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CLSC	Closed-Loop Supply Chain
DEA	Data Envelopment Analysis
DM	Decision-Maker
EOL	End-Of-Life
FL	Forward Logistics
FSC	Forward Supply Chain
LP	Linear Program
MCDM	Multi-Criteria Decision Model
PCA	Principal Component Analysis
RL	Reverse Logistics
RSC	Reverse Supply Chain
SCM	Supply Chain Management

Résumé en français

Introduction

Au cours des dernières décennies, les conséquences du réchauffement climatique, de l'accumulation des déchets et de la pollution sont devenues de plus en plus visibles. Une étude de [Bau+16] a montré que les émissions de gaz à effet de serre ont augmenté de 64% par an en moyenne depuis 1990. Selon [MD+18], les températures ont augmenté d'environ 1 °C depuis la révolution industrielle et sont toujours en augmentation de 0,1 °C à 0,3 °C par décennie. De plus, l'accumulation des déchets solides atteint de nouveaux sommets et la production de plastique a été plus élevée que jamais auparavant au cours des dernières années [Pla16]. Alors qu'une petite proportion des déchets et du plastique est recyclée ou incinérée, la majorité est déposée dans les décharges ou dans la nature. Par ailleurs, les matières premières sont de plus en plus rares, ce qui affecte fortement l'économie mondiale. Les mines de minerai exploitées sont en déclin rapide: dans les zones les plus développés du monde qui sont aussi les anciennes régions industrielles, comme par exemple en Europe et aux États-Unis, un pourcentage important de mines ont été fermées en raison de leur contenu minéral faible ou épuisé [Hen+16]. En Australie, autre important pays producteur de minéraux, le nombre de mines a diminué d'un facteur 2 à 5 depuis le début de leur exploitation [Pri+12].

Pour améliorer la situation actuelle, des actions concrètes voient le jour. Au sein de la société, de multiples acteurs - politiques, scientifiques et entrepreneurs - travaillent à la mise en place d'autres systèmes de production afin de pouvoir effectuer une transition du modèle linéaire classique "production - consommation - abandon" vers un modèle plus vertueux d'économie circulaire.

Le concept de logistique inverse a été introduit afin de répondre à ce défi. Il est défini comme "le processus de planification, de mise en œuvre et de contrôle des flux efficaces et rentables des matières premières, des stocks en cours de fabrication, des produits finis et des informations connexes à partir du point de consommation jusqu'au point d'origine afin de récupérer de la valeur ou d'éliminer le produit de manière appropriée"[RTL98]. Sa mise en place permet de minimiser de manière significative la quantité de déchets ainsi que de réaliser des économies sur la consommation de matières premières [BD03]. De plus, en raison de la sensibilisation croissante des consommateurs aux préoccupations environnementales, le traitement des produits en fin de vie renforce une image positive des entreprises, protégeant ainsi leurs marchés [Tof04].

Afin de mettre en œuvre sa logistique inverse, une entreprise doit concevoir une chaîne d'installations pour récupérer, démonter et traiter les produits usés retournés par les consommateurs. Une telle chaîne comprend souvent des centres de collecte, de démantèlement et de recyclage. Ces installations constituent la chaîne logistique inverse (CLI). Lorsque la CLI travaille en coordination avec la chaîne de production classique (CLC) de l'entreprise, l'ensemble du système est appelé chaîne logistique en boucle fermée (CLBF) [GJVW09] (voir Figure 1).

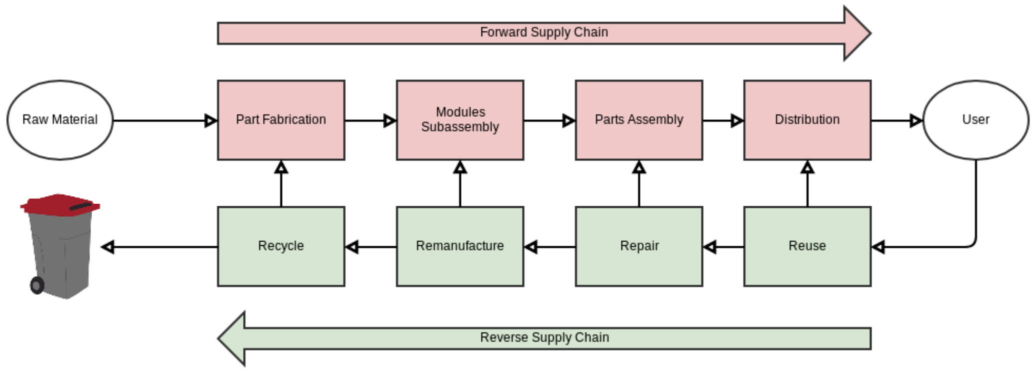


Figure 1: Chaine logistique en boucle fermée

Plusieurs entreprises ont déjà mis en place de tels systèmes de CLBF. Apple, par exemple, offre des rabais aux clients qui, lorsqu'ils achètent un nouveau produit, retournent l'ancien. Apple récupère ensuite les anciens produits et les réintègre dans ses usines afin d'utiliser des pièces des modèles précédents dans leurs nouveaux produits. H&M, le géant mondial de la mode d'origine suédoise, récupère les vêtements d'occasion dans tous ses magasins à travers le monde. Les vêtements retournés peuvent être dans n'importe quelle condition ou être de n'importe quelle marque et H&M les utilisera pour créer une ligne de vêtements entièrement recyclés. Ce type de CLI permet à tous les types de consommateurs de s'impliquer avec la marque, même s'ils n'ont pas initialement acheté leurs vêtements auprès de H&M. Kodak reconditionne ses appareils photo à usage unique après le développement du film. Au cours de la dernière décennie, l'entreprise a recyclé plus de 310 millions d'appareils dans plus de 20 pays.

Les exemples sont nombreux et ce nombre augmente chaque année, mais la majorité des systèmes de production mondiaux sont encore loin de l'économie circulaire. En parallèle, depuis les années 1990, les études scientifiques en conception et planification de CLI et CLBF sont de plus en plus abondantes [GSK15].

Lors de la conception d'une chaîne logistique, l'objectif est de déterminer des variables de décision stratégiques (à long terme) comme le nombre de centres de traitement mis en place ou le choix de leurs emplacements et capacités. Au stade de la planification, les variables de décision les plus importantes sont les quantités de flux entre les différents centres du réseau, appelées variables de décision à moyen terme.

La conception des CLI et des CLBF est un problème stratégique complexe en raison du grand nombre de facteurs (économique, législatif, écologique, logistique, etc.) et du haut niveau d'incertitude (demande, volume qualité des produits retournés, etc...) qui doivent être intégrés dans le processus décisionnel.

Dans [AAVW18], les auteurs ont montré sur quatre études de cas d'entreprises impliquées dans des processus de logistique inverse que tous les aspects de la gestion de la chaîne doivent être étudiés afin de rendre le retraitement des produits en fin de vie efficient; de la prédiction du comportement du client jusqu'à la législation, en passant par le modèle commercial de l'entreprise. Une étude de [GSK15] présente la littérature relative à ce domaine sur les dernières années.

Le premier défi de la conception de CLI est le niveau élevé d'incertitude sur différents paramètres [GFK17].

