, the more we observe significant variations in the RLN design and performance. From S=10 to S=250, we travel an average of almost 30 additional kilometers to recycle one ton of material. Besides, the initial facility investment is 2.5 times the initial value, which decreases the average expected profits significantly on the planning horizon, even though we manage to recycle more building materials from the CRD sites (+17% in average) and sell them on secondary markets. However, such investments would be easily justified by considering a longer planning horizon, thus helping meet waste management targets in the meantime. Finally, when comparing the instances with an identical number of CRD sites, increasing the sample size can yield some benefits, especially in large-sized problems. For example, if we consider 250 collection points, increasing the sample size from N=10 to N=90 allows recycling an additional 618,411 tons of building materials, while decreasing the average transportation distance from 7.7%. Indeed, with a sample size of N=90, the optimal RLND suggests 1 more CC opening, 1 more CC expansion and 1 more CC operating compared to the case N=10. Finally, by increasing the sample size and the number of CRD sites, the average utilization rate of the SSC also increases from 21% and 60% respectively.

3.4.2 Impact of the source-separation centers on the network design performance

<u>Source-separation centers operations: measuring the improvements</u>

In this section, we identified six (6) performance criteria that are impacted by the activation of the SSC in the RLND solution (see table 3.4).

Table 3.4 Criteria selected to conduct the sensitivity analysis

C_1	The recycled quantity of materials (Million tons, Mt)
C_2	The recycling cost per metric ton of material ($/ton)
C_3	The traveled distance to recycle one ton of material (km)
C_4	The total number of shipments required for RLN operations (units)
C_5	The proportion of SMC shipped to the collection centers (%)
C_6	The expected profit ($)

The analysis is performed for $(S,N) = (10,10)$ and $(S,N) = (250,90)$ and the main results are summarized in tables 3.5 and 3.6 respectively. First, we notice that the SSC solution improves waste management in both types of zones: high-density urban areas and low-density rural ones. Overall, we manage to increase the quantity of materials recycled through the RLN in both cases. However, this improvement is amplified in urban areas due to the high utilization rate of the SSC (94% against 34% in rural zones). Indeed, we achieve better average recycling rates at the CCs by shipping near 40% single material containers to these facilities, being significantly higher than the usual rate of SMC shipped to the CCs in urban zones in Quebec. Moreover, poor quality and damaged materials are shipped from the SSC to the closest landfill at an early stage of the recovery process, thus avoiding useless transportation of materials that the CCs would not be able to recover. In addition, trucks consolidation into SMC decreases the total number of shipments along with the overall distance traveled in the meantime. Overall, these results suggest that the flexibility offered by the SSC could be of great help in both rural and urban geographic areas, increasing the expected profits from 5.4% up to 17.6% respectively. The opportunity offered by the relocation of the SSC over time, the elimination of damaged materials with source separation and the treatment of an increased number of single material containers at the CCs are all key factors that improve the RLND performance in the case of dynamic supply sources. This is particularly true in the CRD industry where the demolition processes often induce a significant amount of damaged materials that need to be identified in the early stages of reverse logistics operations (Bernardo et al., 2016).

Table 3.5 Main improvements reached through the SSC operations (*S*=10; *N*=10)

SSC	C_1	C_2	C_3	C_4	C_5	C_6
No	2,03 Mt	86 $/ton	78,4 km	198 771 units	19%	55 091 660 $
Yes	2,21 Mt	91 $/ton	66,1 km	191 691 units	28%	58 055 911 $
Delta (Δ)	8,8%	5,8%	15,7%	3,6%	9%	5,4%

Table 3.6 Main improvements reached through the SSC operations (*S*=250; *N*=90)

SSC	C_1	C_2	C_3	C_4	C_5	C_6
No	1,92 Mt	99 $/ton	99,6 km	199 916 units	16,10%	22 105 662 $
Yes	2,49 Mt	115 $/ton	78,7 km	175 544 units	39%	26 834 016 $
Delta (Δ)	29,7%	16,1%	21%	12,2%	23%	17,6%

Sensitivity analysis on the level of uncertainty

In this section, we aim to analyze the network strategy including the SSC and see how it reacts to uncertainty. To do so, we will consider various uncertainty levels for the following parameters: the dynamic supply sources' locations (SSL), the collected volume at the CRD sites (CV), and the quality of collected materials (MQ). As synthesized in table 3.7, these parameters are attributed discrete realizations with the letters L, A, and H standing for *Low, Average* and *High* uncertainty levels respectively. The data selected for the average values are equal to those used in section 5.1 of this research and considered as a baseline scenario. Also, we assume that the standard deviation for the collected volume is such as $\sigma'^2 < \sigma^2 < \sigma''^2$. Using the information in table 3.7, we build a scenario-based approach in which we compare the results based on the same six (6) criteria already presented in Table 3.4. Note that, in each scenario, a single parameter (SSL, CV or MQ) varies and the other two remain stable at their average value. Also, each scenario is duplicated and evaluated twice: the first time without the use of the SSC (graphs (a)) and then allowing the source-separation strategy (graphs (b)). The primary goal of this experimental design is to evaluate the impact of different uncertainty levels in both cases (without and with SSC). The results are shown in figures 3.3 to 3.8 below, one figure assessing a unique criterion from table 3.4 (C_1 to C_6).

Table 3.7 Scenario generation for the variation in the level of uncertainty

Parameters	**Low (L)**	**Average (A)**	**High (H)**
Collected volume (CV)	$v_{mstu} \sim N'(\mu, \sigma'^2)$	$v_{mstu} \sim N(\mu, \sigma^2)$	$v_{mstu} \sim N''(\mu, \sigma''^2)$
Material quality (MQ) from the CRD sites U [α , β]	[65 % ; 75 %]	[45 % ; 75 %]	[25 % ; 75 %]
Material quality (MQ) from the SSC U [$\bar{\alpha}$, $\bar{\beta}$]	[85 % ; 95 %]	[65 % ; 95 %]	[45 % ; 95 %]
Dynamic supply sources locations (SSL)	$s^d \leqslant 50$	$50 < s^d \leqslant 150$	$150 < s^d$

Criterion C_1: The recycled quantity of materials

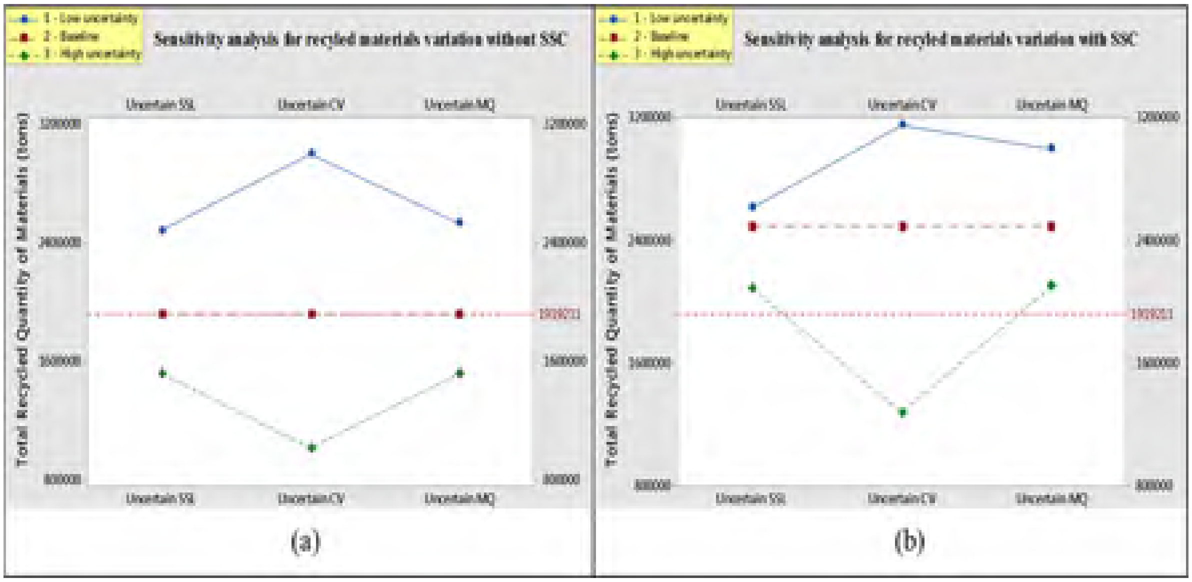

Figure 3.3 Impact of the uncertainties on the total recycled quantity of materials (C_1)

Overall, the uncertainty in the quantity of materials collected is the primary concern and has a direct impact on the total amount of material recycled. For both cases (with and without SCC), high uncertainty on material collected volume generate the lowest total recycled quantity. Indeed, facilities are fully exploited during some periods but underused during others. For the case without SCC, some adjustments are necessary to decrease the treatment capacity of the network. Using the SCC, the total amount of recycled materials is increased due to the flexibility to adjust the RL network capacity. On the other hand, low uncertainty of the collected volume guarantees high utilization rates of infrastructures and allows the RLND to be very efficient. In the case of highly uncertain scenarios targeting SSL and MQ, the impact on the total recycled quantity is moderated. Indeed, even under high uncertainty, thanks to the SSC we manage to obtain better results than in the case of average uncertainty level without SSC. Besides, it is clear that for the SCC strategy, and even with high uncertainty in SSL and MQ, we still manage to recycle more than the base case scenario. However, with high uncertainty in the collected volume, the recycled quantity is less than the baseline without the SCC. Finally, when comparing graphs (a) and (b), we denote that under low uncertainty for SSL and CV, the amount of materials recycled only slightly increases by using SSC. However, the source separation strategy provides better results for MQ.

Criterion C_2: The Recycling Cost per Metric Ton of Material

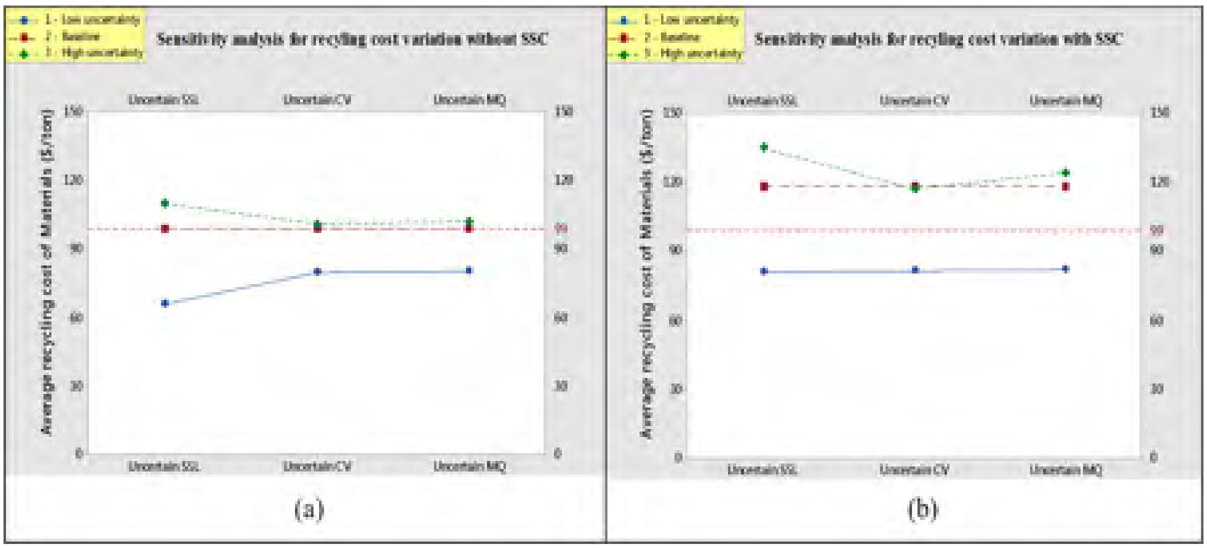

Figure 3.4 Impact of the uncertainty level on the recycling cost per ton (C_2)

The average recycling cost per ton of material, however, is increasing with the inclusion of the SSC. The main reason for this is the fact that operating such infrastructure implies additional expenses for setting, closing and relocating, source separation of the materials and trucks consolidation. Although transportation distances and shipments number are both decreasing, it is insufficient to avoid a slight cost increase of the overall recycling process. However, although we incur extra fees to operate the SSC, in the meantime, source separation offers the opportunity to make additional profit by providing more building materials to the final recyclers. The uncertainty related to the CV does not significantly impact the results and we observe the same behavior (see Figure 3.4 (a) and (b). However, the SSL causes some issues in the three uncertainty configurations (low, average and high). Also, we conclude that a high change in SSL leads to an extensive use of SSC and average recycling cost increase by 19.4% in the worst case scenario (high uncertainty in SSL with SSC strategy).

Criterion C_3: The traveled distance to recycle one ton of material

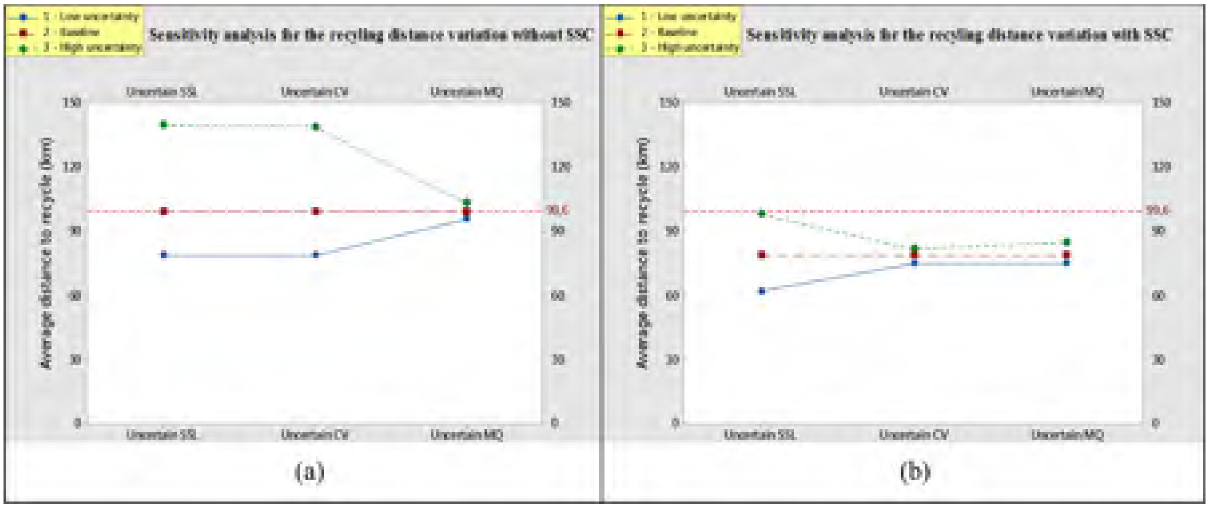

Figure 3.5 Impact of the uncertainty level on the distance to recycle (C_3)

This criterion shows one of the most significant improvements observed with the SSC strategy. This time, the MQ presents the same behavior in figure 3.5 (a) and (b) regardless of the uncertainty variations, with an average of 25.9% decrease in the distance traveled to recycle the materials. However, highly uncertain SSL or CV increase the average transportation distance when the SSC option is not active. Indeed, for both parameters, we expect an average of 139 km to recycle under high uncertainty, a value that could be decreased to 98 km and 82 km respectively under the SSC strategy. In the case of highly uncertain CV, shipments' consolidations at the SSC help to cope with the large range of incoming containers. Also, under high uncertainty of the supply sources locations, we observe the relocation of SSC closer to big CRD waste generators, being, in the meantime, at a short distance from the landfilling areas, which also decreases the average distance for building materials' elimination by landfilling.