En effet, au moment où la CLI est conçue, les informations précises sur le flux de produits usés qui vont être retournés par les consommateurs ne sont pas souvent disponibles [GFK17] et ce manque d'information doit être intégré dans le processus décisionnel [Bin+16]. Cette incertitude sur les flux en terme de quantité et de qualité, d'une plus grande variété de sources de flux, de fonctions plus complexes en termes de coût, de services et d'impacts environnementaux, et d'opportunités de marché inexplorées [Alm+16]; [Ara+15]; [HKK07] génère de nouveaux risques économiques pour l'entreprise.

Pour faire face à cette incertitude, de nombreuses approches ont été proposées dans la littérature. Les plus courantes sont l'optimisation stochastique, l'optimisation floue et l'optimisation robuste. Cependant, ces méthodes classiques sont soit basées sur des données historiques concernant les paramètres incertains, soit basées sur le concept d'aversion au risque et négligent la plupart du temps les opportunités qui peuvent se produire dans certains cas [DGC15]. Par ailleurs, des études psychologiques montrent qu'un décideur se comporte différemment lorsqu'il/elle considère l'incertitude comme un risque ou bien une opportunité [Gra06], ce qui peut fortement influencer la conception de la CLI créée. Dans ce manuscrit, nous proposons de nouveaux outils permettant de prendre en compte cette bipolarité du comportement du décideur lors de la conception de CLI dans un contexte d'ignorance totale quant à la réalisation des paramètres incertains.

Le deuxième obstacle important lors de la conception de CLI concerne la durabilité des systèmes mis en œuvre. Historiquement, la conception de CLI a été principalement réalisée dans le but de maximiser le profit de l'entreprise ou de minimiser son impact environnemental, mais si la question est abordée sous l'angle du développement durable, c'est-à-dire "répondre aux besoins du présent sans compromettre la capacité des générations futures à répondre à leurs propres besoins "(*Rapport Bruntland pour la Commission mondiale sur l'environnement et le développement (1992)*) trois dimensions doivent être prises en compte simultanément: la dimension économique, la dimension environnementale et la dimension sociale [Seu+08]. Ensuite, un équilibre satisfaisant doit être trouvé entre les performances de chaque dimensions. Cette approche est connue sous le nom de "Triple Bottom Line" (TBL) [SM08]. Dans ce contexte, le deuxième objectif de la thèse est d'apporter un soutien méthodologique aux décideurs en proposant de nouveaux modèles de décision mutli-objectifs dans le but d'améliorer la conception durable des CLI et CLBF.

Le manuscrit est organisé de la manière suivante.

Le premier chapitre contient l'introduction et décrit en particulier le contexte dans lequel se placent nos recherches. Le deuxième chapitre présente un état de l'art passant en revue les notions et méthodes fréquemment utilisées pour l'optimisation sous incertitude et l'optimisation multi-critères dans la littérature. Il fournit une analyse des modèles mathématiques et des approches de résolution proposées pour la conception des CLI sous incertitude et la conception durable des CLI. Cette analyse permet de mettre en évidence les lacunes de la littérature pour lesquelles nous proposons des contributions dans les trois chapitres qui suivent.

Ainsi, dans chacun des chapitres suivants, nous détaillons un problème de recherche auquel nous répondons par une approche méthodologique et un outil d'aide à la décision. Nous développons ensuite des expérimentations numériques démontrant la pertinence l'outil proposé. Enfin, nous concluons et apportons des perspectives.

Le manuscrit se termine par une conclusion générale et un ensemble de propositions pour de futures recherches.

Chapitre 2: État de l'art

L'état de l'art est divisé en deux grandes parties: la première partie concerne l'optimisation sous incertitude et la deuxième l'optimisation multi-critères.

Dans la première partie, les notions de programmation linéaire et en nombres mixtes sont rappelées. L'incertitude dans les modèles d'optimisation est introduite à travers le concept d'ensemble de scénarios.

Plusieurs méthodes classiques permettant de prendre en compte l'incertitude dans les modèles de décision sont ensuite présentées, notamment l'optimisation stochastique, l'optimisation floue et l'optimisation robuste. Nous rappelons en particulier que l'optimisation stochastique repose sur des distributions de probabilités sur les paramètres incertains. En optimisation floue, la densité de probabilité des paramètres incertains n'est pas nécessairement connue. L'incertitude de ce type de problème vient de l'ambiguïté (le choix entre plusieurs alternatives est indéterminé) et de l'imprécision (les frontières nettes et précises pour certains domaines d'intérêt ne sont pas délimitées) sur les paramètres. Enfin, en optimisation robuste, aucune information n'est donnée sur les paramètres incertains: le décideur est dans l'ignorance totale et cherche à prendre la décision la moins risquée (contexte d'aversion au risque) quelque soit les valeurs prises par les paramètres incertains.

Les approches classiques de la littérature sont donc soit dépendantes de distributions de probabilité, soit très conservatrices à cause d'une forte aversion au risque.

Dans le monde réel et en particulier dans le domaine de la logistique inverse, des distributions de probabilités fiables sur les paramètres ne sont pas souvent disponibles ce qui rend les méthodes de résolution stochastiques peu efficaces. Afin de rendre moins conservateurs les modèles robustes, nous proposons de distinguer des zones de risques et d'opportunités ou l'attitude du décideur n'est pas la même [Gra06].

Ainsi notre première problématique est la suivante:

(1) **Comment la prise en compte de la bipolarité du comportement du décideur vis-à-vis des zones de risques ou d'opportunités impacte-t-elle la conception de CLI? Comment modéliser cette bipolarité dans un contexte d'ignorance totale du décideur?**

Dans la deuxième partie de l'état de l'art, nous analysons les approches de la littérature qui s'inscrivent dans la démarche du développement des chaînes logistiques durables. Pour tenir compte des différents piliers du développement durable, une modélisation multi-critères est nécessaire afin de prendre en compte plusieurs objectifs simultanément dans un problème de décision. Le concept de solution optimale au sens de Pareto est ainsi introduit.

Nous présentons ensuite les méthodes qui permettent résoudre des programmes multi-objectifs en gestion de production et qui permettent de trouver des solutions Pareto optimales. Celles-ci peuvent être classées en 2 catégories: à savoir la méthode epsilon-contrainte et les modèles de décision multi-critères (MDM). Les propriétés particulières de chaque méthode sont discutées dans [Bra+08].

Une méthode epsilon-contrainte consiste à prioriser un objectif principal tout en exprimant d'autres objectifs sous forme de contraintes. Fixer différentes valeurs de contrainte pour les objectifs secondaires permet d'approximer le front de Pareto [Hai71]. Cette méthode est bien adaptée à l'extension d'une approche économique à objectif unique à des modèles bi-objectifs ou multi-objectifs intégrant des critères environnementaux et/ou sociaux. En effet, en considérant par exemple le modèle économique comme objectif principal, cette approche permet aux décideurs de mesurer l'impact financier des contraintes environnementales et/ou sociales [Esk+15].

Les MDM peuvent être utilisées pour gérer un plus grand nombre de critères contradictoires [Esk+15] en prenant en compte le comportement du décideur dans le processus de prise de décision afin de trouver la solution Pareto optimale qui lui plaît le plus.

Après une étude approfondie de la littérature sur la conception de CLI durables, nous proposons d'aborder les problématiques suivantes :

(2) **Quelles relations existent entre les objectifs économique, social et environnemental lors de la conception d'une CLI durable ?**

(3) **Comment l'attitude du décideur influence-t-elle le choix de la solution finale?**

(4) **Comment modéliser et prendre en considération l'équité entre plusieurs régions lors de la conception de la chaîne logistique ?**

Dans le chapitre 3, nous abordons la première problématique (1).

Chapitre 3: Conception de chaînes logistiques inverses sous incertitude avec le critère R_*

Le critère R_* est développé et mis en application dans le cadre de la conception de la chaîne logistique en boucle fermée sur la base d'une chaîne logistique directe existante qui comprend des fournisseurs, des centres de production et de distribution. Nous considérons que les centres de distribution existants peuvent être transformés en centres hybrides de distribution et de collecte (HDC) ou en centres exclusivement de collecte pour récupérer les produits en fin de vie. De nouvelles installations peuvent également être mises en place : de nouveaux HDC pour prendre en charge le flux des produits en fin de vie, des centres de démantèlement pour le désassemblage des produits en fin de vie, des centres de réparation, des centres de recyclage permettant la transformation des composants en matière première et des centres d'élimination pour les produits ou résidus de produits qu'il est impossible de retraiter. La chaîne logistique peut se construire progressivement. Le budget disponible pour le développement au début de chaque période dépend des bénéfices reçus lors des périodes précédentes et des investissement déjà réalisés. Nous considérons que les paramètres suivants sont incertains : la demande en produits neufs et reconditionnés, la quantité de produits retournés ainsi que le temps nécessaire pour retraiter ces produits. Pour intégrer cette incertitude dans le processus décisionnel, un ensemble discret de scénarios est défini. Afin de prendre en compte le comportement du décideur en matière de risques et d'opportunités, nous proposons d'utiliser le critère R_* pour sélectionner la solution finale. Ce critère permet au décideur de choisir un seuil de robustesse (noté e) séparant une zone de risque et une zone d'opportunité. L'attitude du décideur ne sera pas considérée la même dans les deux zones ainsi définies : le risque sera minimisé lorsque l'ensemble des solutions possibles ne permet pas un profit supérieur au seuil e quelque soit le scénario considéré, et les opportunités maximisées lorsqu'au contraire, il en existe. Ainsi, on utilise une approche robuste dans la zone de risque (la valeur du profit obtenue dans le pire scénario est maximisée) et une approche optimiste dans la zone d'opportunité (la valeur du profit dans le meilleur scénario est maximisée). Pour démontrer les avantages et l'applicabilité du modèle développé et la pertinence du critère R_*, jamais utilisé auparavant pour des problèmes de conception en logistique, nous effectuons des expérimentations numériques et faisons une comparaison avec des critères classiques utilisés dans la littérature.

Les résultats obtenus montrent que l'utilisation du critère R_* permet de mieux explorer la zone d'opportunité sans perdre le contrôle de la robustesse de la solution. En effet, ce critère donne au décideur un plus grand contrôle sur l'investissement qu'il est prêt à faire pour ouvrir de nouveaux centres de logistique inverses, apportant plus de profit dans un bon scénario tout en contrôlant les pertes lorsqu'un mauvais scénario se produit. En particulier, nous montrons que dans le cas où la demande initiale est élevée, le taux de retour est élevé et le temps de retraitement des produits usés est court (i.e. le meilleur scénario) par rapport au cas où la demande et le retour sont faibles et le temps de retraitement est long (i.e. pire scénario), la solution trouvée avec le critère R_* permet de réaliser jusqu'à 36% de profit en plus que la solution robuste pour le meilleur scénario contre seulement 3% de pertes dans le pire scénario. Nous effectuons une analyse de la variance entre les scénarios selon la valeur choisie pour le seuil de robustesse e et proposons des recommandations managériales.

Cette étude révèle de nombreuses nouvelles pistes de recherche. Par exemple, l'étude du cas ou l'incertitude est représentée par un ensemble discret de scénarios avec des probabilités imprécises ou par un ensemble continu de scénarios. Le modèle proposé peut également être étendu en considérant non seulement les meilleurs et les pires scénarios, mais tous les scénarios intermédiaires. Par exemple, un critère de *Leximax* pourrait être appliqué afin de classer les solutions avec les mêmes meilleurs et pires scénarios. Nous poursuivons cette dernière piste dans le chapitre 4.

Chapitre 4: Conception de chaînes logistique inverses sous incertitude avec le critère $LexiR_*$

Dans ce chapitre, nous proposons une amélioration du critère R_*, à savoir, le critère lexicographique R_* (noté $LexiR_*$). Ce nouveau critère est capable de différencier les solutions en prenant en compte tous les scénarios (et non pas uniquement le meilleur et le pire), tout en gardant les propriétés de bipolarité du critère R_*. Deux méthodes d'implémentation pour le $LexiR_*$ sont proposées, une méthode exacte sous forme d'algorithme et une méthode approchée sous forme de programme linéaire mixte. La performance des approches développées est évaluée sur une étude numérique pour un problème de conception de CLI. Nous comparons les résultats fournis par le critère $LexiR_*$ avec les résultats fournis par les critères classiques *Leximin* et *Leximax*, ainsi qu'avec le critère R_* proposé au chapitre précédent.

L'analyse des résultats montre que l'utilisation du critère $LexiR_*$ au lieu du critère R_* permet le même contrôle du risque sur le pire scénario, et les mêmes opportunités sur le meilleur scénario, mais en plus il devient possible de sélectionner la solution apportant le plus de profit sur les scénarios intermédiaires. Nous montrons par ailleurs que plus la valeur choisie pour le seuil e est pessimiste (respectivement optimiste), plus les résultats du critère $LexiR_*$ se rapprochent de ceux trouvés avec le critère *Leximin* (respectivement *Leximax*). Pour des valeurs de e intermédiaires, le $LexiR_*$ permet de trouver des opportunités intéressantes qui ne sont pas proposées par d'autres critères.

Nous analysons les temps de résolution pour l'algorithme $LexiR_*$ et le programme linéaire mixte $LexiR_*$ et montrons que l'algorithme $LexiR_*$ a un temps de résolution beaucoup plus long, mais permet de trouver une solution exacte, contrairement au programme linéaire mixte $LexiR_*$ qui offre seulement une solution approximative, mais obtenue en un temps plus court. Du point de vue méthodologique, les recherches futures pourraient être orientées vers la généralisation du critère $LexiR_*$ à un ensemble continu de scénarios. Du point de vue de la chaîne d'approvisionnement, les performances environnementales et sociales doivent être évaluées en plus des performances économiques afin de trouver une solution durable pour la CLI ou la CLBF créée. C'est sur ce dernier point que se focalise le chapitre suivant.

Chapitre 5 : Conception de chaînes logistiques inverses durable en considérant l'équité

Dans ce chapitre, nous considérons la mise en place d'une CLBF durable : les trois dimensions de la durabilité sont modélisées, à savoir la dimension économique, la dimension environnementale et la dimension sociale. Nous proposons un modèle multi-objectifs comprenant un objectif pour chaque dimension.

Le modèle de CLBF étudié dans ce chapitre est basé sur le modèle présenté dans le chapitre 3. Quelques adaptations ont été apportées pour simplifier sa formulation ainsi que pour étudier quelques nouvelles fonctionnalités :

- Premièrement, l'incertitude sur les paramètres n'est plus prise en compte dans le processus décisionnel. En effet, l'inclusion de deux nouvelles dimensions (environnementale et sociale) dans le modèle apporte beaucoup de complexité dans la résolution. De ce fait, nous avons décidé de laisser de côté l'incertitude dans un premier temps.
- Ensuite, dans le premier modèle (voir chapitre 3), chaque installation avait un emplacement prédéfini sur lequel elle pouvait être installée ou non. Dans le nouveau modèle présenté ici, plusieurs emplacements potentiels sont considérés pour chaque installation. Cette adaptation permettra d'analyser la relation entre la répartition des différents centres et les impacts environnemental et social.