Criterion C_4: The total number of shipments required for RLN operations

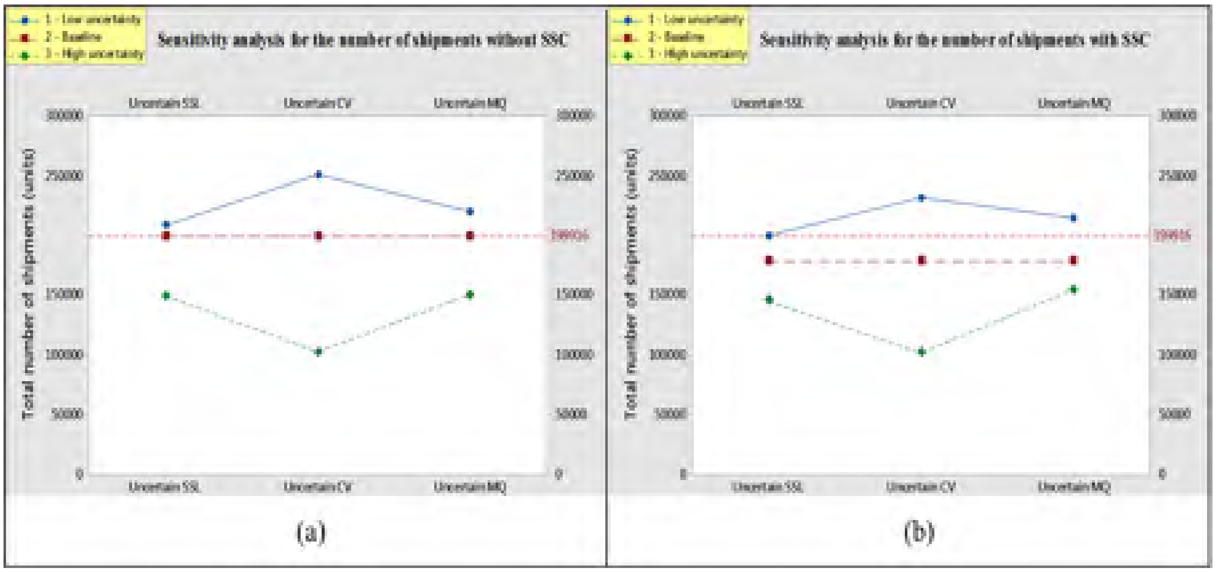

Figure 3.6 Impact of the uncertainty level on the total number of shipments (C_4)

As expected, figure 3.6 shows that the total number of shipments involved in the waste management activities through the reverse logistics network is impacted by the volume of materials collected at the CRD sites. Usually, having fewer shipments is perceived positively since the reduction in the transportation activities would reduce greenhouse gas emissions and avoid road congestion. However, in this particular case, the number of shipments can be very low because of the lack of materials available for collection and recycling. In the end, this situation leads to underused CCs and profit loss because of unfulfilled demand. However, uncertainty targeting SSL and MQ show slightly the same results, with an average decrease of 5.5% in the total number of shipments, going from 2.3% up to 11.7%. It is interesting to note that in the case of low uncertainty, there is almost no change in the number of shipments between both strategies in (a) and (b). Indeed, source separation reduces the number of shipments by the consolidation of MMC into SMC. Nevertheless, the adoption of source separation strategy increases the number of shipments between the CCs and the secondary markets due to the availability of more materials for recycling as shown in figure 3.3 (Criterion C_1).

Criterion C_5: The proportion of SMC shipped to the collection centers (%)

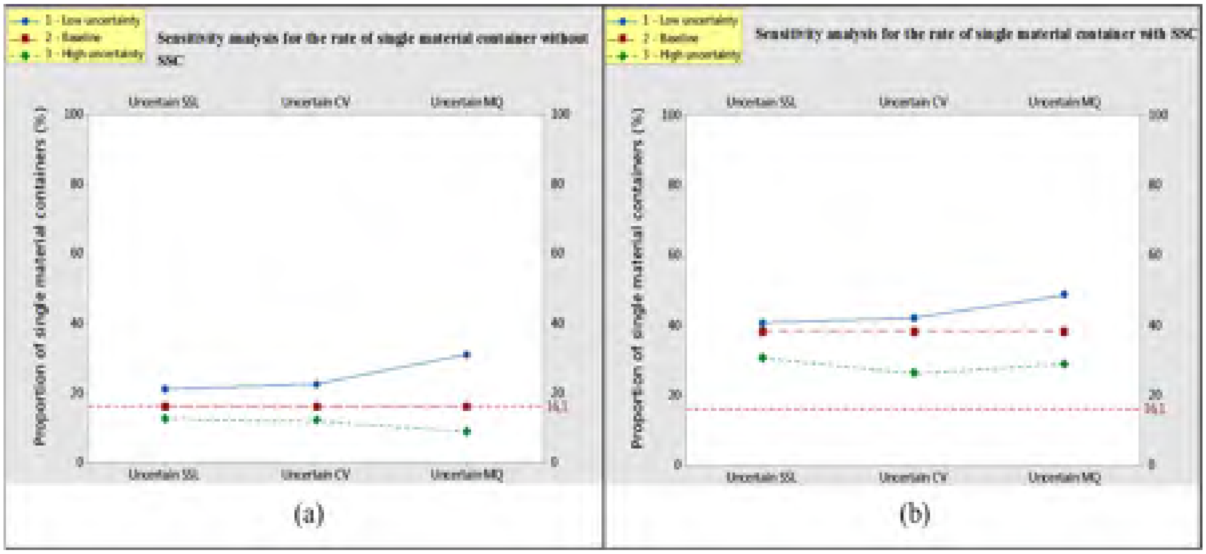

Figure 3.7 Impact of the uncertainty level on the proportion of SMC (C_5)

Processing mixed materials containers at collection centers is a challenging task if we compare with the single-material containers due to the different treatments necessary before getting material ready to ship to final users of recycled materials. This is a real concern in the CRD industry where a wide range of materials are mixed and involve some specific treatments to improve the quality of recycled materials. The SSC strategy helps in increasing the number of SMC performing source separation of the materials by eliminating many poor quality batches. Thus, figure 3.7 shows that an increase in the proportion of single material containers in the network is observed with SCC activation regardless of the level uncertainty considered in the parameters SSL, CV, and MQ. However, we notice that the main factor of influence is the quality level of the collected materials. Indeed, in the baseline scenarios, the proportion of SMC in the network reaches 39% with the SSC but only 16.1% without source separation. The most significant improvement occurs in the case of a highly uncertain MQ where the proportion of SMC is increased. Finally, the proportion of SMC is always better in the case of SCC activation compared to the strategy where SSC are not used and even for the high uncertainty in SSL, CV, and MQ.

Overall, the experiments highlight the value of flexibility achieved through the use of SSC and under the uncertain reverse logistics environment. Indeed, with a high level of uncertainty, flexibility can play an important role to perform efficient waste management for the CRD sector. Profit improvement is mainly due to the benefits provided by the source separation of the building materials at an early stage of the recycling process. Moreover, transportation activities are jointly optimized with the SSC adoption which offers the opportunity to have access to source separation in high-density urban zones, where the lack of available space sometimes compromises on-site sorting. However, previous analysis revealed that the potential improvements in reverse logistics operations due to the SSC adoption is limited in the following specific cases: 1) the collected volume of material is too low (under 60-65% utilization rate of the existing collection centers), 2) the recycling rate improvement achieved with source separation is below 8-12% (depending on the volume of materials collected), and 3) the average distance between the supply sources and the collection centers is very low (< 35 km). Although the SSC strategy is more efficient under highly uncertain scenarios, obviously we reach the highest expected profits when we face low uncertainty (see figure 3.8). In these cases, the accuracy of the information regarding SSL, CV, and MQ allows setting the best RLND, optimizing waste management operations. Ideally, to obtain the best profit, supply chain managers should try to put additional efforts for better estimation of SSL, CV, and MQ in order to avoid high variability of these parameters. For instance, in the CRD industry, the use of building information modeling (BIM) in the future can contribute to better quality data and parameters estimation during the early stages of the reverse logistics network configuration (Akinade et al. 2018).

Criterion C_6: The average expected profits

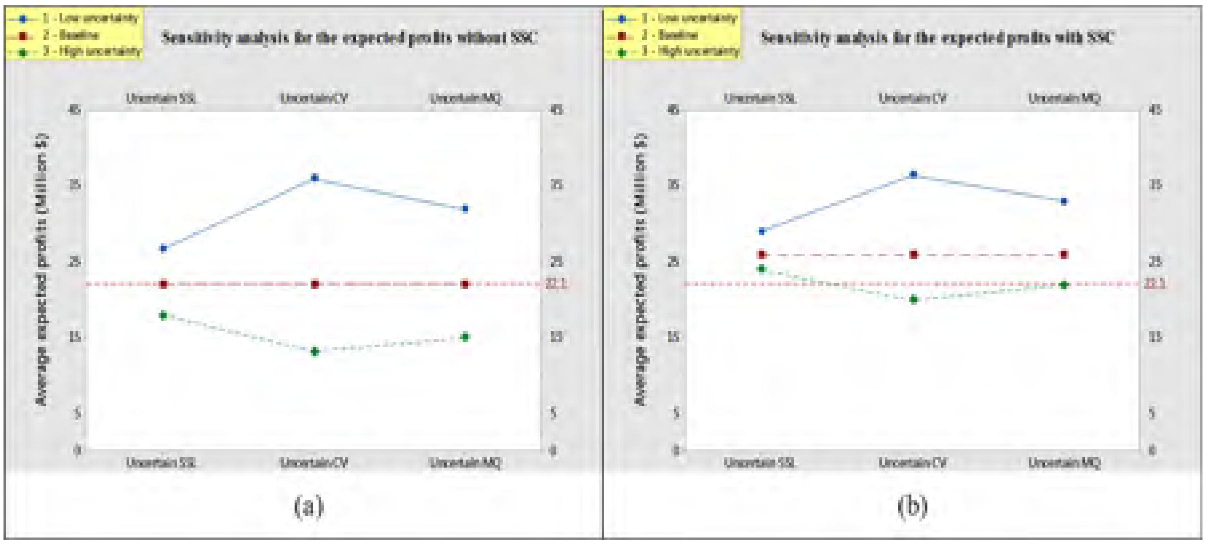

Figure 3.8 The impact of the uncertainty level on the average expected profits (C_6)

3.5 Conclusion and further research

In this article, we developed a two-stage stochastic model for reverse logistics network design under uncertainty. We proposed an application of our model through a case study in the CRD industry in the Canadian province of Quebec, being a sector where the efficiency of waste management activities is critical for sustainability purposes. We adopted a sampling average approximation procedure in order to deal with a high number of scenarios simultaneously. The main contribution of this work lies in the setting of the SSC to cope with the dynamic nature of the supply and the quality issues of the materials. Indeed, these characteristics are the major concerns for the design of an efficient RL network that optimize waste management operations, particularly in high-density urban zones where the collection and sorting operations can be quite challenging. We demonstrated that the SSC provide a potential solution to design a resilient network under various uncertainty levels, especially in case the parameters are highly uncertain. The CRD industry is an excellent example to illustrate the impact of dynamic supplies on waste management efficiency.

Although the two-stage stochastic approach proposed in this article provides good results, the quality of the solution could be improved by using a multi-stage stochastic approach that allows corrective actions at the beginning of each period. However, the SAA procedure showed its limitations as the computational running time can exceed 3 hours for the largest-sized problems (S = 250 and N = 90). If the number of supply sources exceeds 250, or if we increase the sample size significantly, exact resolution approaches could fail to solve complex formulations such as two-stage or multi-stage stochastic programming models. In this case, it may be necessary to develop new advanced resolution techniques such as decomposition or meta-heuristics in order to solve the problem faster.

Finally, this research is the first step toward sustainability by improving material waste management through the reverse logistics channel. Indeed, although the proposed model addresses an economic objective rather than discussing environmental impacts, it focuses on the efficiency of uncertainty management that ultimately leads to increasing the quantity and the quality of recycled materials while preventing the landfilling option. However, the environmental dimension related to the RLND is not quantified yet in this article. As it is a recurrent issue regarding waste management (Rahimi and Ghezavati 2018, Edalatpour et al. 2018), an eco-efficient stochastic model that takes into account both the profit and the environmental impact of RL activities will be the subject of future research directions.

CHAPTER 4

A CARBON-CONSTRAINED STOCHASTIC MODEL FOR ECO-EFFICIENT REVERSE LOGISTICS NETWORK DESIGN UNDER ENVIRONMENTAL REGULATIONS IN THE CRD INDUSTRY

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Abstract

This paper addresses a novel multi-period, multi-echelon and multi-objective two-stage stochastic model (MOTSM) under environmental constraints for eco-efficient reverse logistics network design (RLND). The goals of this optimization model are to maximize the expected profit and minimize landfilling activities to encourage the recycling of the materials. In comparison with the previous stochastic optimization models in this area, which mainly focus on the expected optimal value, this paper emphasizes the importance of source-separation of the materials under both landfilling and greenhouse gases emission (GHG) constraints. To address this challenge, our model includes source separation centers (SSC) that allow the separation of the collected materials and shipments consolidation at an early stage of the reverse logistics channel. The quantity of materials collected and the recycling rates at collection centers (CC) are uncertain due to quality issues. We solve this problem using a Sampling Average Approximation procedure (SAA) to deal with uncertainty, and we use the ε-constraint method to cope with multiple objective functions. An application of the model is illustrated through a case study of wood waste recycling from the construction, renovation and demolition (CRD) industry in the province of Quebec in Canada. This research reveals that the flexibility provided by the source-separation strategy allows reducing the impact of multiple uncertainties on the environmental performance of the network. The experiments highlight the necessity to carefully implement environmental

policies and demonstrate the complexity for the reverse logistics network to achieve both compliance and eco-efficiency in the meantime under an uncertain environment.

4.1 Introduction and context

The past century has seen the global market demand increase dramatically for a wide variety of products and services (Rajeev et al. 2017). This is partly the result of a population in constant growth and an industry in perpetual development around the world. Consequently, in the 21st century, natural resources consumption by mankind exceeds the earth capacity on a long-term horizon. Thus, there is indisputably the need to pay more attention to emerging critical matters such as energy use, technology efficiency, consumption of raw materials and waste management practices such as recycling, only to mention a few. Unsurprisingly, supply chains have a major role to play in this evolution toward more sustainable operations as they are huge polluters and resources consumers. To ensure the transition of the global industry toward sustainability, lately we witness the emergence of an increasing number of governmental programs targeting supply chains all over the world. Indeed, many sectors are impacted by these governmental regulations, among them, the electric and electronic equipments (Gu et al. 2016; Salhofer et al. 2017), the automotive (Wang et al. 2017), chemical industry (Wallbank et al. 2017), durable products (Huang et al. 2017), packagings (Arnaud, 2017) and finally in the case of this research, the construction, renovation and demolition (CRD) industry (Trochu et al. 2018). Compliance to these governmental legislations is one of the main reasons for the growing attention toward reverse logistics (RL) lately, and more specifically in the past decade if we refer to academic publications (Min and Kim, 2012; Govindan et al. 2015). Nowadays, it is commonly recognized that supply chains can make a difference by improving RL operations, beginning with the network design, being highly strategic decisions that affect the network performance on a long-term horizon.

As the CRD industry is considered to be one of the biggest industrial waste generators in many countries (General Building Contractor Association, annual report 2012), research efforts are required to help increasing the amount recycled materials from this sector when the elimination by landfilling is still overused (Kinobe et al. 2015). It is a real concern in the case of the wood material recycling in Canada, firstly because of the significant amount of wood used in the buildings (Yeheyis et al., 2013), but mainly because wood is a type of material with promising recovery opportunities (Sathre et al., 2014). Therefore, the CRD industry in the province of Quebec has been recently the target of both wood landfilling restrictions and GHG emissions control with a cap-and-trade system. The objective of the authorities is to prevent excessive wood landfilling on the territory and promote the recycling of the wood building materials. However, some uncertain factors such as the amount of wood collected from the CRD sites and the quality of the collected batches are major concerns that put the eco-efficiency of the recycling process at danger. Indeed, performing the recycling activities with low-quality wood (with paint, moisture, insect treatment and so on) in order to avoid landfilling systematically may be harmful to the environment. Thus, it appears some trade-offs are inevitable and the RL network must be designed to cope with uncertainty in order to make the best decisions.

An effective way to succeed in doing so is to develop innovative decision-making models that provide the practitioners with useful insights regarding RLND decisions. Although research progress have been made in the field of reverse logistics, there is still a gap toward modelling the characteristics of sensitive sectors being environmental burdens for the society (Brandenburg et al., 2014), such as the CRD industry. In addition, the inclusion of uncertainty in the modelling process is still scarce in the literature (Agrawal et al. 2015). Thus, in this article we develop an innovative advanced MOTSM for reverse logistics network design that captures some key challenging characteristics of the CRD industry, such as the unknown available amount of materials at the collection sites, the variable quality of the building wood material collected and the dynamic collection zones (i.e. CRD sites) that are moving from one location to another over time.