Nous intégrons l'étude du concept de l'équité en ce qui concerne le choix des différents lieux d'implantation de la CLBF. L'équité est définie comme "la situation dans laquelle tout le monde est traité de manière juste et égale" (*dictionnaire Cambridge*). Dans notre cas, nous nous intéressons particulièrement à la prise en compte de l'équité environnementale et de l'équité sociale lors de l'implantation d'une CLBF : la répartition de des impacts environnemental et social doivent être équitablement répartis dans l'ensemble des lieux. Ainsi, les trois objectifs considérés sont les suivants: L'objectif économique est la maximisation du profit de la CLBF. L' objectif environnemental est d'induire le moins de dégradation possible de l'air, du sol et de l'eau ainsi qu'utiliser le moins d'énergie possible dans les régions les plus polluées. L'objectif de la dimension sociale est la maximisation de la création d'emplois dans les régions avec les plus haut taux de chomage.

Peu d'études de la littérature ont abordé l'équité dans la prise de décision lors de la conception de CLBF durables [Mot+18]; [CSC18]. De plus, nous n'avons trouvé aucun article tenant compte de l'équité en ce qui concerne la distribution de la pollution environnementale. Afin de mettre en œuvre un modèle où le but est la réalisation de l'équité dans les objectifs environnementaux et sociaux, nous nous sommes basés sur l'étude de [MS94] qui analyse les 20 mesures d'équité les plus couramment utilisées dans les problèmes de conception et localisation d'installations. Nous avons choisi d'utiliser la mesure d'iniquité de Gini (noté G) [DSS73]; [Erk93]. Ce coefficient satisfait le principe d'optimalité au sens de Pareto qui implique que si sa valeur s'améliore, alors aucun des groupes évalués ne sera plus mal en point. Dans notre modèle, nous avons adapté le coefficient de Gini pour le considérer comme un objectif, plutôt que comme un simple outil analytique. Afin de maximiser l'équité, nous cherchons à minimiser le coefficient de Gini dans les objectifs environnementaux et sociaux.

Pour résoudre le modèle, nous utilisons dans un premier temps des fonctions d'agrégation classiques utilisées en MDM : l'agrégation basée sur les normes $||.||_1$ et $||.||_\infty$ et l'agrégation *Leximin*. Chacune de ces approches classiques a ses avantages. Cependant, aucune d'elles ne permet un changement de comportement du décideur vis-à-vis des valeurs des fonctions objectives. Nous abordons ce problème en introduisant deux nouvelles approches de MDM basées sur des opérateurs bipolaires. Une comparaison des approches dans leur ensemble est effectuée.

La première méthode de résolution proposée est notée OPT_{R_*}. Elle est définie de la manière suivante:

Soit D_o l'évaluation de la déviation entre l'objectif o et la solution optimale si l'on considérait que l'objectif o était le seul objectif pris en compte dans le problème, pour la solution x,

$$OPT_{R_*}(D_o, e) = \begin{cases} \min \max_{o\in|n|} D_o & \textbf{si } \exists\ D_o \geq e \\ \min \min_{o\in|n|} D_o & \textbf{sinon} \end{cases} \tag{1}$$

En d'autres termes, nous considérons ici que e est l'écart relatif par rapport à la solution idéale que le décideur est prêt à accepter pour chaque objectif. Le comportement du décideur ne sera pas pris en compte de la même manière si l'une des déviations est supérieure à e ou si elles sont toutes plus petites.

La deuxième approche proposée (notée OPT_{HYB}) est une approche hybride entre l'approche *Leximin* et l'approche OPT_{R_*}. En effet, il s'agit d'une approche bipolaire dans le sens où nous considérons que tant que le seuil acceptable d'équité environnementale et sociale est respecté, le décideur est satisfait et l'objectif principal est de maximiser le profit. Au contraire, si un ou plusieurs objectifs ne satisfont pas le seuil acceptable, le décideur choisit de faire un compromis en sélectionnant la solution avec la déviation maximale la plus basse parmi tous les critères, et applique une méthode de résolution *Leximin*.

La formulation de OPT_{HYB} est donnée comme suit :

$$OPT_{HYB}(D_0, e) = \begin{cases} leximin_{o\in|n|} D_o & si\ \exists\ o \in O\ tel\ que\ D_o \geq e \\ \min D_1 & sinon \end{cases} \tag{2}$$

Les résultats obtenus permettent de faire les observations suivantes:

- Les solutions trouvées avec l'approche $\|.\|_1$ ont la déviation moyenne la plus petite par rapport à la solution idéale. Cependant, cette approche ne permet pas toujours de trouver une solution satisfaisante pour tous les objectifs: un objectif très bon peut compenser un objectif très mauvais.

- Avec l'approche $\|.\|_\infty$, tous les objectifs sont également satisfaisants, mais certaines opportunités sont manquées.
- L'approche *Leximin* améliore les résultats de l'approche $\|.\|_\infty$. Cependant, elle ne permet pas au décideur de contrôler ses préférences entre plusieurs solutions équivalentes.
- L'approche OPT_{R_*} offre la possibilité au décideur de choisir le niveau de réalisation souhaité pour chaque objectif. Si ce niveau est atteint, il est alors possible d'explorer les opportunités dans l'espace de solutions. D'un autre coté, cette méthode ne permet pas de choisir sur quelle fonction objectif le décideur préfère trouver de nouvelles opportunités. Ce manque de contrôle peut être corrigé avec le critère OPT_{HYB}.
- L'approche OPT_{HYB} est conçue de manière à permettre de choisir un niveau acceptable pour les objectifs environnemental et social et ensuite maximiser la valeur de l'objectif économique uniquement. En conséquence, cette méthode fournit les meilleurs résultats pour l'objectif économique. Elle peut être adaptée pour prioriser l'objectif le plus important pour le décideur.

Pour approfondir davantage ces observations et fournir au décideur des informations managériales pratiques, nous avons analysé pour chaque solution le nombre de centres ouverts (tous types compris) et la répartition des emplacements des centres créés. Sur la base de cette analyse, les observations complémentaires suivantes sont faites :

Le nombre de centres ouverts est lié au profit : plus le nombre centres ouverts est grand, plus la CLBF sera en mesure de collecter et de retraiter de plus grandes quantités de produits de fin de vie et d'en récupérer de la valeur.

Quelle que soit la méthode de résolution, les centres de collecte de produits usés sont toujours établis dans tous les emplacements. On peut donc supposer que cette répartition permet d'aboutir à la meilleure équité sociale et environnementale.

Ces résultats génèrent plusieurs pistes de recherche intéressantes. La principale consiste à inclure de l'incertitude dans le modèle, car, comme nous l'avons vu dans les premiers chapitres, toutes les informations sur les paramètres à prendre en compte lors de la mise en œuvre d'une nouvelle CLBF ne sont pas toujours facilement prévisibles ou disponibles.

Conclusion générale

1 - Conclusion

La mise en place de CLBF est un enjeu essentiel pour passer de l'économie linéaire à l'économie circulaire, et pour répondre aux besoins actuels de production plus propre, de réduction des déchets, de réduction des coûts, de rentabilité, de durabilité, de réduction des changements climatiques et de responsabilité sociale. Une conception réussie de CLBF repose sur une modélisation appropriée de l'incertitude en termes de risque et d'opportunités, ainsi que sur la prise en compte des trois dimensions du développement durable.