The goal of this new model formulation is to answer the following research questions:

- What is the optimal RLND for the recycled wood material in the CRD industry under uncertainty and environmental regulations?

- What is the impact of the source separation of the collected materials on the RLND performance and how does it serve eco-efficiency?

- How quality uncertainty does affect the network behavior under environmental regulations?

To the best of our knowledge, there is no advanced multi-objective stochastic formulation that captures the characteristics of the CRD industry for eco-efficient RLND purposes. Moreover, usually objective functions (OF) are profit or cost-oriented, however in this work we propose an innovative OF that minimizes landfilling flows to adapt to a new environmental regulation. This paper is structured as follows. Section 2 provides a theoretical background related to recent MOTSM applications. In section 3, we present the development and the formulation of the model. Section 4 synthesizes our experiments and main results regarding the recycled wood case study in the Canadian province of Quebec. Finally, conclusions and future research directions are derived in section 5. The reader is referred to chapter #3, section 3.3.4 (page 91) for detailed information regarding the SAA resolution procedure used to solve the MOTSM.

4.2 Literature review

Nowadays, sustainable supply chain management is a serious preoccupation for both practitioners and academics. In order to achieve sustainability, it is imperative for supply chains' operations to be performed in an eco-efficient way, being one of the fundamental pillars of sustainability (Elkington, 1998). Even though a lot of progress have been made developing RLND models during the last decades, very few of them address multiple objectives and uncertainty in the meantime (Agrawal et al. 2015; Govindan et al. 2015). Indeed, while the first quantitative models for RLND problems emerged in the 1990s (Fleischmann et al., 1997), more advanced formulations such as multi-objective stochastic models (MOSM) are still very recent. In this literature review, we will focus on the previous applications of MOSM in the field of reverse logistics network design.

Among the first research to propose such models, Amin and Zhang (2012) developed a MOSM to make strategic decisions regarding plants and collection centers' locations for product recovery and tactical decisions for the flows going through the network. The objective functions minimize the total network cost while maximizing the use of friendly materials and clean technologies at plants. In this work, two well-known approaches for solving multi-objective models are compared, namely the ε-constraint and the weighted-sums methods. The demand and return of the products in the reverse logistics channel are considered as uncertain parameters. The proposed example in the copier remanufacturing industry shows the superiority of the solutions obtained with the ε-constraint method. It also underlines the necessity of considering a higher number of scenarios for more conclusive results, which is one of the reasons why we chose a SAA resolution approach in this work.

Table 4.1 synthesizes the information on recent MOSM. In this table, we notice that the totality of the papers include uncertainty targeting the demand parameter. However, there is still few of them considering uncertainty related to the quality issues (Vahdani and Mohammadi, 2015; Azadeh et al., 2016) while it is an aspect that can impact the feasibility of the network design decisions (Trochu et al., 2018). In addition, although the large majority of the models present cost or profit-oriented objective functions, recently some authors felt the need to address different types of goals such as maximization of on-time delivery or waiting time minimization (Amin and Zhang, 2012; Vahdani and Mohammadi, 2015), maximization of the service level (Feito-Cespon et al., 2017), risk minimization (Zeballos et al., 2016), and recently the models start including environmental objective functions (Yuexin and Yunwei, 2017; Rahimi and Ghezavati, 2018; Fatollahi-Fard and Hajiaghaei-Keshteli, 2018).

Table 4.1 Main features of the previous multi-objective stochastic models for RLND

Authors (year)	**Horizon**	**Products**	**Uncertain parameters**	**Objectives**	**Case Study**
Amin and Zhang (2012)	SP	Multi	demand	Min costs - Min defect rates - Max on-time delivery	Computers
Amin and Zhang (2013)	SP	Multi	demand and returns	Min costs - Max clean technology use - Max use of friendly materials	Copiers
Ramezani et al. (2013)	SP	Multi	demand - selling price - cost of processing products	Max profits - Max responsiveness - Max quality	General
Ashfari et al. (2014)	MP	Multi	demand - recovery rates - warehouses capacity	Min transportation and inventory costs - Max customer satisfaction	Automotive
Subulan et al. (2015)	SP	Multi	demand - returns - disposal rates	Min costs - Max demand satisfaction	Acid Industry
Vahdani and Mohammadi	SP	Multi	demand - returns - recycling rates	Min costs - Min waiting times	General
Zeballos et al. (2016)	MP	Multi	supply and demand	Max profits - Min risks	General
Ameknassi et al. (2016)	MP	Multi	demand - facility capacities - transportation costs	Min costs - Min GHG emissions	Microwaves
Azadeh et al. (2016)	MP	Single	demand - parts' quality - transportation time	Min costs - Max products quality	General
Yuexin and Junwei (2017)	SP	Multi	demand - returns - sales price - POCD costs	Min costs - Min GHG emissions	General
Feito-Cespon et al. (2017)	SP	Multi	demand - rate of waste	Min costs - Max SEI - Max service level	Plastic recycling
Rahimi and Ghezavati (2018)	MP	Multi	demand - rate on investments	Max profits & social impact - Min environmental impact	CRD waste
Fathollahi-Fard and Hajiaghaei-Keshteli (2018)	SP	Single	demand - purchasing and manufacturing costs	Min costs and risks - Min environmental impact	General
Proposed model	*MP*	*Multi*	*Collected quantity & quality Recycling rates*	*Max profits and Min landfilling flows*	*CRD industry*

SP: Single Period; MP: Multi-Period.

Overall, in the field of RLND, very few advanced formulations address multiple objectives and uncertainty simultaneously (Agrawal et al. 2015). In addition, it has been noticed recently that there is a lack of quantitative modelling approaches targeting industries that represent an environmental burden for the society (Brandenburg et al., 2014). The CRD sector has been neglected until now although it is considered as one of the biggest waste generators in the industry, being responsible for nearly 40% of the global raw material extraction worldwide (Yeheyis et al. 2013). None of the proposed models in table 4.1 would fit the CRD industry characteristics, especially regarding the dynamic nature of the suppliers' locations. In addition, there is a need to address innovative objective functions in order to comply with emerging environmental regulations in this sector. Thus, the model developed in this article could provide useful insights to the CRD industry decision-makers to take a step toward an eco-efficient reverse logistics network design.

4.3 Model development

4.3.1 Proposed methodology

To address the gap highlighted in the literature review regarding the decision models, we develop in our work an advanced MOTSM based on a mixed-integer linear programming formulation. The behavior of the reverse logistics network we consider is detailed below.

Network structure

In the following, let S be the set of dynamic supply sources of the model. Here, the term "dynamic" means that we consider a set of time periods T and that the location of the material collection points are changing from one period t_n to the next one t_{n+1}. For this reason, we consider a binary matrix φ_{st}, which values are equal to 1 if supply source $s \in S$ is operating during the period $t \in T$, and 0 if not. We assume that each supply source is visited only once during the planning horizon (i.e. for each supply source, the totality of the materials are collected in a single period). The materials collected from the supply sources are shipped, sorted, processed, and finally sold to the recyclers which demand is assumed to be known and stationary over time. However, before reaching the recyclers, the materials go through a collection center $f \in F$ (an existing center $F^E \subset F$, or a potential one $F^P \subset F$ to be open in a predefined location). These processing facilities are responsible for the material sorting and recovery before shipping the containers to the recyclers. In this model, we consider two different container sizes: small for 20 tons and large for 40 tons capacity. As the large trucks often have difficulties reaching the urban supply sources, we use the 40 tons containers at the source separation centers (SSC) for shipments consolidation. The next section details the use of the SSC in our network.

Source Separation centers (SSC)

In this research, we consider that the quality level of the materials collected at the supply sources is uncertain and affects the recycling rates at the collection centers. Thus, we assume this parameter (i.e. recycling rates at collection centers) is uncertain in the current model formulation. In addition, in order to cope with the dynamic supplies, we allow the opening of SSC in a set of predefined locations. These logistics units are used for source-separation of the mixed materials and shipments consolidation that allow shipping single-material containers (SMC) to the collection centers. If a mixed-material container (MMC) is sent to a source separation center before reaching the CCs, then we assume that we achieve higher recycling rates. Thus, by introducing the SSC activities, we induce a correlation between the source-separation of the collected materials and the achievable recycling rates at the CCs. This reasoning is based on the following assumptions:

- Source-separation of the materials avoids poor mix and limits their quality degradation during the shipments

- The sorting operations at the CCs are more efficient with SMC than with MMC.

For these reasons, in the proposed experiments we consider r_{mqtu} and $\tilde{r}_{mqtu}$ respectively the recycling rates we can achieve at the collection centers in case the materials are shipped directly from the supply sources (dealing with MMC) or if they have been processed at the source separation centers (thus dealing with SMC). Both uncertain parameters on the recycling rates (r_{mqtu} and $\tilde{r}_{mqtu}$) are randomly generated in each scenario $u \in U$ and follow uniform distributions such as $r_{mqtu} \in [\alpha\,;\beta]$ and $\tilde{r}_{mqtu} \in [\tilde{\alpha}\,;\tilde{\beta}]$ with $\alpha < \tilde{\alpha}$ and $\beta < \tilde{\beta}$.

Finally, we assume that the quantities of materials collected from the supply sources at each time period along with their quality level repartition are also uncertain. We use a single uncertain parameter v_{mqstu} to denote the volume of material $m \in M$ of quality level $q \in Q$ collected at the supply source $s \in S$ during period $t \in T$ in scenario $u \in U$. We assume that v_{mqstu} is normally distributed such as $v_{mqstu} \sim N\ (\mu\ , \sigma^2)$.

Material recyclers

One of the contributions of our model is to consider the various emissions released during the different recycling processes. Indeed, in the proposed MOTSM, we consider a set of recycling activities $a \in A$ that can be performed with the recycled materials depending on their quality levels. We associate the emission factor e^R_{amq} for performing activity $a \in A$ with one metric ton of material $m \in M$ of quality level $q \in Q$ at the recyclers. This way, the same recycling activity performed with the same material type will release more carbon emissions if the recyclers receive low-level quality batches. As some recycling processes require specific quality standards, we consider the binary matrix V_{amq}, equal to 1 if activity $a \in A$ can be performed with material type $m \in M$ of quality level $q \in Q$, and 0 if not. With, the same reasoning, we use parameter d_{mqart} as the demand for material $m \in M$ of quality level $q \in Q$ to perform activity $a \in A$ at recycler $r \in R$ during period $t \in T$. In the model, we assume that the demand satisfaction is not a hard constraint and the materials reach the recyclers only in case it is profitable. The structure of the proposed reverse logistics network is depicted in figure 4.1 below.

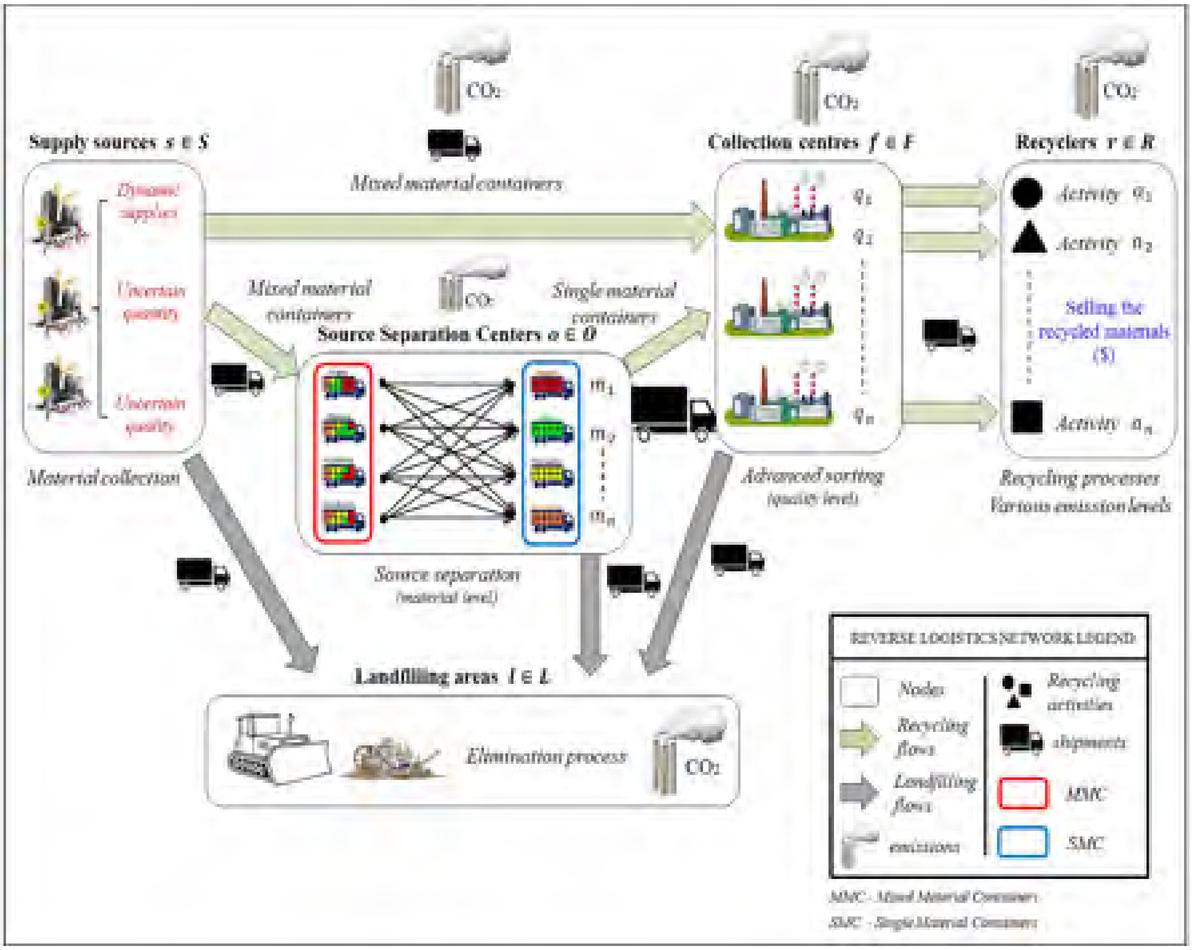


Figure 4.1 Reverse logistics network configuration in the CRD industry

4.3.2 Multi-objective stochastic formulation

This section describes the MOTSM notations. It provides insights regarding the economic and environmental parameters, the first-stage and second-stage decision variables, the objective functions and the constraints of the model, both economic and environmental.