Dans ce contexte, nous proposons dans un premier temps de nouveaux outils de prise en compte de l'incertitude. En particulier, nous proposons une nouvelle approche de modélisation utilisant le critère R_* pour prendre en compte l'optimisme du décideur à la fois dans les zones de risque et d'opportunité. Cette approche est comparée à des méthodes robustes et stochastiques dans une expérimentation numérique approfondie. Les résultats obtenus montrent que son utilisation permet d'explorer de nouvelles opportunités sans perdre le contrôle de la robustesse.

Nous proposons ensuite un raffinement du critère R_*, à savoir le critère $LexiR_*$ qui permet d'améliorer encore les résultats trouvés. Deux méthodes de résolution sont développées pour appliquer le critère $LexiR_*$. La première se présente sous la forme d'un algorithme et la deuxième sous la forme d'un programme linéaire mixte. Nous analysons les temps de résolution pour les deux méthodes et montrons que l'algorithme $LexiR_*$ prend plus de temps de calcul, mais permet de trouver une solution exacte, contrairement au programme linéaire mixte $LexiR_*$ qui offre seulement une solution approximative mais obtenue en un temps plus court.

Dans un second temps, nous étudions un problème de conception de CLBF où les trois dimensions de la durabilité sont prises en compte simultanément dans un modèle de décision multi-objectifs. Nous étudions plusieurs méthodes prenant en compte l'attitude du décideur dans un contexte d'optimisation multi-critères et nous les comparons. Puis nous proposons deux nouvelles méthodes de résolution notée OPT_{R_*} et OPT_{HYB}. Nous montrons que l'utilisation de la méthode OPT_{R_*} permet d'explorer de nouvelles opportunités tout en garantissant un niveau de satisfaction générale sur tous les objectifs. La méthode OPT_{HYB} peut être utilisée pour sélectionner un objectif prioritaire et maximiser les opportunités sur celui-ci en gardant un niveau satisfaisant de réalisation pour les deux autres objectifs.

Une analyse de l'équité sociale et environnementale entre différents lieux d'implantation de la CLBF est effectuée. Nous montrons que les solutions menant aux meilleurs profits sont les solutions où le décideur prend la décision d'ouvrir plus de centres dans la partie inverse de la CLBF. De plus, les solutions conduisant à la meilleure équité sociale sont les solutions où les centres sont répartis dans les différentes régions en fonction du taux d'emploi de chaque région. Enfin, le type de centre mis en place dans chaque région a un impact sur l'équité environnementale.

2 - Perspectives

Cette étude révèle de nombreuses pistes possibles pour la recherche future.

Par rapport à la considération de l'incertitude dans les modèles de conception de CLI et de CLBF, les critères R_* et $LexiR_*$ peuvent être généralisés pour prendre en compte des ensembles continus de scénarios. En effet, ces critères pourraient ainsi être utilisés dans les cas où l'incertitude ne peut pas être représentée par un ensemble de cas discrets. De plus, le seuil de robustesse e pourrait être exprimé par une valeur floue, permettant ainsi d'explorer de potentielles opportunités au voisinage de la valeur initiale choisie par le décideur et ainsi permettre plus de flexibilité dans la décision. Enfin, d'autres opérateurs bipolaires avec différentes propriétés devraient être étudiés et comparés à ceux que nous proposons. En effet, de nombreux opérateurs bipolaires existent et permettent de représenter une grande variété de comportements différents du décideur. L'étude de tels opérateurs pourrait donc fournir une analyse intéressante de la relation entre différentes attitudes possibles face à l'incertitude et les décisions prises sur la conception de CLI ou de CLBF.

Par rapport à la durabilité des CLI et CLBF, une importante piste de recherche est la prise en compte de l'incertitude dans les modèles multi-critères. De plus, la dimension sociale pourrait être complétée en intégrant d'autres aspects en plus de la création de l'emploi (e.g. le développement local, la santé, la satisfaction des clients...). Les objectifs de minimisation de l'impact environnemental et d'équité environnementale, ainsi que de maximisation de l'impact social et d'équité sociale pourraient être étudiés simultanément dans un même modèle afin d'analyser comment la prise en compte de l'équité influence les performances des deux impacts. Enfin, une étude de la position des solutions trouvées avec les différentes méthodes de décision multi-critères sur le front de Pareto pourrait être effectuée. En effet, une telle étude permettrait de visualiser quelles parties du front de Pareto sont explorées par les différents critères.

Liste des Publications

Articles publiés

- Zoé Krug, Romain Guillaume, Olga Battaïa "Résolution d'un programme linéaire sous incertitude avec l'Uninorme R_*", ROADEF 2018. *National conference with proceedings*
- Zoé Krug, Olga Battaïa, Romain Guillaume "The use of two-stage approach with R_* criterion to solve a multi-period closed loop supply chain design problem", Logistics Analytic 2018. *International conference without proceedings*
- Zoé Krug, Romain Guillaume, Olga Battaïa "Lexicographic R_* Criterion For Decision Making Under Uncertainty in Reverse Logistics", MIM 2019. *International conference with proceedings*
- Zoé Krug, Olga Battaïa, Romain Guillaume "A Sustainable Closed Loop Supply chain design problem", EURO 2019. *International conference without proceedings*
- Romain Guillaume, Olga Battaïa, Zoé Krug "Decision under ignorance: a comparison of existing criteria in a context of linear programming", EDSI 2019. *International conference without proceedings*
- Zoé Krug, Olga Battaïa, Romain Guillaume "Résolution d'un problème de décision sous incertitude avec le $lexiR_*$", ROADEF 2020. *National conference with proceedings*

- Zoé Krug, Romain Guillaume, Olga Battaïa "A comparison of criteria for decision under ignorance in context of linear programming", IPMU 2020. *International conference with proceedings*

- Zoé Krug, Olga Battaïa, Romain Guillaume "Exploring opportunities in establishing a closed loop supply under uncertainty", International Journal of Production Research 2020

Articles soumis

- Zoé Krug, Romain Guillaume, Olga Battaïa "Design of Reverse Supply Chains under Uncertainty: the Lexicographic R_* criterion for exploring opportunities", *submitted to an international peer-review journal*

- Zoé Krug, Richard Oloruntoba, Olga Battaïa, Romain Guillaume, Claudia Oliver-Cortadellas "Equity in a multi-objective Sustainable Closed-Loop Supply Chain Design Problem", *submitted to an international peer-review journal*

Chapter 1

Introduction

Contents

1.1 Industrial Context

Climate change and pollution hit higher records every year and the situation has never been more worrying. A study from [Bau+16] has shown that greenhouse gaz emissions increase by 64% a year in average since 1990. In France, the carbon footprint per person has raised by 20% in the last 25 years [Bau+16]. According to [MD+18] the temperatures have increased by approximately 1°C since the industrial revolution and are still escalating of 0.1°C to 0.3°C every decade. Accompanying this disquieting fact, the accumulation of solid waste is reaching new heights. The production of plastic has been higher in the last decade than ever before [Pla16]. While a small portion is recycled or incinerated, the majority is either discarded into landfill or littered into natural environments, including the world's oceans. As a direct effect, we are now witnessing the apparition and development of the "7th continent": an accumulation of waste of approximately three times the size of France [Leb+18] in the Pacific ocean. Waste accumulation has numerous harmful effects on both land and see wild life, and pollution is now affecting approximately 75% of land species and 66% of see species [Ric+18].