SETS

$i, j \ldots n$	$\in N$	Nodes of the network
$s \in S$	$\subset N$	Set of supply sources
$o \in O$	$\subset N$	Set of potential source separation centers

$k \in K^O$ Set of potential sizes of source separation centers

$f \in F = F^E + F^P$ Set of collection centers

$F^E \subset F$ Set of existing collection centers

$F^P \subset F$ Set of potential collection centers

$k \in K^E$ Set of additional capacities for collection center expansions

$k \in K^P$ Set of opening collection center capacities

$l \in L \quad \subset N$ Set of landfilling areas

$r \in R \quad \subset N$ Set of material recyclers

$z \in Z$ Available truck sizes (small and large)

$m \in M$ Set of collected materials

$q \in Q$ Set of quality levels for the materials

$a \in A$ Set of activities performed with the recycled materials

$t \in T$ Set of time periods

$u \in U$ Set of scenarios

Parameters

- **Economic parameters**

Supply sources related parameters

$$\varphi_{st} = \begin{cases} 1 & \text{if supply source } s \in S \text{ is operating at period } t \in T \\ 0 & \text{if not} \end{cases}$$

Source Separation centers related parameters

σ_{ok} = Fixed setting cost for source separation center $o \in O$ of size $k \in K^O$

λ_{ot} = Variable unit operating cost for source separation center $o \in O$ at period $t \in T$

η_{ot} = Closing cost for separation center $o \in O$ at period $t \in T$

M = Minimum filling rate at a source separation center in order to maintain it open

h^O_{okt} = Available capacity in case source separation center $o \in O$ is opening with a size $k \in K^O$ at period $t \in T$

Collection centers related parameters

c^R_{mt} = Recycling cost of one ton of mixed material $m \in M$ at the collection center at period $t \in T$

$\tilde{c}^R_{mt}$ = Recycling cost of one ton of single material $m \in M$ at the collection center at period $t \in T$

Ω_f = Fixed operating cost for an existing collection center $f \in F$ during the planning horizon

δ_{fk} = Expansion cost of existing collection center $f \in F^E$ to size $k \in K^E$

Θ_{fk} = Closing cost of existing collection center $f \in F^E$ to size $k \in K^E$

π_{fk} = Opening cost for potential collection center $f \in F^P$ of size $k \in K^P$

g_{ft} = Annual processing capacity at collection center $f \in F$ at period $t \in T$

h^E_{fk} = Additional capacity if collection center $f \in F^E$ is expanding to capacity $k \in K^E$

h^P_{fk} = Available capacity in case new collection center $f \in F^P$ is opening with a size $k \in K^P$

Landfilling related parameters

c^L_{mt} = Landfilling cost of one ton of material $m \in M$ at a landfilling area at period $t \in T$

Recyclers related parameters

d_{mqart} = Demand for material $m \in M$ of quality level $q \in Q$ to perform activity $a \in A$ at recycler $r \in R$ during period $t \in T$

b_{mt} = Selling price of 1 metric ton of material $m \in M$ at period $t \in T$

$$\mathrm{V}_{amq} = \begin{cases} 1 & \text{if activity } a \in A \text{ can be performed with material } m \in M \text{ } of \text{ quality level } q \in Q \\ 0 & \text{if not} \end{cases}$$

Transportation related parameters

$t_{ij} =$ Transportation cost for shipping one metric ton of materials between origin node $i \in N$ and destination node $j \in N$

$\xi_{ij} =$ Transportation distances between origin node $i \in N$ and destination node $j \in N$

$\omega_z =$ Loading capacity of a truck with a size $z \in Z$

- **Environmental parameters**

Emission and landfilling limitations

E_t^{max} = Maximum emission quotas allocated by the government for period $t \in T$
L_{mt}^{max} = Maximum landfilling quantity of material $m \in M$ allowed for period $t \in T$
E_t^{tot} = Total amount of emissions released during period $t \in T$
cr_t^+ = Unit price of selling one emission credit in the cap-and-trade market
cr_t^- = Unit price of buying one emission credit in the cap-and-trade market

Transportation related emissions

ε_{zijt} = Emission per km for a shipment of materials with a truck of size $z \in Z$ between node $i \in N$ and node $j \in N$ at period $t \in T$ (tCO_2e)

We calculate $\varepsilon_z = e_z^{ET} + \left[(e_z^{FT} - e_z^{ET}).\left(\frac{\sum_{m\in M}\sum_{q\in Q} X_{mqijtu}}{\omega_z}\right)\right], \forall z\epsilon Z, \forall i\epsilon I, \forall j\epsilon J, \forall t \in T, \forall u \in U.$
With e_z^{ET} = Emission factor per km for an empty truck of size $z \in Z$ (tCO_2e)
and e_z^{FT} = Emission factor per km for a fully loaded truck of size $z \in Z$ (tCO_2e)

Collection and sorting related emissions

e_{it}^F = Fixed emissions released when using node $i \in N$ at period $t \in T$
e_{it}^V = Variable emissions released when processing 1 metric ton of material at node $i \in N$ at period $t \in T$

Recyclers' activities and landfilling related emissions

e^R_{amq} = Emission factor for performing activity $a \in A$ with one metric ton of material $m \in M$ of quality level $q \in Q$ at recyclers (tCO_2e)

e^L_m = Emission factor for landfilling one metric ton of material $m \in M$ (tCO2e)

- **Uncertain parameters**

p_u = Probability of scenario $u \in U$

r_{mqu} = Recycling rate at the collection centers for material type $m \in M$ of quality level $q \in Q$ in scenario $u \in U$ without source separation

$\tilde{r}_{mqu}$ = Recycling rate at the collection centers for material type $m \in M$ of quality level $q \in Q$ in scenario $u \in U$ with source separation

v_{mqstu} = Collected quantity of material $m \in M$ of quality level $q \in Q$ at supply source $s \in S$ at period $t \in T$ in scenario $u \in U$

- **First-stage decision variables**

$$\beta_f = \begin{cases} 1 & \text{if sorting center } f \in F \text{ is operating during the planning horizon} \\ 0 & \text{if not} \end{cases}$$

$$\alpha_{fkt} = \begin{cases} 1 & \text{if collection center } f \in F^E \text{ should be expanded to size } k \in K^E \text{ at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$\psi_{fkt} = \begin{cases} 1 & \text{if collection center } f \in F^E of \text{ size } k \in K^E \text{should be closed at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$\theta_{fk} = \begin{cases} 1 & \text{if a new collection center } f \in F^P \text{ of size } k \in K^P \text{ should be opened} \\ 0 & \text{if not} \end{cases}$$

$$\nabla_{okt} = \begin{cases} 1 & \text{if SSC } o \in O \text{ of size } k \in K^O \text{ should be opened at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$\zeta_{ot} = \begin{cases} 1 & \text{if SSC } o \in O \text{ should be closed at period } t \in T \\ 0 & \text{if not} \end{cases}$$

$$N_{it} = \begin{cases} 1 & \text{if a network node } i \in N \text{ is used at period } t \in T \\ 0 & \text{if not} \end{cases}$$

- **Second-stage decision variables**

X_{mqijtu} = Flow of material of type $m \in M$ of quality level $q \in Q$ transported from origin node $i \epsilon N$ to destination node $j \in J$ at period $t \in T$ in scenario $u \in U$

N_{stu} = Number of trucks required to perform collection activities on supply site $s \in S$ at period $t \in T$ in scenario $u \in U$

N_{otu} = Number of required trucks to perform consolidation activities at source separation center $o \in O$ at period $t \in T$ in scenario $u \in U$

EM^{+}_{tu} = Excess quantity of carbon credits sold at the end of period $t \in T$ in scenario $u \in U$

EM^{-}_{tu} = Deficit quantity of carbon credits that must be purchased at the end of period $t \in T$ in scenario $u \in U$

Economic objective (O_1)

The main objective of our multi-objective stochastic model is to maximize the profits made by selling the recycled materials to the secondary markets.

Revenues of the materials selling to the recyclers

$$REV^{MAT} = \sum_{m \in M} \sum_{q \in Q} \sum_{r \in R} \sum_{t \in T} \sum_{f \in F^E \cup F^P} b_{mt} \, X_{mqfrtu} \qquad \forall u \in U \tag{4.1}$$

- *Facility related costs (FRC): Opening + Closing + Expansions*

At collection centers (existing and potential)

$$FRC^{CC} = \sum_{f \in F^E \cup F^P} \Omega_f + \sum_{k \in K^E \cup K^P} \left(\sum_{t \in T} \delta_{fk} \alpha_{fkt} + \Theta_{fk} \psi_{fkt} + \pi_{fk} \theta_{fk} \right) \tag{4.2}$$

At the source separation centers

$$FRC^{CD} = \sum_{o \in O} \sum_{t \in T} \sum_{k \in K^O} (\sigma_{ok} \nabla_{okt} + \eta_{ot} \, \zeta_{ot}) \tag{4.3}$$

- *Sorting operation costs at existing and potential collection centers*

Without source separation (mixed material containers MMC)

$$SORT^{MMC} = \sum_{m \in M} \sum_{t \in T} c_{mt}^{R} \left(\sum_{q \in Q} \sum_{f \in F^E \cup F^P} \sum_{s \in S} X_{mqsftu} \right) \qquad \forall u \in U \tag{4.4}$$

With source separation (single material containers SMC)

$$SORT^{SMC} = \sum_{m\in M}\sum_{t\in T}\tilde{c}^{R}_{mt}\left(\sum_{q\in Q}\sum_{f\in F^E\cup F^P}\sum_{o\in O}X_{mqoftu}\right) \qquad \forall u\in U \tag{4.5}$$

Landfilling costs

$$LD = \sum_{m\in M}\sum_{t\in T}c^{L}_{mt}\sum_{q\in Q}\sum_{l\in L}\left(\sum_{s\in S}X_{mqsltu} + \sum_{f\in F^E\cup F^P}X_{mqfltu} + \sum_{o\in O}X_{mqoltu}\right) \quad \forall u\in U \tag{4.6}$$

Source Separation centers' operations

$$CR = \sum_{o\in O}\sum_{t\in T}\lambda_{ot}\sum_{m\in M}\sum_{q\in Q}\sum_{s\in S}X_{mqsotu} \qquad \forall u\in U \tag{4.7}$$

Transportation costs

$$TC = \sum_{i\in I}\sum_{j\in J}t_{ij}\,\xi_{ij}\sum_{q\in Q}\sum_{m\in M}\sum_{t\in T}X_{mqijtu} \qquad \forall u\in U \tag{4.8}$$

Carbon credits management costs

$$CC = \sum_{t\in T}cr^{-}_{t}EM^{-}_{tu} - \sum_{t\in T}cr^{+}_{t}EM^{+}_{tu} \qquad \forall u\in U \tag{4.9}$$

As the network decisions FRC^{CC} and FRC^{CD} include first-stage decisions variables, they are not scenario-dependant. The remaining costs are second-stage decision variables. Thus, the profit-maximizing function of the reverse logistics network can be written as follow:

$$\boldsymbol{Max\ O_1} = \sum_{u\in U}p_u(REV^{MAT}) - (FRC^{CC} + FRC^{CD})$$
$$-\sum_{u\in U}p_u(SORT^{MMC} + SORT^{SMC} + LD + CR + TC + CC) \tag{4.10}$$

To achieve eco-efficiency, we need to limit the emissions released by the RL network. To do so, we consider 4 major sources of emissions. First, we calculate the transportation emissions for the material shipments through the network. Then, we take into account the collection activities at the supply sources and the sorting operations at the SSC and the CC. In addition, one of the contributions of this model is to consider the emissions caused by the recycling processes we can perform according to the quality of the materials. Finally, we account for the landfilling emissions. For each scenario, we calculate the emissions as follow:

Transportation emissions

$$EM^{TR} = \sum_{i \in I} \sum_{j \in J} \xi_{ij} \sum_{z \in Z} \sum_{t \in T} \varepsilon_{zijt} \qquad \forall u \in U \qquad (4.11)$$

Collection and sorting emissions

$$EM^{CS} = \sum_{i \in I} \sum_{t \in T} e_{it}^{F} N_{it} + \sum_{i \in I} \sum_{t \in T} e_{it}^{V} \sum_{m \in M} \sum_{j \in J} \sum_{q \in Q} X_{mqijtu} \qquad \forall u \in U \qquad (4.12)$$

Emissions associated to recycling activities

$$EM^{RA} = \sum_{a \in A} \sum_{m \in M} \sum_{q \in Q} e_{amq}^{R} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} X_{mqijtu} \qquad \forall u \in U \qquad (4.13)$$

Landfilling emissions

$$EM^{LD} = \sum_{m \in M} e_{m}^{L} \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} X_{mqijtu} \qquad \forall u \in U \qquad (4.14)$$

In order to control the emissions of the reverse logistics network, we calculate the total emission level by: $E_t^{tot} = EM^{TR} + EM^{CS} + EM^{RA} + EM^{LD} \qquad \forall u \in U \qquad (4.15)$

There are two goals into minimizing the emissions of the network. First, it allows complying with the governmental GHG emission limitation. In addition, it represents an economic advantage regarding the cap-and-trade system for carbon credits.

Landfilling restriction objective (O_2)

The second concern in order to achieve eco-efficiency of the RL network is to minimize the landfilling flows. The latter are composed of the flows coming from the supply sources, the flows from the SSC after source-separation and finally the flows from the collection centers. For each scenario, the calculation of the landfilling flows is as follow:

Landfilling from the supply sources

$$LA^S = \sum_{m \in M} \sum_{q \in Q} \sum_{s \in S} \sum_{l \in L} \sum_{t \in T} X_{mqsltu} \qquad \forall u \in U \qquad (4.16)$$

Landfilling from the source separation centers

$$LA^O = \sum_{m \in M} \sum_{q \in Q} \sum_{o \in O} \sum_{l \in L} \sum_{t \in T} X_{mqoltu} \qquad \forall u \in U \qquad (4.17)$$

Landfilling from the collection centers

$$LA^F = \sum_{m \in M} \sum_{q \in Q} \sum_{f \in F^E \cup F^P} \sum_{l \in L} \sum_{t \in T} X_{mqfltu} \qquad \forall u \in U \qquad (4.18)$$

In order to minimize the landfilling flows of the reverse logistics network and over all the scenarios, we consider the second objective function:

$$\boldsymbol{Min\ O_2} = \sum_{u \in U} p_u \left(LA^S + LA^O + LA^F\right) \qquad (4.19)$$

Subject to the following constraints

Demand satisfaction

$$\sum_{f \in F^E \cup F^P} X_{mqfrtu} \leq \sum_{a \in A} d_{mqart} \, \mathrm{V}_{amq} \quad \forall m \in M, \forall q \in Q, \forall r \in R, \forall t \in T, \forall u \in U \quad (4.20)$$

Flow conservation at the supply sources

$$v_{mqstu} \cdot \varphi_{st} = \sum_{f \in F^E \cup F^P} X_{mqsftu} + \sum_{l \in L} X_{mqsltu} + \sum_{o \in O} X_{mqsotu}$$
$$\forall m \in M, \forall q \in Q, \forall s \in S, \forall t \in T, \forall u \in U \quad (4.21)$$

Flow conservation at collection centers

$$\sum_{s \in S} X_{mqsftu} + \sum_{o \in O} X_{mqoftu} = \sum_{r \in R} X_{mqfrtu} + \sum_{l \in L} X_{mqfltu}$$
$$\forall m \in M, \forall q \in Q, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \quad (4.22)$$

Flow conservation at potential source separation centers

$$\sum_{s \in S} X_{mqsotu} = \sum_{f \in F^E \cup F^P} X_{mqoftu} + \sum_{l \in L} X_{mqoltu}$$
$$\forall m \in M, \forall q \in Q, \forall o \in O, \forall t \in T, \forall u \in U \quad (4.23)$$

Achievable recycling rates at collection centers without source separation

$$\left(\sum_{s \in S} X_{mqsftu} \right) r_{mqu} \geq \sum_{r \in R} X_{mqfrtu} \quad \forall m \in M, \forall q \in Q, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \quad (4.24)$$

Achievable recycling rates at collection centers with source separation

$$\left(\sum_{o\in O} X_{mqoftu}\right)\tilde{r}_{mqu} \geq \sum_{r\in R} X_{mqfrtu}$$
$$\forall m \in M, \forall q \in Q, \forall f \in F^E \cup F^P, \forall t \in T, \forall u \in U \tag{4.25}$$

Treatment capacity at the existing collection centers

$$\sum_{m\in M}\sum_{q\in Q}\left(\sum_{s\in S} X_{mqsftu} + \sum_{o\in O} X_{mqoftu}\right) \leq g_{ft}\,\beta_f + h_{fk}^{E}\,\alpha_{fkt}$$
$$\forall k \in K^E, \forall f \in F^E, \forall t \in T, \forall u \in U \tag{4.26}$$

Treatment capacity at potential collection centers

$$\sum_{m\in M}\sum_{q\in Q}\left(\sum_{s\in S} X_{mqsftu} + \sum_{o\in O} X_{mqoftu}\right) \leq h_{fk}^{P}\,\theta_{fk}$$
$$\forall k \in K^P, \forall f \in F^P, \forall t \in T, \forall u \in U \tag{4.27}$$

Treatment capacity at potential source separation centers

$$\sum_{m\in M}\sum_{q\in Q}\sum_{s\in S} X_{mqsotu} \leq h_{okt}^{O}\,\nabla_{okt} \qquad \forall k \in K^O, \forall o \in O, \forall t \in T, \forall u \in U \tag{4.28}$$

Throughput flow at potential source separation centers (minimum filling rate)

$$(h_{okt}^{O}\,M)\nabla_{okt} \leq \sum_{m\in M}\sum_{q\in Q}\sum_{s\in S} X_{mqsotu} \leq h_{okt}^{O}\,\nabla_{okt} \qquad \forall o \in O, \forall k \in K^O, \forall t \in T \tag{4.29}$$

Source Separation centers' opening and closing constraints

$$\zeta_{ot} + \sum_{k \in K^O} \nabla_{okt} \leq 1 \qquad \forall o \in O \;, \forall t \in T \qquad (4.30)$$

Collection centers expansions are limited to 1 per facility

$$\sum_{k \in K} \sum_{t \in T} \alpha_{fkt} \leq 1, \qquad \forall f \in F \qquad (4.31)$$

Trucks loading capacity at supply sources

$$\sum_{m \in M} \sum_{q \in Q} v_{mqstu} \leq \sum_{z \in Z} \omega_z \, N_{stu}$$
$$\forall s \in S, \forall t \in T, \forall u \in U \qquad (4.32)$$

Trucks loading capacity at source separation centers

$$\sum_{m \in M} \sum_{q \in Q} \sum_{s \in S} X_{mqsotu} \leq \sum_{z \in Z} \omega_z \, N_{otu} \qquad \forall o \in O, \forall t \in T, \forall u \in U \qquad (4.33)$$

Compliance to the environmental constraints

- *Emission cap-and-trade system implemented by the authorities*

$$\sum_{i \in I} \sum_{j \in J} \xi_{ij} \sum_{z \in Z} \varepsilon_{zijt} + \sum_{i \in I} e^F_{it} \, N_{it} + \sum_{i \in I} e^V_{it} \sum_{m \in M} \sum_{j \in J} \sum_{q \in Q} X_{mqijtu} + \sum_{a \in A} \sum_{m \in M} \sum_{q \in Q} e^R_{amq} \sum_{i \in I} \sum_{j \in J} X_{mqijtu}$$
$$+ EM^-_{tu} - EM^+_{tu} \leq E^{max}_t \qquad \forall t \in T, \forall u \in U \qquad (4.34)$$

- *Maximum landfilling quantities*

$$\sum_{q \in Q} \sum_{s \in S} \sum_{l \in L} X_{mqsltu} + \sum_{q \in Q} \sum_{o \in O} \sum_{l \in L} X_{mqoltu} + \sum_{q \in Q} \sum_{f \in F^E \cup F^P} \sum_{l \in L} X_{mqfltu} \leq L^{max}_{mt}$$
$$\forall m \in M, \forall t \in T, \forall u \in U \qquad (4.35)$$

Integer and binary constraints

$$X_{mqijtu} \in \mathbb{R}^{+} \text{ Where } \mathbb{R}^{+} = \{x \in \mathbb{R}, x \geq 0\},$$
$$\forall m \in M, \forall q \in Q, \forall i \epsilon I, \forall j \epsilon J, \forall t \in T, \forall u \in U \qquad (4.36)$$

$$N_{stu}, N_{otu}, EM_{tu}^{-}, EM_{tu}^{+} \in \mathbb{N}, \quad \forall s \epsilon S, \forall o \epsilon O, \forall t \in T, \forall u \in U \qquad (4.37)$$

$$\beta_f, \alpha_{fkt}, \theta_{fk,} \varphi_{st}, \nabla_{okt}, \zeta_{ot}, N_{it}, \mathsf{V}_{amq} \in \{0,1\}$$
$$\forall f \in F^E \cup F^P, \forall k \in K^E \cup K^P, \forall o \epsilon O, \forall s \epsilon S, \forall t \epsilon T, \forall a \epsilon A, \forall m \epsilon M, \forall q \epsilon Q \qquad (4.38)$$

The first constraint (4.20) ensures that the recyclers receive at most the desired amount of recycled materials with the specific quality level from the collection centers during each period to perform all the activities required. The second constraint (4.21) regulates the flow of materials leaving the supply sources at each period either by shipping them to an existing or a new CC, a source separation center or a landfilling area. Constraint (4.22) and (4.23) ensure the incoming flows at collection centers are redirected either to a recycler or a landfill, and that income flow at the SSC are shipped to both CC and landfills. Constraints (4.24) and (4.25) set the maximum achievable recycling rates at both existing and potential collection centers per material and quality levels in both cases of source-separated or mixed material containers. Constraints (4.26) to (4.28) are the collection centers, potential CC and potential SP capacity constraints. Constraint (4.29) sets the capacity of the SSC and the minimum utilization rate required for each period. Constraint (4.30) is related to the binary variables for opening and closing the SSC. Constraint (4.31) limits the number of expansions for the collection centers. Constraints (4.32) and (4.33) establish the truck resources required to perform collection activities at supply sources and consolidation at the SSC. Constraint (4.34) ensures the respect of the cap-and-trade system. Depending on the emissions released during each time-period under each scenario, carbon credits will be sold or purchased on the carbon market. Constraint (4.35) sets the limit quantity landfilled for each material at each time-period. Finally, constraints (4.36) - (4.38) are the integer and binary constraints.

In our mathematical formulation, constraint (4.35) defines the maximum landfilling amount of materials tolerated and will be used as the ε-constraint in the resolution process. The ε-constraint method is a well-known technique for solving optimization problems with multiple objectives. Usually, in this type of problem, there is no optimal solution that can optimize all the objectives at the same time. This is the reason why the decision-makers are often looking for the best possible trade-offs among the various objectives. We refer to these trade-offs as the "Pareto-optimal" or "efficient" solutions of the problem. This set of solutions is called efficient because a single objective function cannot be improved without a deterioration of at least one of the other objectives (Mavrotas, 2009). This resolution approach has been used to solve supply chain multi-objective optimization problems repeatedly in the past decade (Yue and You, 2013; Ameknassi et al., 2016), only to name a few. Basically, the ε-constraint consists in prioritizing one of the objective functions while using the other ones as constraints of the model. Then, by performing a sensitivity analysis on the value of epsilon, we manage to obtain the Pareto-front. In our case, we want to maximize the economic benefits while minimizing the landfilling. Let us consider the following bi-objective optimization problem:

$$\left\{ \begin{matrix} max\, f_1(x) \\ \min f_2(x) \end{matrix} \right\} \textit{subject to } x \in R \tag{4.39}$$

Where $f_1(x)$ and $f_2(x)$ are the objectives functions of the problem. We name x the vector of decision variables and R the feasible region of solutions. If we refer specifically to our model, the first objective function is to maximize the profits of the material selling to the recyclers and the second objective is to minimize the total flow of materials that end up landfilled. As it is often the case in multi-objective problems, we decide to prioritize the economic objective and we set the environmental one as a constraint of the model (Eskandarpour et al., 2015). Thus, (4.39) becomes:

$$\begin{array}{rc} & max\ f_1(x) \\ \textit{subject to} & f_2(x) \leq \varepsilon \\ & x \in R \end{array} \tag{4.40}$$

From this new problem, we obtain the set of Pareto-optimal solutions by variation of the epsilon value. In our case, the value of epsilon will vary around the governmental target in terms of landfilling quantities proposed in the case study. Thus we have the following:

$$\begin{aligned} & max\ O_1(x) \\ \textit{subject to} \quad & O_2(x) \leq \varepsilon \\ & x \in R \end{aligned} \tag{4.41}$$

4.4 The case study of wood waste recycling from the CRD industry

In this section, we propose an application of our model for the design of the reverse logistics network to optimize the wood recycling process from the CRD industry in the Canadian province of Quebec. With a very large territory and many forests, Canada is among the countries with the highest wood material rate inside its buildings. Indeed, it is common to reach between 25% to 30% of wood among the total CRD waste collected at the CRD sites (Yeheyis et al., 2013). These days, the recycled wood sector is facing some important challenges in Quebec. Usually, over 60% of the wood waste collected at the CRD sites is not recovered, partly because the recycling process is more expensive than the cost of elimination by landfilling (RECYQ-QUEBEC, 2012). This concern led the local authorities to enforce regulations in order to encourage the recycling of CRD materials and prevent excessive landfilling in this area, while monitoring the carbon emissions associated to the recycling process in the meantime for sustainability purposes.

The province of Quebec is the largest Canadian province with a territory of 1,667,441 km^2, however unequally populated with almost 52% inhabitants concentrated in 3 regions out of 17. These characteristics make the RLND for recycling the wood from the CRD industry a challenge to serve adequately the entire territory. For the purpose of this study, some information was collected from key industry players in Quebec, such as historical data provided by wood recyclers (3R-MCDQ). In addition, other entities such as the SIQ (Statistical Institute of Quebec) or RECYQ-QUEBEC organizations, in charge of waste management in the province, were used as additional sources to obtain accurate data. With an average of 0.65 tons of waste generated per inhabitant annually in Quebec, the building material waste collected on the CRD sites was estimated around 5.3 million tons per year. Thus, we assumed that we collect an average of 1.326 million tons of wood (~ 25%) in a time-period of one year. Three quality levels of collected wood are considered in this study. Quality level 1 is free of contaminants and presents a very high demand due to its high recycling potential. However, quality level 2 is usually slightly contaminated, sometimes by contact with other building materials or by previous treatments (painting, chemical treatment against moisture, insects) or simply by time degradation. Quality level 2 accounts for 65% to 70% of the total wood collected. Finally, quality level 3 is a highly contaminated wood, sometimes with dangerous substances, being potentially harmful to the environment and/or for human health. This type wood is likely to be landfilled all the time and is very difficult to recycle.

As the historical data about the exact number and locations of CRD sites were not available, we divided the total amount of waste generated into 250 collection sites taking into account the population density of the regions. Among the recurrent wood recycling activities in Quebec, we mainly find energy cogeneration (52%), particleboard manufacturing (25%), cellulosic ethanol fabrication (11%), cement manufacturing (6%), logs and pellets (5%), and the remaining 1% for other applications (3R-MCDQ, 2014). However, each recycling activity has its own requirements in terms of wood quality in order to be performed. Data regarding the emission factors used to calculate the carbon released by the wood recycling network was carefully selected from different reliable sources such as the French Environment and Energy Management Agency (ADEME), the Quebec Ministry of Environment and the Canadian Federal Emissions Inventory for Climate Change. Below, figure 4.2 illustrates the main features of the reverse logistics network for the wood recycling process from the CRD industry in Quebec.

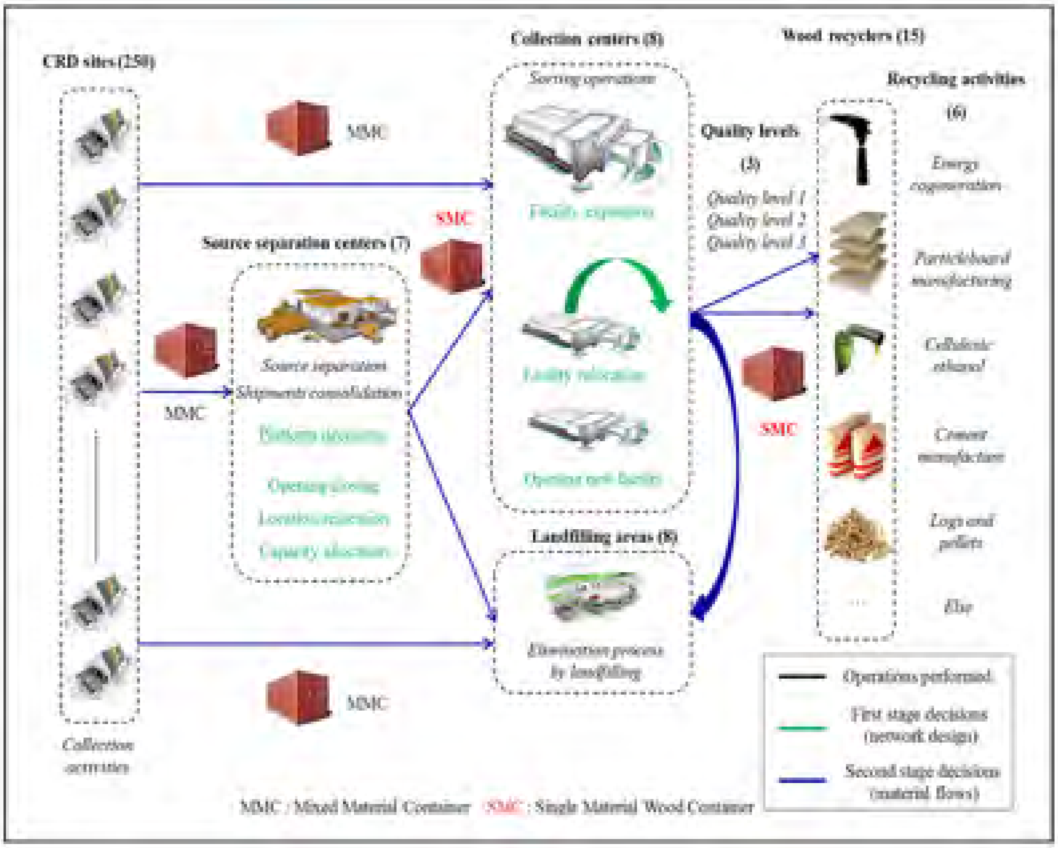


Figure 4.2 Reverse logistics network for wood building material recycling

In order to evaluate the network behavior under landfilling restrictions and emission control, the first step of our analysis is to establish the Pareto-front (see figure 4.3 below).

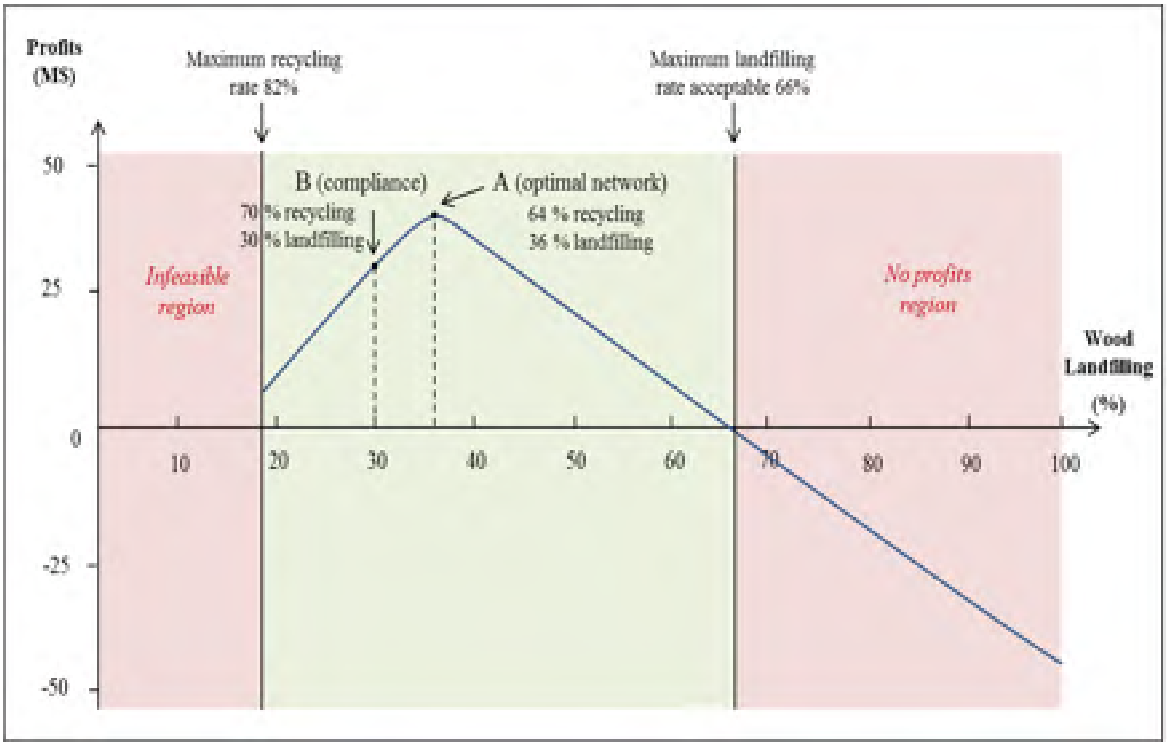


Figure 4.3 Trade-offs between profits and landfilling – Pareto-front

This diagram provides useful information regarding the impact of landfilling restrictions on the network performance. First, we see that the optimal network suggests a landfilling level at 36% (point A). Thus, recycling more than 64% of the wood is decreasing the value of the solution, being the case for example under the regulation compliance where we have to recycle at least 70% (point B). We also notice an infeasible region for this problem due to recycling rates limitation of the wood because of its quality. Indeed, the recycling rates achievable at the CCs limit the wood recycling at a maximum of 82%. Moreover, recycling under 34% of the wood, there is no possibility for making profits as the costs of logistics infrastructures and operations exceed the recycled wood selling.