Open-pit dump *(photo credit: shutterstock)*

Benxi steel industries in 2013

Furthermore, in addition with the concerns about climate change and pollution, we are also experimenting a crisis of scarcity of raw materials greatly affecting the world economy. A paper by [HSH19] particularly shows that even in the best case scenario in which new policies are put in practice to reach the sustainable development goals of the COP21, the oil industry should know production difficulties by 2025, only 5 years from now. Apart from oil, the exploited ore grades mines are also rapidly declining. In Europe and in the United States of America (prior industrial regions of the world) a non negligible percentage of mines have been shut down due to their low mineral content [Hen+16]. A study of [Pri+12] also shows that, in Australia, another important mineral-producing country, the number of ore grades mines has decreased by a factor of 2 to 5 from the beginning of their exploitation.

These environmental effects we are witnessing are partly due to the classic linear model production - consumption - abandonment on which have been based the majority of our production systems up to now.

In a classic model, the Supply Chain (SC) is defined by [CH99] as "the group of manufacturers, suppliers, distributors retailers and transportation, information and other logistics management service providers that are engaged in providing goods to consumers". Thus, it represents the entire network allowing the delivery of products or services from raw materials to end customers (see Figure 1.1).

The organization of the different actors of the SC is referred in the following as Forward Logistics (FL). It relies on Supply Chain Management (SCM), defined as “a set of methods used to effectively coordinate suppliers, producers, depots, and stores, so that commodity is produced and distributed at the correct quantities, to the correct locations, and at the correct time, in order to reduce system costs while satisfying service level requirements" [SL+08].

As such, it doesn’t take into account the reprocessing of used products after consumption and generates large amounts of waste.

In order to be able to improve the current situation, concrete actions have to be taken very fast. Fruit of scientific proposals and political commitments, one of the promoted actions is to define corporate responsibilities of manufacturers on the treatment of EOL products so as to switch from a classic FL model to an alternative circular economy model.

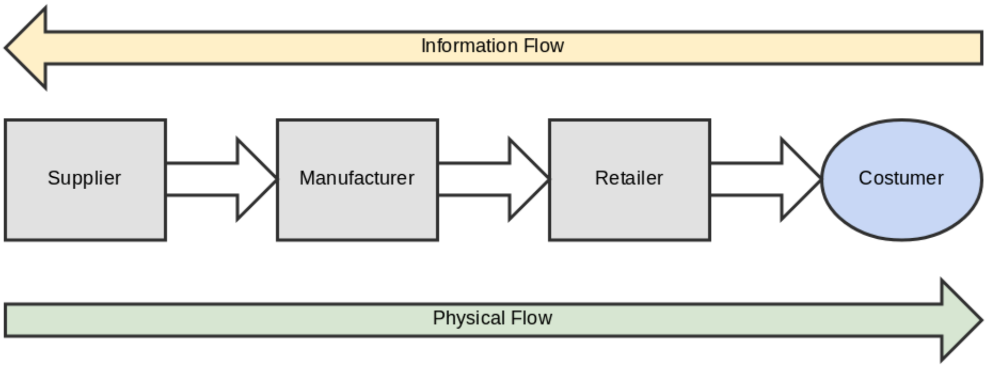


Figure 1.1: Supply Chain

In France, a first law is introduced in 1975 organizing the collection and processing of EOL products. This law precises that EOL collection, transportation and processing must be done in a clean way, so as to avoid "any risk to the environment and to human health". A few years later the law of the 13st July 1992 (also known as Royal law) marks a turning point in our waste management methods. It aims to strengthen the 1975 law and requires companies to recycle their waste. From 1992, waste represents a source of energy and raw materials that are no longer allowed to be wasted or destroyed. Thus the selective collection and recycling of waste policies are imposed by the principle of Extended Producer Responsibility of the government, also called "polluter-payer". This type of regulation is generalised in the whole world, for instance, the Waste Electrical and Electronic Equipment (WEEE) directive which contains mandatory requirements on collection, recycling, and recovery for all types of electrical goods, became a European law in 2003 and was then also introduced in Canada, Japan, China, and many states in the US [QFN+10].

Recently, abundant examples of recent initiative to go further in circular economy models implementation also include: G7 Declaration made in June 2015: “The G7 Alliance on Resource Efficiency promotes circular economy, refurbishment and recycling strategic actions to limit consumption of natural resources and reduce waste ”, documents “Roadmap on the circular economy” (April 2015) and “Towards a circular economy: zero waste program for Europe "(July 2014) written by the European Commission, the conference "Closing the loop - Circular economy: boosting business, reducing waste ”organized by the European commission in June 2015 as well as the public consultation on the circular economy carried out by the European Union (EU) in August 2015.

Recent studies demonstrate the positive impact of the circular economy not only on the environment but also on the economy. According to the McKinsey Center for Business and Environment, the choice of a circular economy would reduce by 1.800 billion Euro (25%) the cost of raw materials in the European economy by 2030. Furthermore, direct economic benefits can be obtained by the reuse of materials and/or components [BD03]. In addition, the revaluation of EOL products would allow improving the image of the company and protecting its market, which is an indirect source of additional economic benefits [Tof04].

A circular economy model relies on Reverse Logistics (RL) implementation. Oppositely to FL, The American Reverse Logistics Executive council defines RL as "the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal" [RTL98]. (See Figure 1.2)

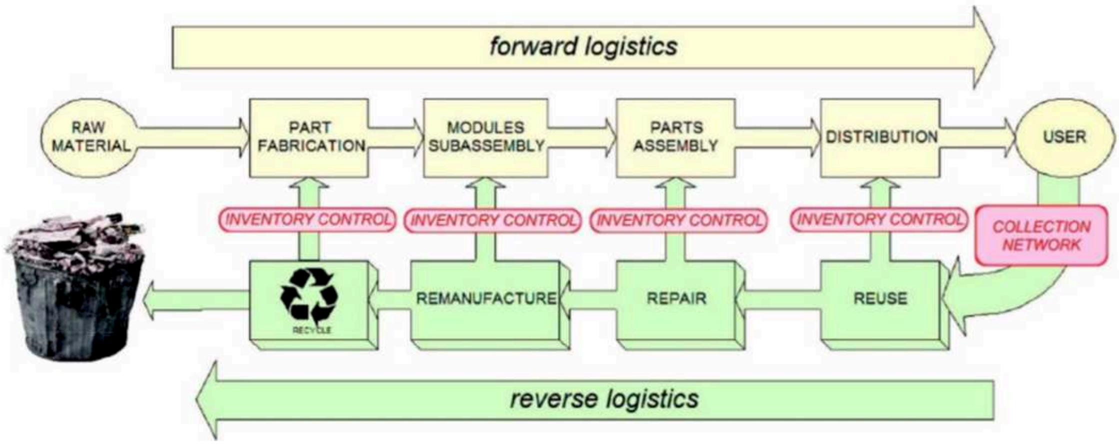


Figure 1.2: End-of-life treatment process [HKK07]

In order to implement RL, a company must conceive disassembly and recovery facilities that integrate the reverse flow of EOL products (i.e. collection centers, dismantlers, recycling centers...). Those new facilities constitute the Reverse Supply Chain (RSC). When the RSC works in coordination with the classic Forward Supply Chain (FSC) of the company, the whole system is called Closed-Loop Supply Chain (CLSC) [GJVW09]

Several companies have already implemented such systems. For instance, Apple offers discounts to costumers who, when they buy a new product, return their old one. Apple then collects the old models and brings the products back to their factories in order to use parts from previous models in their newer products. H&M accepts used clothing at all of their stores worldwide. The clothes can be of any condition or brand, and H&M will use the clothing they have collected to create an all-recycled clothing line. This type of RSC allows all types of consumers to get involved with the brand, even if they didn't purchase their garment from H&M. Kodak re-manufactures its single-use cameras after the film has been developed. Over the past decade, the company has recycled more than 310 million cameras in more than 20 countries.