Based on this Pareto-front, we propose to evaluate three main scenarios in the following experiments that will provide a better understanding of the network behavior:

1) evaluation of the optimal network for wood recycling (point A);
2) evaluation of the “compliance network” with landfilling limitations (point B);
3) and finally, the evaluation of this same “compliance network” but this time without the possibility to use the source separation centers.

By following these methodological steps, we will show how the landfilling regulation actually decreases the value of the solution and affects the performance of the reverse logistics network. Moreover, we will highlight the importance to consider the source separation strategy to maintain a good quality solution under the legislation.

4.4.1 Optimal reverse logistics network design for wood recycling

As a comparison reference, the reader will find in figure 4.4 the current average repartition of the recycled wood use in the province of Quebec.

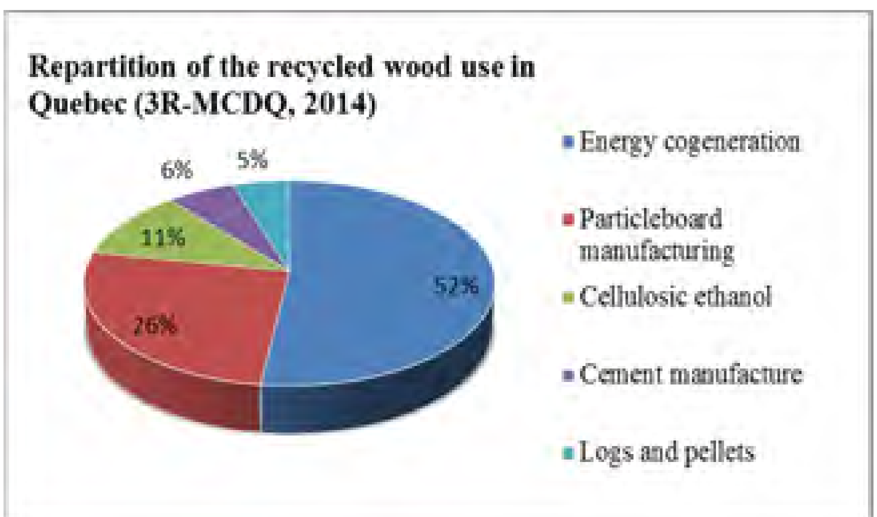


Figure 4.4 Current wood recycling in the Province of Quebec

As previously shown in figure 4.3, the best solution for wood waste recycling in the CRD industry suggests we recycled 64% of the collected wood (point A). To do so, 6 existing CC are operating and among them, 4 should increase their treatment capacity. In addition, 3 new CC are opening in appropriate locations. In this optimal RLND, the SSC are used extensively, with 29 of them operating out of a maximum of 35 (7 source separation centers per period and 5 time periods). Under the optimal configuration, we reach excellent average utilization rates with 79% for the CC and 96% at the SSC. More accurate information about the network emissions is provided in figure 4.5, with a specific focus on the decomposition of the emissions associated with the recycling activities.

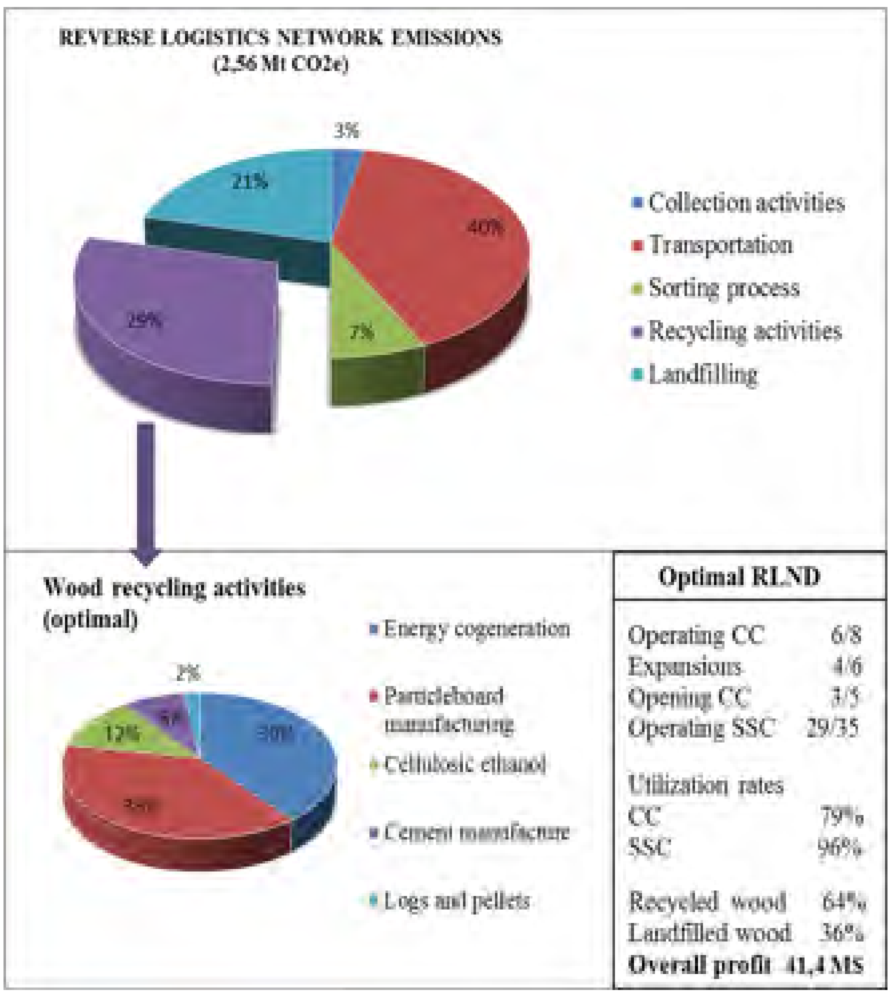


Figure 4.5 Optimal network design characteristics

4.4.2 Enforcing the landfilling regulation: the new "compliance network"

According to the recent waste management plan in the province, the building contractors have to recycle a minimum of 70% of the building material waste generated during CRD activities. However, in case of the wood building material and considering the high emissions caused by low-quality batches, recycling this much is decreasing the efficiency of the network (24.7% profit loss). The network still operates 6 of the existing collection centers, however only 2 are expanding compared to 4 in the optimal configuration. As we need to provide extra capacity to recycle more wood in this scenario, 3 new collection centers are opening but with larger capacities than before. Part of the wood flow from the supply sources are redirected to these new large facilities, thus implying the opening of 22 source separation centers instead of the 29 SSC operating in the optimal scenario. Therefore, complying with the landfilling regulation forces the recycling of some low quality batches to meet the target, which increases the overall level of emissions of the network. In the meantime, the proportion of wood used for each recycling activity has changed due to the 79,500 additional tons of wood recycled. Compared to the optimal network, the regulation raises the overall emission level from 8.9%, showing a significant increase in the emissions associated to the recycling processes. Figure 4.6 summarizes the information regarding the compliance network.

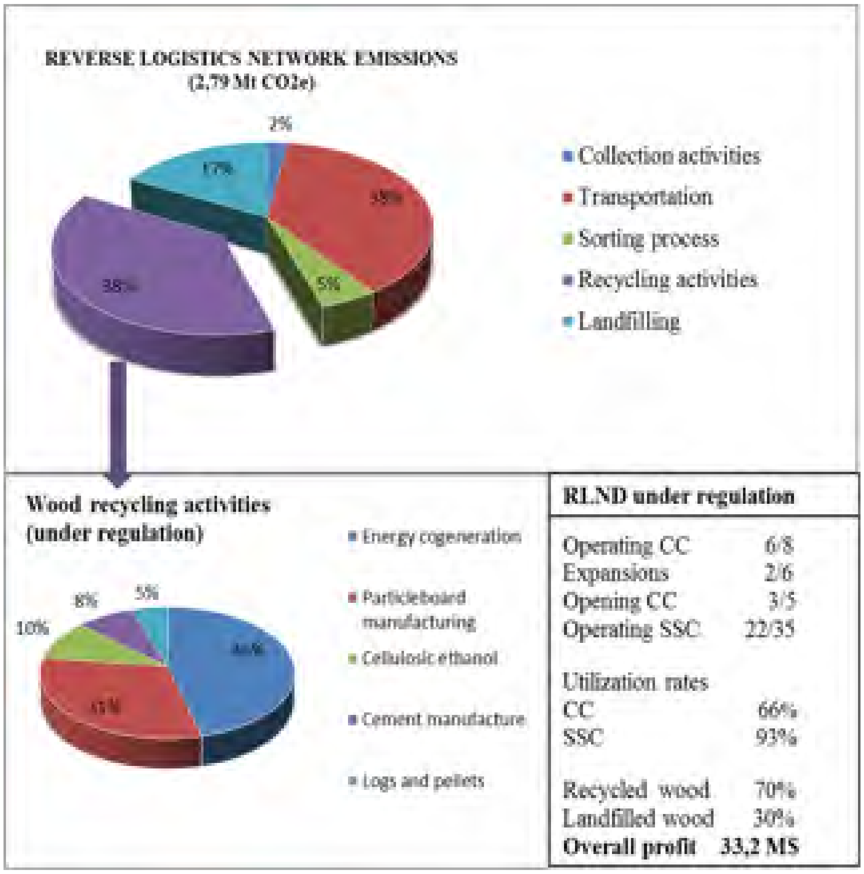


Figure 4.6 Compliance network design characteristics

4.4.3 The role of the source separation centers in the CRD industry

In this part, we evaluate again the network behaviour under compliance (i.e. point B in the Pareto diagram, figure 4.3), however this time without the possibility to operate the SSC. The immediate impact of this constraint is that a significant quantity of poor quality wood is redirected to the CCs instead of being eliminated at an early stage of the reverse logistics network. Moreover, the collection centers have to process a lot more mixed material containers, which impacts the recycling rates in a negative way. To deal with this extra volume of CRD materials, we operate 1 additional existing CC and we locate 1 extra CC. This time, failing to eliminate low-quality batches raises the overall emission level by 16.4% compared to the optimal scenario, being 6.8% higher than when we use the source separation strategy (see figure 4.7 below).

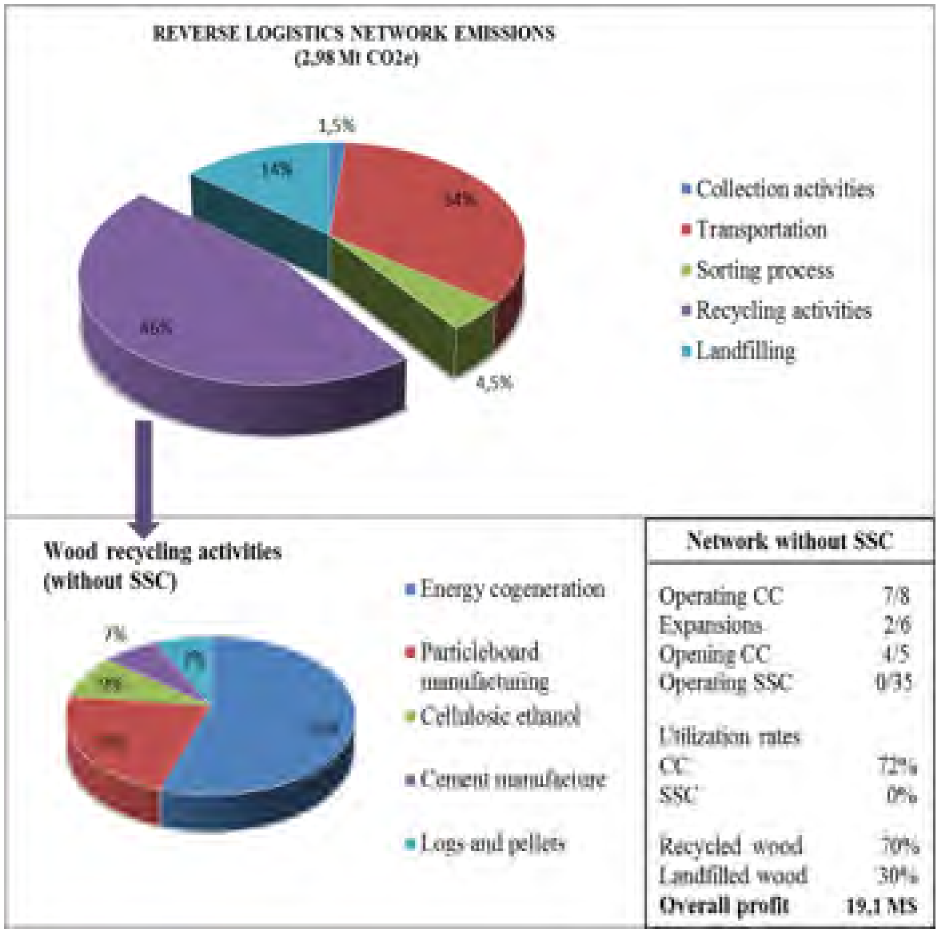


Figure 4.7 Compliance network without using the source separation strategy

Without the source-separation strategy, the recycling activities now represent the main source of emissions of the reverse logistics network with 46%, being almost equivalent to the combination of the landfilling and transportation emissions (48%). As a significant number of shipments containing poor quality wood reach the CCs in this scenario, a larger quantity of this wood reaches the recyclers and increases the total emissions compared to the previous scenario. The results suggest that source-separation represents a promising solution to reduce the carbon footprint of the wood recycling process in the CRD industry. It is also interesting to observe that the wood recycling activities in this last case (i.e. compliance network without SSC) show a very similar repartition compared to the current use of recycled wood in Quebec (figure 4.4). Thus, the analysis of these three scenarios could provide useful insights to the Quebec authorities regarding the potential issues of imposing recycling targets for materials under uncertain quality. In addition, the results of the optimal scenario could be helpful to adjust the repartition of the recycling activities that would allow reducing the associated emissions. The reader is referred to appendix VI for additional details regarding the reverse logistics network metrics for the three (3) scenarios evaluated in this section.

4.4.4 Sensitivity analyses on the uncertainty for the recycled wood quality

The previous experiments highlight the importance of carefully selecting recycling targets, especially in the case of building materials for which the quality level is unpredictable. Indeed, depending on the quality of the collected lots, it is sometimes the best decision to landfill more wood instead of performing recycling processes that would be harmful to the environment by releasing toxic emissions. To assess the impact of the uncertainty targeting the wood quality on the reverse logistics network, we established different Pareto-diagrams (figure 4.8), each one of them associated to a different scenario: Poor Quality (S_1), Medium Quality (S_2) and Superior Quality (S_3).

In each of these scenarios, we assume that we observe a variation in the trend regarding the quality of the collected batches during the planning horizon. The data used to conduct these experiments are shown in table 4.2 below.