Examples are numerous and their number increase every year, but the global supply networks are still far away from circular economy. Since the 1990s, the number of academic studies dedicated to RSC and CLSC design and planning increase as well [GSK15]. The aim of design is to determine strategic (long-term) decision variables like the number of facilities implemented or their locations and capacity. In the planning stage, the most important decision variables are the quantities of flows between the different facilities of the network, known as mid-term decision variables.

A strategic vision of the expansion of the CLSC has been introduced through multi-period models where facilities can be set up at any period of time [BGH17]; [DGC15]. These models are more relevant for the context of reverse logistics. For instance in [DR+13], the authors considered a multi-period CLSC network design problem in which facility capacities could be increased or decreased dynamically over time for all echelons. Facility and depot locations could be changed and the type of depots and their general size could be modified. More examples of recent dynamic CLSC models are available in [KMF15]; [MS16].

The design of RSC and CLSC is a complex strategic problem due to the large number of factors that must be integrated into the decision-making process (economic, legislative, ecological, logistics, etc.) and the high level of uncertainty (product demand, volume of returns, fractions of parts recovered for the various product recovery processes, etc.). In [AAVW18], the authors particularly showed on four case studies of companies involved in RL processes that all aspect of RL management have to be accurately investigated in order to make the reprocessing of EOL products beneficial, from the prediction of the customer's behaviour to the legislation including the business model of the company.

A comprehensive review of [GSK15] analyses the existing studies in this area. An important number of models have been developed for different settings. The impact of different logistics structures on the profitability of re-manufacturing systems has been analyzed.

Several studies [Che+15]; [Fle+01]; [Üst+07] suggest that the focus on CLSC is more relevant for OEM (Original Equipment Manufacturer) since designing the forward and reverse flows separately results in sub-optimal solutions. Nevertheless, the production cost structure, collection rate, product life cycle and component durability must be carefully coordinated in order to maximize cost savings in CLSC network [GVWA07] and companies facing large and increasing flows of EOL products should have a different RL network structure than the ones with a low rate of returned products [GJ+06]. Furthermore, [ASVW08] show that the profitability of RL systems is strongly dependent on the product life cycle as well as on the competition faced by OEMs. The problem that in reality, the high level of uncertainty of the different parameters [GFK17] makes this design of RSC or CLSC very challenging.

1.2 Uncertainty in Reverse Supply Chain design

Uncertainty relates to something which is not sure, which may or may not happen, or which nature or shape is vague. In SCM several parameters are often considered uncertain in the literature [GFK17]. We classify them in two main categories:

1. The system uncertainties: They relate to the uncertain parameters implied by the implementation of the supply chain and its functioning. Thus, they are present in both the FSC and the RSC. They include for instance delivery times, production and transportation costs, center capacities...etc.

2. The environmental uncertainties: They relate to the parameters external to the supply

chain, independent of the setting of the designed supply chain. In this category we can include for example the demand of products, the reprocessing time of used product, the return quantity and quality of products. Indeed, the products may be highly degraded due to consumer usage or have higher quality due to modifications realized during the usage phase.

In comparison to classic FSC, the literature acknowledges environmental uncertainty as being a much more challenging factor in RSC design and describes more various sources of uncertainty [GFK17]. Indeed, at the moment when the RSC is designed, precise information about future amount of EOL products cannot be available [GFK17] and this lack of information should be integrated in the decision making process about RSC [Bin+16]. Particularly, new economic risks arise out of less predictable reverse flows of EOL products coming from the customer. in terms of quantity but also quality of returned products, a wider variety of flow sources, more complex functions in terms of cost, services and environmental impacts, and unexplored market opportunities [Alm+16]; [Ara+15]; [HKK07].

To deal with this difficulty, many approaches have been proposed in the literature. The most common ones are stochastic, fuzzy and robust optimization (further detailed in Section 2.2). However these classic methods are either based on data about the uncertain parameters, or are risk oriented and neglects opportunities potentially occurring in some cases [DGC15]. Furthermore, psychological evidences show that a DM often behaves differently regarding if he/she sees uncertainty as a risk or as an opportunity [Gra06] which may influence a lot the choice of the final solution. In this manuscript, we propose to address this subject by proposing new tools helping to take opportunities into account at the same time as risks when designing RSC in a context of complete ignorance of the DM.

1.3 Sustainability in Reverse Supply Chain design

The second major challenge of RSC design regards the sustainability of the implemented systems. Historically, the implementation of RSC has mostly been done with aim to maximize the profit of the company or to minimize its environmental impact, but if the question is considered from the perspective of sustainable development, that is to say "meet the needs of the present without compromising the ability of future generations to meet their own needs" (*Bruntland Report for the World Commission on Environment and Development (1992)*) three dimensions have to be accounted simultaneously: the economic dimension, the environmental dimension and the social dimension [Seu+08](see Figure 1.3). Then, a satisfying balance has to be found between economic performance, environmental performance and social performance. This approach is known as Triple Bottom Line (TBL) approach [SM08].

In the last few years the area of sustainable CLSC development has sparked growing interest among researchers. The study of [Esk+15] particularly reviews numerous papers published in international peer-reviewed journal giving attention to this subject.

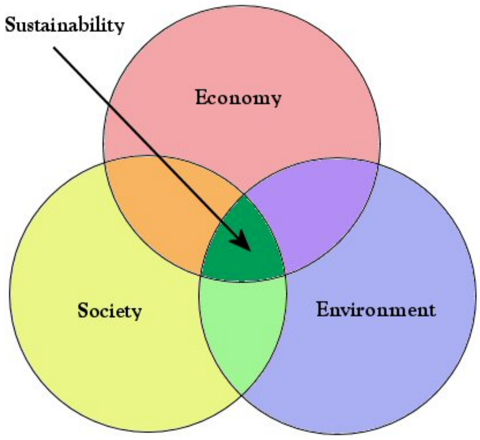


Figure 1.3: Sustainability considerations

1.3.1 Environmental dimension

According to the literature and following the study of [PRT14], environmental factors with the greatest impact on the environment can be divided into 4 main categories:

- Impact of transportation between facilities: according to [ZTMR17], the transportation network of a supply chain is the largest source of environmental hazards in the logistic system due to the high levels of emitted carbon dioxide. It is measured from the number of trips and the distance of these, the type of transportation, as well as the amount of product transported.

- Impact of production: it is the impact generated by the production of one product in each facility (due to the energy consumption, the emitted carbon dioxide, the water pollution...). As such, it includes the facility emissions, the energy and the water consumption.

- Impact of facility establishment: it is the impact generated by the construction of a new facility regarding the emissions and energy consumption of materials used during the construction.