Table 4.2 Sensitivity analyses on the impact of the quality of the collected wood

	Repartition for 1 ton of wood collected at the supply sources		
Scenarios	**Quality level 1**	**Quality level**	**Quality level 3**
Poor quality (S1)	5%	70%	25%
Medium quality (S2)	15%	70%	15%
Superior quality (S3)	25%	70%	5%

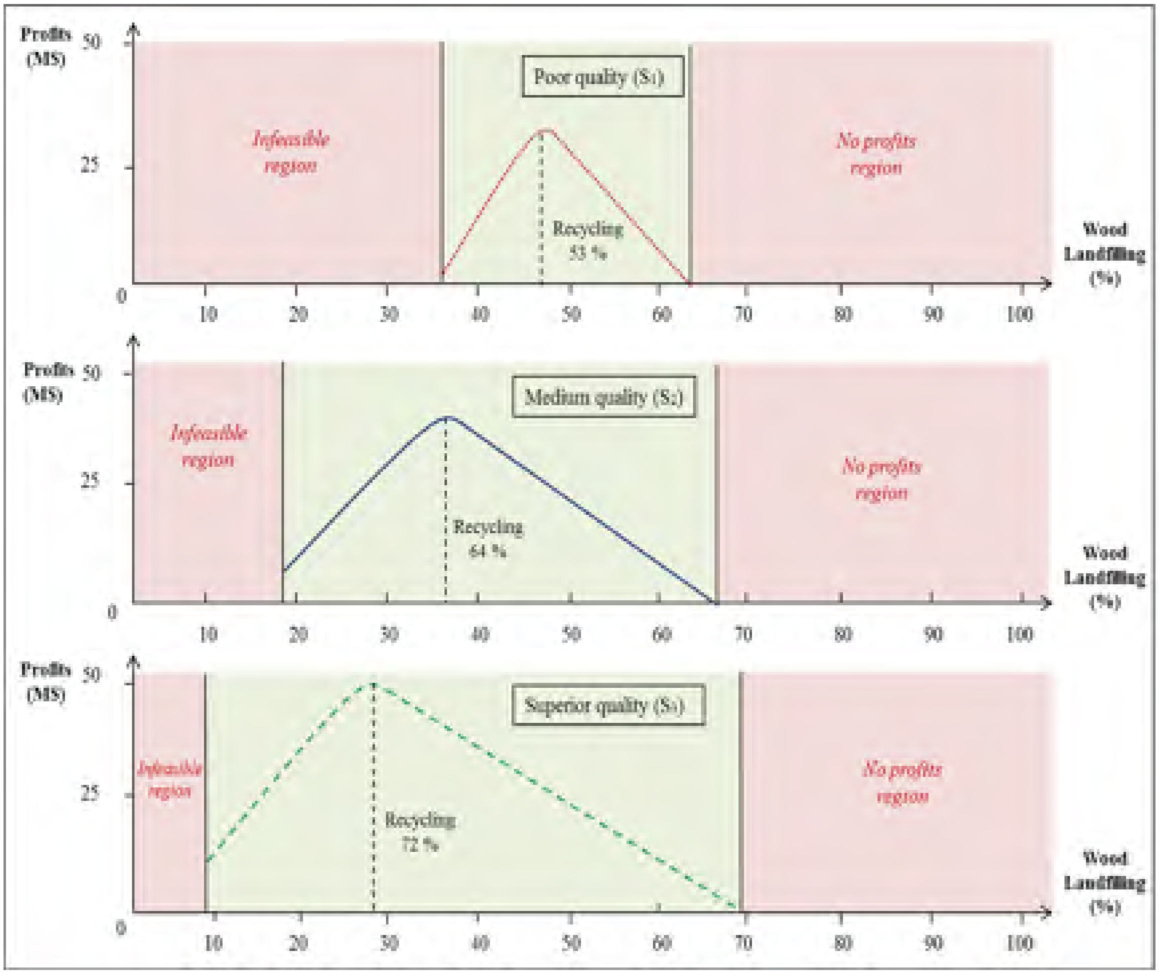


Figure 4.8 Impact of the uncertain wood quality on the optimal landfilling level

In figure 4.8, scenario S_2 is the one we already presented in figure 4.3, which is used as a baseline for the comparison with the other scenarios, although here we represent only the range with profits. First, we observe an extension of the “profitable area” when the quality of the wood increases (i.e. the green area). Indeed, an enhanced quality implies higher average recycling rates at the CCs, meaning that we manage to reduce the infeasibility region by recycling up to 91% of the collected wood in superior quality scenarios. However, under the poor quality scenarios, the maximum amount of recycled wood decreases down to 66%. The maximum proportion of wood landfilling however is less sensitive and remains between 63% to 69% in any scenario. Indeed, if the amount of wood eliminated exceeds 70% there is not enough selling on the secondary markets to support the costs of the reverse logistics network.

The optimal recycling rates vary from 53% to 72%. Any deviation from the optimal solutions implies a profit loss, either by landfilling acceptable quality wood that would be usable in a recycling process, or by recycling too much low-quality wood that releases toxic emissions, thus being penalized by the cap and trade system in place. Moreover, in the poor quality scenario, we are in the impossibility to comply with the recycling target of 70%. Indeed, complying with the regulation would require shipping poor quality wood to the recyclers that would be unacceptable to perform the recycling operations.

The main reverse logistics network characteristics for the three (3) optimal configurations under each scenario are synthesized in table 4.3. We observe that significant facility investments such as CCs expansions or new openings are not an option under scenario 1. However, when the wood quality increases, such investments are encouraged in order to optimize the reverse logistics operations for wood recycling. In case of the poor quality scenario (S_1), we observe an extensive use of the SSC, which can be explained by the necessity to eliminate a maximum of unusable wood instead of shipping it to the CCs, thus avoiding pointless transportation activities. In addition, the operating SSC are mostly located closer to the landfills, which decreases the average elimination distance by 26.6% compared to the baseline scenario (S_2). However, in scenario 3, the set of active source-separation centers is quite different from the one used under scenario 1, this time operating the SSC that are strategically located to reach the collection centers. Overall, compared to the baseline scenario, we incur a 28.3% profit loss under scenario 1, whereas scenario 3 allows a 16.2% increase in the average expected profit.

Table 4.3 Optimal networks' characteristics under wood quality variation

Scenarios	CC operating (existing)	CC expansions	CC utilization rate	CC opening (new)	SCC operating
Poor quality (S_1)	7/8	0/6	59%	1/5	33/35
Medium quality (S_2)	6/8	4/6	79%	3/5	29/35
Superior quality (S_3)	6/8	5/6	88%	4/5	21/35
Scenarios	**Avg. distance to recycle**	**Avg. distance to landfill**	**Source separation**	**Optimal recycling level**	**Overall profits**
Poor quality (S_1)	80,8 km	41,1 km	41%	53%	29,7 M$
Medium quality (S_2)	91,1 km	56,3 km	34%	64%	41,4 M$
Superior quality (S_3)	101,5 km	68,6 km	31%	72%	48,1 M$

4.5 Conclusion

In this article, we present a multi-objective stochastic model to optimize the reverse logistics network design decisions for waste management purposes. We apply this model in the context of wood material recycling in the CRD industry in Quebec, being a sector targeted by emerging environmental regulations. The results show the complexity of setting recycling targets without affecting the reverse logistics network performance, especially in an uncertain environment where the unpredictable quality of the materials affects the efficiency of the recycling processes and its emission level. As a promising solution to reduce the environmental impacts caused by the uncertainty related to the materials' quality, the source-separation strategy is tested and provides the opportunity to eliminate poor quality lots at an early stage of the RL channel. Moreover, by performing container consolidation into single material shipments, the source-separation operations increase the average recycling rates at the collection centers, thus diverting materials from the landfills and decreasing the overall emission level in the meantime.

In this research, our model addresses both the economic and the environmental aspects of supply chain management, being two of the three pillars of sustainability (Elkington, 1998). However, the inclusion of social aspects in the model would help dealing with waste management operations in a sustainable way. In addition, the experiments showed that for the local authorities it can be a difficult decision to set some recycling targets for the materials in an uncertain environment. Thus, we believe that a sensitivity analysis on the legislation parameters can be an interesting study, providing insights to the governments before enforcing recycling targets in a specific area that could affect the potential of reverse logistics operations.

CONCLUSION

Nowadays, designing sustainable supply chains has become a critical matter for the well-being of the future generations. To this aim, the design of efficient reverse logistics networks that allow performing sustainable RL operations is a topic of great interest. Unfortunately, although it is acknowledged that a suitable RLND is critical toward seeking sustainability, the decision-makers in the industry are often struggling with the complexity of this process involving many challenges. Indeed, evolving from an economic-oriented business to a vision that includes environmental and/or social considerations is not an easy task. Usually, it suggests supply chain reengineering and some compromises that require advanced skills and knowledge, which are often difficult to find among companies. Thus, to ensure the transition toward sustainability, an increasing number of legislations and programs are enforced by governments that leave no choices to the companies but to comply and take a step forward.

Contribution

To serve this purpose, the research presented in this thesis contributes to the development of innovative decision-making models that help with the design of efficient RL networks. Our work comes to enrich the literature of quantitative models applied to RLND problems, a very popular topic during the past two decades. The idea behind the models presented in this thesis is to integrate strategic and tactical decisions to assist the supply chain managers into building efficient RL networks and being able to measure their performance with various metrics. Thus, the proposed formulations address the decisions regarding facility locations and capacity allocations, facility relocation or closing decisions, potential expansions, and flow management through the reverse channel. By making the best-related decisions, our optimization models suggest ways of improving waste management operations and cope with the legal framework. To ensure the realistic nature of this work and its transferability to the industry, case studies are presented in the construction, renovation and demolition industry in the Canadian province of Quebec. Indeed, we found that there was a gap in assessing the best decisions for waste management in this sector from a logistics perspective while considering key aspects that make the RL network design a complex task in this industry.

The models developed in this work were used to answer the following research questions:

- How are the optimal reverse logistics network configuration and performance affected by the presence of dynamic supply sources and multiple uncertainties targeting the collected wood waste volume and quality in the CRD industry ?

- What role can play the source-separation centers and what is the impact of the source-separation strategy on the reverse logistics network configuration and performance under uncertainty in the CRD industry ?

- What are the impact of environmental regulations on the reverse logistics network design and performance under multiple uncertainties in the CRD industry ? and how does the source-separation strategy impact the compliance with the regulations ?

Main findings

In the first article (Chapter #2), we presented a mixed-integer linear programming model to minimize the total cost of the wood recycling process in the CRD industry in Quebec. By adopting a scenario-based approach and evaluating the variations of critical uncertain factors, we demonstrated that the performance of a RL network configuration can vary significantly from one scenario to another. In addition, we highlighted that these significant differences between the networks' efficiency can be problematic under the regulation setting recycling targets in this region. However, in practice, the decision-makers must choose a unique network configuration that will efficiently handle various supply sources locations, waste collected quantities, and quality of the materials. Although the proposed scenario-based approach is efficient to highlight the issues caused by the uncertainty, it essentially based on the discrete realisation of the random parameters, which considerably reduces the number of tractable scenarios. As a future research direction, we suggested the development of a stochastic version of this model to avoid this limitation and propose the best supply chain configuration for a longer planning horizon over multiple randomness outcomes.

Thus, in the second article (Chapter #3), we developed a two-stage stochastic model for reverse logistics network design under uncertainty. The proposed SAA resolution approach allowed considering a large number of scenarios simultaneously and to design the best-expected reverse logistics network over a multi-period planning horizon. The decisions taken by this model are quite similar to those presented in the first article, except that this work emphasizes the importance of performing source separation at some dynamic platforms that can be relocated during the planning horizon. In this paper, we showed that the source separation strategy is an effective way to reduce the impact of uncertainty by providing more flexibility to the RL operations, especially in the case of high-density urban collection zones where the sorting process can be quite challenging. By performing sensitivity analyses, we demonstrated that the source separation centers provide a potential solution to design a resilient network under various uncertainty levels. However, the proposed model addresses only an economic objective rather than discussing environmental impacts. The latter being a recurrent issue regarding waste management practices, the 3rd article of this thesis presented an eco-efficient stochastic version of the model that takes into account both the profit and the environmental impacts of the reverse logistics activities.

In this last article (Chapter #4), the stochastic programming formulation presented in chapter #3 was extended to a multi-objective stochastic formulation. Compared to the network presented in paper #2, we included a second objective function that seeks to minimize the amount of materials that are ultimately eliminated by landfilling after leaving the collection sites. In addition, we added a second environmental constraint regarding the greenhouse gases emissions monitoring and control via a cap-and-trade system, being quite similar to the one effective in the Quebec province these days. In this last contribution, we maintained the opportunity to use the source-separation platforms as it was allowed in article #2. What mainly emerged from this article is the importance of considering the environmental objective in this problem. Indeed, with the previous stochastic model, the optimal RLND led to recycling more materials in order to seek the maximum profits, however the damage caused by the toxic emissions released while recycling the wood was neglected. By including this concern in the multi-objective formulation, we showed that when facing uncertainty targeting the quality of the recycled materials, some trade-offs had to be made to obtain the optimal network configuration and performance. Moreover, these experiments highlight the necessity to carefully implement environmental policies and demonstrate the complexity for the reverse logistics network to achieve both compliance and eco-efficiency in the meantime under an uncertain environment.

Overall, despite the critical need to increase the recycling of used products and materials to encourage the transition toward sustainability, this research provides some warnings against seeking extensive recycling at all costs. Indeed, in an uncertain environment it appeared that, sometimes, recycling more actually implies more harm to the environment. In addition, another concern is the complex choices regarding the recycling targets while setting new environmental laws. Thus, some governmental regulation and programs initially enforced to reduce the environmental damages might have the opposite effect if the objectives are not chosen carefully. This observation applies even more when facing multiple uncertainties targeting key parameters such as the materials' quality.

Managerial insights

We believe that the research presented in this thesis may be useful to understanding the importance of designing a resilient reverse logistics network under an uncertain environment. We highlighted the fact that the supply chains' quest for sustainability can be significantly impacted, not only by multiple uncertainties, but also by a legal framework that is too stringent. Thus, from one hand, the supply chain decision-makers could benefit these results to anticipate the potential outcomes of an upcoming regulation in order to adjust the reverse logistics network accordingly for compliance purposes. On the other hand, the authorities could use these results to anticipate the potential impacts of a new regulation on the supply chains under compliance and wonder if it could endanger sustainability. From our point of view, nowadays there are still too many environmental laws enforced without conducting any logistics analysis beforehand. This situation sometimes leads to undesirable outcomes that are harmful for both the environment and the society. As it is close to the case studies proposed in our work, we will quote the example of the wood landfilling regulation in the state of Massachusetts in 2006, which turned out to be a total logistics failure as the RL network could not deal properly with the amount of recycled wood involved.

Limitations and further research leads

While taking a step back, we would discuss the following limitations to this research:

- First, in this thesis we developed our reflexion based on the need for evolving toward sustainability among supply chains, which we seek through enhancing the efficiency of the reverse logistics network design. However, if we literally refer to the definition of what should be "*a sustainable reverse logistics network design*", then our models should include somehow the social dimension that is missing in our research. Models quantifying the social impacts of supply chain decisions are still very scarce in the literature, and in this work, we chose to focus on both economic and environmental aspects of the RLND on purpose.

- In addition, regarding the stochastic model formulations presented in Chapter 3 and 4, they were both applied to case studies involving at most 250 waste collection sites, however we are aware that increasing the size of the problem could significantly complicate the resolution process. Powerful computational capacity would certainly be required to solve instances going up to 1,000 collection points, while alternative resolution approaches such as metaheuristics could be required if this number increases even more.

- Moreover, regarding the uncertain parameters we chose to consider in our models, we are convinced that other choices could have been of great relevance to the research toward sustainability while designing RL networks. However, for complexity and feasibility purposes, we cannot study all of them in the same model. For example, we established that the legislation targets are a sensitive matter while enforcing a law.

Thus, considering uncertainty on the target of a potential regulation appears to be a topic of interest. Instead of adopting a supply chain perspective that tries to adapt to a governmental program, we could adopt the authorities' perspective and evaluate what environmental target would not endanger sustainability in a first place.

- In addition, a few assumptions that we made could be modified to fit even more the reality faced by companies. For example, the carbon market parameters are not changing during the planning horizon, however we know that the carbon metric ton selling/buying price is not a static parameter and is updated on a trimester (or a year) basis. Moreover, if we adopt a governmental perspective, a multi-stage stochastic model that would allow adjusting the recycling targets based on the observation of the randomness in the quality of the materials at each stage is a promising lead. Indeed, based on a declaration from the companies listing what they received on a year basis, the government could decide to lower the recycling mandatory targets for the next year to avoid toxic emissions release in case of poor quality batches. The interest of such model is that the government would adjust mandatory requirements in a preventive way, instead of having the supply chain managers adjusting the reverse logistics operations and the recycling decisions in a corrective manner.

- Finally, we presented case studies in the CRD industry, being initially motivated by one of the specificities of this sector: the dynamic nature of the waste collection points over time. We believed that this aspect presented a challenge for the supply chain managers in terms of designing a suitable reverse logistics network design for recycling operations, a fact that contributed to justify this research. However, the large majority of industrial sectors are used to deal with static suppliers. Indeed, most of the time companies are setting their waste deposits (i.e. collection points) in advance and their locations are not necessarily changing. Thus, we understand that the models presented in chapters 2, 3 and 4 might not be suitable for a wide variety of sectors. However, this research could provide valuable insights to the supply chain managers in the CRD industry that aim for sustainable reverse logistics operations.

APPENDIX I

LISTING OF THE 38 FACILITIES USED IN THE CASE STUDY

Facility	Street address	Postal code	Coordinates (lon - lat)	
1	220 rue de Rotterdam	G3A 1T4	46,75883	-71,45950
2	11450 boulevard industriel	G9A 5E1	46,40551	-72,71264
3	1060 rue Fréchette	J0K 2M0	45,54464	-73,48161
4	3525 Boulevard Laurier Est	J2R 2B2	45,63755	-72,90979
5	75 rue Savard	G4W 0H9	48,82813	-67,57264
6	435 Montée Cushing	J8G 1B9	45,61129	-74,42559
7	815 rue Vernon	J9J 3K4	45,45237	-75,80691
8	5 rang Moreau	J0A 1M0	45,92999	-71,99627
9	146, rang 9	J1A 2S1	45,42871	-72,69650
10	225 rue du progrès	J0K 3K0	45,52472	-75,49257
11	118 rue des équipements	G5R 3Z3	47,83659	-69,50282
12	3200 Boulevard industriel	J3L 4X3	45,41083	-71,96439
13	61 rue Montcalm	J0K 1A0	45,89935	-73,66577
14	1985 rue Jean Marie Langlois	J5R 5Z8	45,39876	-73,50248
15	315 rue Jackson	G1N 4C4	46,80277	-71,26341
16	18055 rue Gauthier	G9H 2A6	46,28879	-72,55064
17	16795 rue Oakwood	H9H 5C9	45,46329	-73,86731
18	1131 rue Principale	J0E 1A0	45,41943	-72,77021
19	2400 montée Saint François	H7E 4P2	45,70740	-71,46118
20	493, deuxième Avenue	G8L 1V3	46,62997	-72,70915
21	3389, quatrième rue	G9T 5K5	46,07887	-71,94941
22	365 Boulevard Bonaventure	G6P 6V7	48,22094	-79,01307
23	303 Boulevard Industriel	J6J 4Z2	45,88973	-72,54540
24	1005 rue Réha	J2B 8A9	45,62751	-73,51838
25	10930 rue Sherbrooke Est	H1B 1B4	45,46930	-73,43318
26	5431 rue Jonergin	J3Y 2S1	45,65137	-73,68278
27	3030 montée Saint François	H7E 4P2	45,42565	-75,73352
28	31 boulevard Saint Joseph	H8S 2K9	45,61913	-73,56715
29	9501 boulevard Ray Lawson	H1J 1L4	46,28537	-73,38358
30	1752 rue Saint Cléophas	J0K 2N0	45,38869	-72,74561
31	530 rue Édouard	J2G 3Z6	46,15706	-70,61171
32	8191 route 204	G6B 2S1	45,68790	-74,15601
33	6000 route Sir Wilfrid-Laurier	J7N 2Z8	45,68687	-74,15662
34	4 chemin du Tremblay	J4B 6Z5	45,55504	-73,43128
35	3878 Boulevard Frontenac Est	G6H 4G2	46,12434	-71,24602
36	17245 rang Sainte-Marguerite	J7J 2E9	45,75559	-73,94137
37	9990 Boulevard Métropolitain	H1B 1A2	45,62651	-73,54706
38	107 chemin Maine central	J0B 1J0	45,48808	-71,57484

lon: Longitude; **lat**: Latitude.

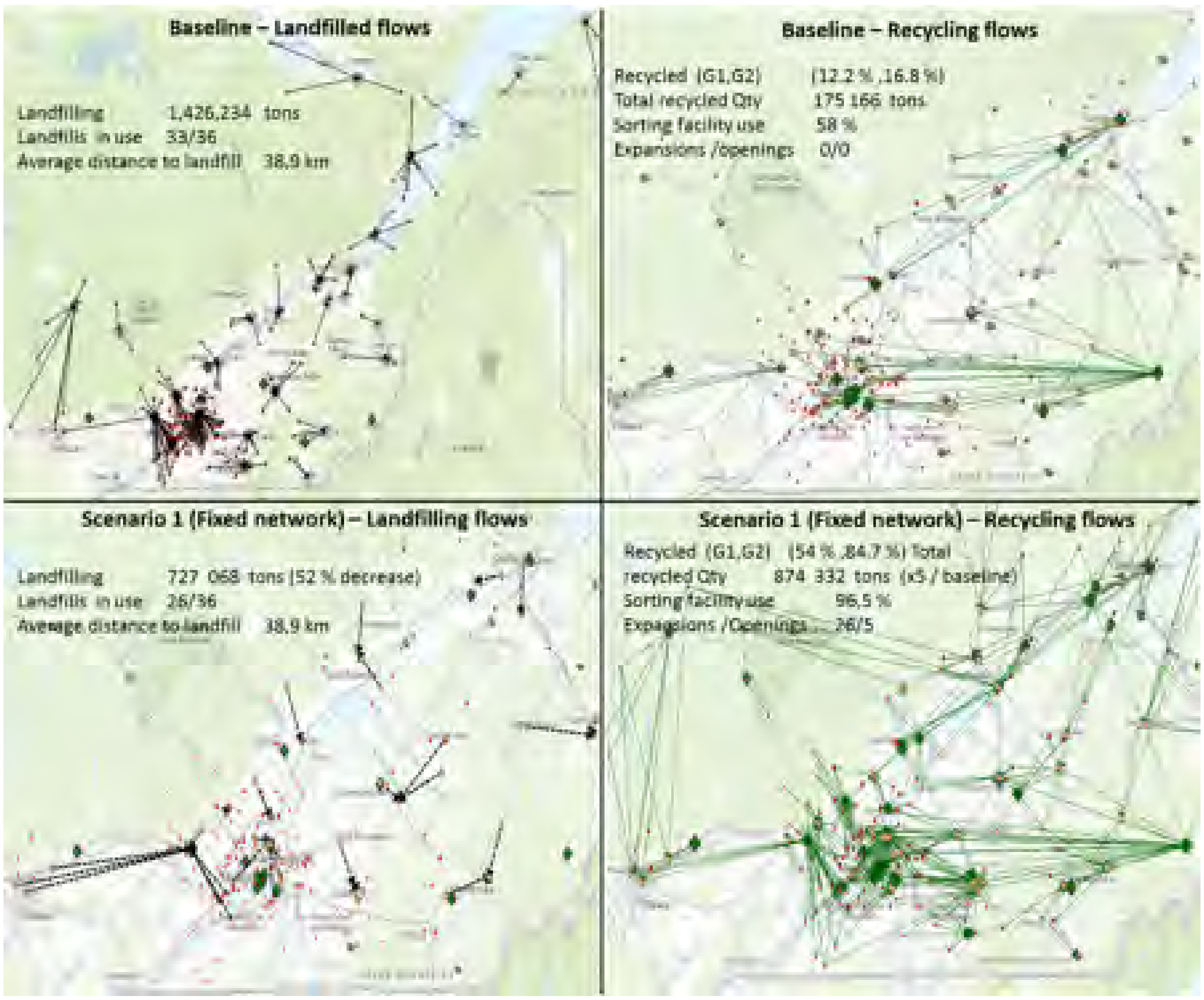
APPENDIX II

SCENARIO-BASED APPROACH UNDER UNCERTAINTIES

	Supplier location			Supplied volume			Quality level		
	LS1	LS2	LS3	low	avg	high	low	avg	high
SC1	✓				✓			✓	
SC2	✓				✓				✓
SC3	✓				✓		✓		
SC4	✓			✓				✓	
SC5	✓			✓					✓
SC6	✓			✓			✓		
SC7	✓					✓		✓	
SC8	✓					✓			✓
SC9	✓					✓	✓		
SC10		✓			✓			✓	
SC11		✓			✓				✓
SC12		✓			✓		✓		
SC13		✓		✓				✓	
SC14		✓		✓					✓
SC15		✓		✓			✓		
SC16		✓				✓		✓	
SC17		✓				✓			✓
SC18		✓				✓	✓		
SC19			✓		✓			✓	
SC20			✓		✓				✓
SC21			✓		✓		✓		
SC22			✓	✓				✓	
SC23			✓	✓					✓
SC24			✓	✓			✓		
SC25			✓			✓		✓	
SC26			✓			✓			✓
SC27			✓			✓	✓		

APPENDIX III

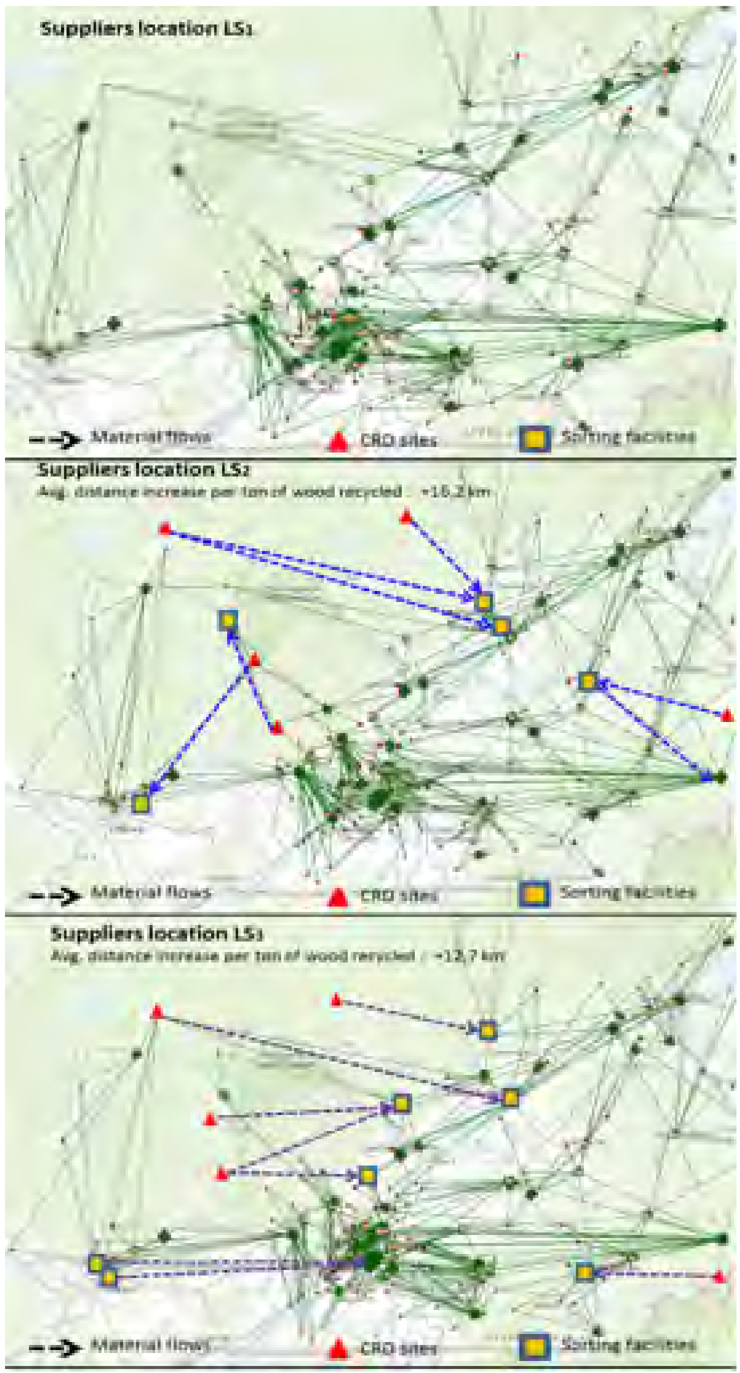
BASELINE SCENARIO VS SCENARIO 1: RECYCLING & LANDFILLING FLOWS



Graphs from Supply Chain Guru Software (LLamasoft Company)

APPENDIX IV

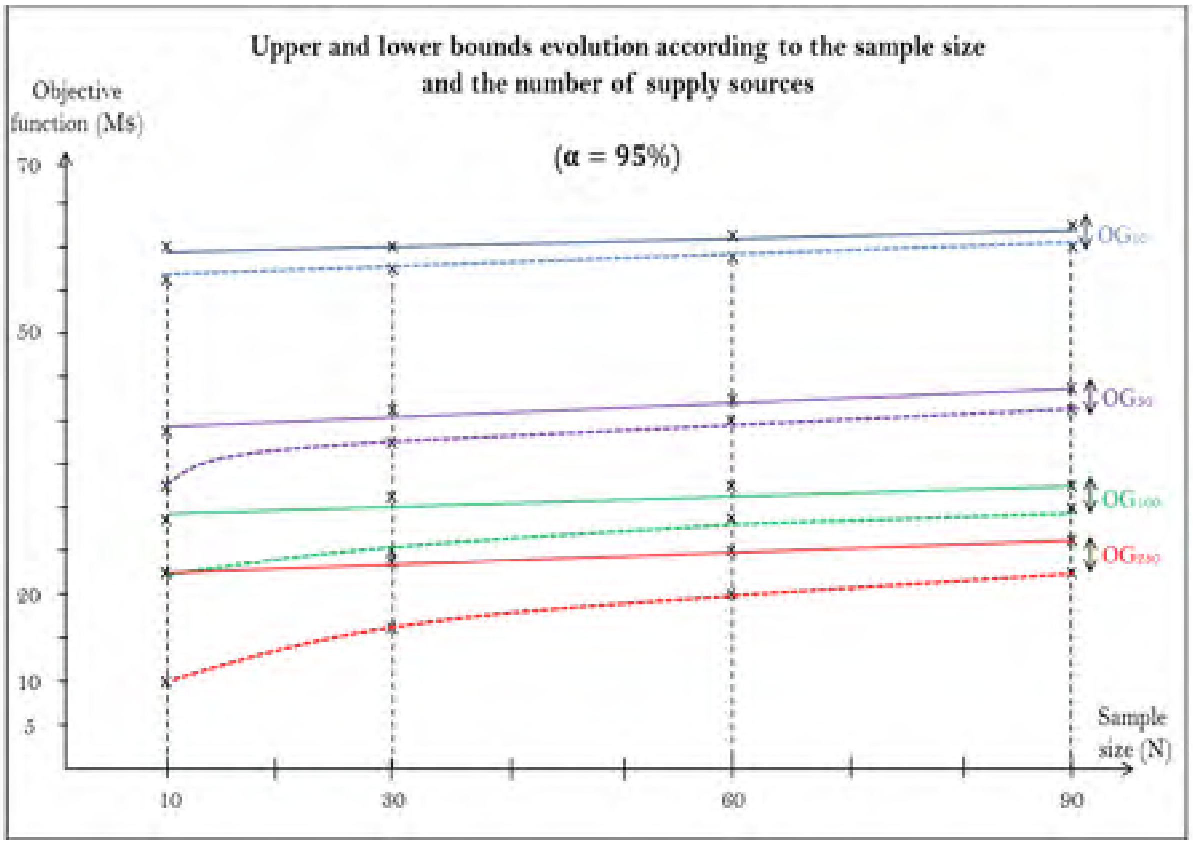
RECYCLING DISTANCE INCREASE WITH SUPPLIERS LOCATIONS LS_2 & LS_3



Graphs from Supply Chain Guru Software (LLamasoft Company)

APPENDIX V

BOUNDS AND OPTIMALITY GAPS ACCORDING TO THE SAMPLE SIZE (EXAMPLE WITH S=10, 50, 100 AND 250)



APPENDIX VI

SUMMARY OF THE 3 MAIN RLN CHARACTERISTICS

Facilities' metrics	CC operating (existing)	CC expansions	CC utilization rate	CC opening (new)	SCC operating
Optimal RLND	6/8	4/6	79%	3/5	29/35
RLND under regulation (With SSC)	6/8	2/6	66%	3/5	22/35
RLND under regulation (No SSC)	7/8	2/6	72%	4/5	N/A
Δ_1 (%)	0%	50%	13%	0%	20%
Δ_2 (%)	12,5%	0%	6%	20%	N/A
Network metrics	Avg. distance to recycle	Avg. distance to landfill	Source separation	Recyclers' service level	Overall profits
Optimal RLND	91,1 km	56,3 km	34%	76%	41,4 M$
RLND under regulation (With SSC)	104,9 km	62,6 km	26,1%	82%	33,2 M$
RLND under regulation (No SSC)	122 km	79,7 km	N/A	61%	19,1 M$
Δ_1 (%)	15,1%	11,2%	23,2%	6%	19.8%
Δ_2 (%)	16,3%	27,3%	N/A	21%	42.4%

CC: Collection centers; SCC: Source-separation centers; RLND: Reverse logistics network design; Avg: Average; Δ_1: Variation between the optimal RLND and the RLND under regulation; Δ_2: Variation between the RLND under regulation with and without SSC.

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