- Impact of disposing of waste: is the impact of disposal of one unit of product in the landfill after consumption calculated in terms of emissions and/or soil pollution.

Quantifying those environmental impacts in not always an easy tasks. They are most of the time quantified through techniques such as Life Cycle Assessment or Life Cycle Analysis (LCA). This methodology aims at assessing environmental impacts related to a product at each stage of its life, from the extraction of the raw material, through every steps of the manufacturing, distribution and use of the product, to the recycling or disposal stage. For every stages, an inventory of the energy and material used as well as GHG emissions produced is studied. This inventory can be done through surveys and case studies, however, it requires accuracy and availability of data about the studied product and request full cooperation from all actors implied in the different life stages of the product. For the last years, some production company have published the environmental impacts of the different stages of their production in recognized databases, making easier the process of retrieving data.

1.3.2 Social dimension

Social sustainability is the dimension the less understood and the less studied in the literature. It has been defined as "the formal and informal processes; systems; structures; and relationships actively supporting the capacity of current and future generations to create healthy and livable communities. Socially sustainable communities are equitable, diverse, connected and democratic and provide a good quality of life" (WACOSS). However, this definition is still under development [Esk+15]. As such, it includes numerous aspects. The aspects the most found in the literature and the most relevant to take into account when designing a RL network are the following:

- Development: this aspect of the social dimension includes all impacts related to the development, internal (for instance the job creation, the amount of wadges...) or external to the company (for instance the regional development). However, the SCM related literature acknowledges the job creation to be the main indicator of development.
- Health and Safety: this aspect regards the employees well-being. It is often evaluated through indicators such as the number of sick leaves taken by the employed, the turnover ratio. It can also include much more general concepts such as the respect of the human rights, general labour conditions, level of education, or access to culture.
- Service level: this last aspect regard the satisfaction of costumers and costumer related issues.

The quantification of the social dimension is often very hard for various reasons. First, there is no recognized standard against which it can be appraised [MBS07]. Thus, the evaluation of social factors is often submitted to the subjectivity of the assessor. Second, Since the social impact is often qualitative by nature, it is difficult to build a single metric to measure it[Esk+15]. For those reasons, the majority of social parameters are often disregarded when designing a RSC or a CLSC. The most studied social factors are related to the development section, and particularly to employment. For instance, in [SFFHK18], the authors study a supplier selection-allocation problem when designing a CLSC and focus on job creation maximization, differentiating permanent ongoing jobs and casual jobs, respectively referred hereafter as fixed and variable jobs. Another study by [Mot+18] defined a social benefit indicator which prefers job creation in the less developed regions.

Once identified and quantified, the environmental and social impact can be evaluated at the same time as the economic profit in a mutli-objective optimisation model. The goal is then to find a compromising design satisfying as much as possible each one of the objectives.

1.4 Outline of the thesis

In this context, the objective of the thesis is to provide decision-makers with methodological support and propose new decision models with aim to improve RSC and CLSC design.

In a first time, the objective will be to mathematically formalize the risks and opportunities related to the uncertainty present at the strategic level of RSC and CLSC design. Once this work accomplished, new tools helping DM to conceive their own RSC or CLSC will be implemented. At this end, bipolar optimization methods for decision under uncertainty will be elaborated in order to take into account the ambivalence risk/opportunity related to the context dynamics.

In a second time, the objective will consist in proposing multi-criteria decision models, taking into account environmental, economic and social objectives at the same time.

The manuscript is organized in the following way.

The first Chapter presents a state of the art reviewing popular notions and methods used for optimization under uncertainty and multi-criteria optimization in the literature. It provides an analysis of the mathematical models and solution approaches proposed in the production literature, and particularly in RL. From this state of art, we highlight the issues related to RSC design under uncertainty and sustainable RSC design and identify the particular research problems later addressed in this work.

Three Chapters then follow one another corresponding to three problems solved. In each of them, we detail the research problem, we then propose a methodological approach and a decision support tool to respond to the problem. Finally we develop an industrial case, we conclude and present some perspectives on the work.

The manuscript is finalized with a general conclusion and advises for future research.

Chapter 2

State of the art

Contents

In this Chapter, we recall some general definitions from combinatorial optimisation, decision making and multi-criteria optimisation that will be used in our contributions. At the same time, we analyse the models and methods used for CLSC design and the results obtained in the previous studies in this area.

2.1 Linear and Mixed Integer Linear optimization

In linear optimization, we seek to minimize (or maximize) a linear objective function, submitted to a set of linear constraints. This type of optimization is particularly applied to solve middle to long term decision problems (strategic and tactic level of decision). In addition, it has been proven well suited to supply chain design and transportation problems [MG07]. Furthermore, linear problems are often easily solvable [MG07]. Compared to linear optimization, Mixed integer optimization adds one additional condition that at least one of the variables can only take integer values. In Supply Chain design, integer (often binary) variables represent such strategic decisions as opening or not of a facility. The value of such a binary variable is 1 when the facility is open and 0 otherwise. Generally, a Mixed Integer Linear Program (MIP) can be presented in the following form (see model 2.1):

Notations

- N: the set of decisions variables,
- M: the set of constraints,
- x_i: the decision variable $i \in N$,
- $a_{i,j}$: the coefficient of decision variable $i \in N$ for constraints $j \in M$
- p_i: the profit of decision variable $i \in N$,
- b_j: the coefficient of constraints $j \in M$,

$$
\begin{array}{ll}
\max & f(x) = \sum_{i \in N} p_i x_i \\
s.t. & \\
(a) & \sum_{i \in N} a_{i,j} x_i \leq b_j \quad \forall j \in M \\
(b) & \quad x \in \mathbb{X} \subseteq \mathbb{R}^+
\end{array}
\tag{2.1}
$$

$\mathbb{X}$ can be $\{0, 1\}$ or $\mathbb{N}$

2.2 Optimization under uncertainty

2.2.1 Scenario set

Depending on the considered uncertain parameters, uncertainty will be either considered on the profit coefficient p_i, on the constraint coefficient $a_{i,j}$ and/or b_j.

To model the uncertainty we are given a *scenario set* S, which contains all possible vectors of the uncertain parameters coefficients, called *scenarios*. We thus only know that one scenario $s \in S$ will occur, but we do not know which one until a solution is computed. Two methods of defining scenario sets are popular in the existing literature (see, e.g, [KY13], [BBC11] and [Min10]). The first one is discrete uncertainty representation, $S^D = \{s_1, \cdots, s_K\}$ contains

$K > 1$ explicitly listed scenarios. The second one is interval scenario set. In the case where uncertainty is considered on the profit coefficient p_i, an interval scenario set is described as $S^I = \prod_{i \in N} [\underline{p}_i, \overline{p}_i]$.

Then, several methods exist to take into account uncertainty in decision processes. A first approach consists in reducing the level of uncertainty present in the model with the use of surveys of existing cases. A second approach is to study existing data so as to be able to approximate as reliably as possible the uncertain parameters with probability distributions. Finally a third approach is to take the best possible decision without knowledge on the realization of the uncertain parameters when no reliable data is available.

According to those different approaches, the uncertain parameters can be divided into 3 groups regarding the information level of the Decision-Maker (DM) [GFK17]:

- Group 1 (G1): Random parameters for which the probability distributions are known for the decision maker. In this case, a probability distribution is provided for the scenario set.

- Group 2 (G2): Fuzzy parameters. In general, there exist two types of uncertainties including ambiguity and vagueness under the fuzzy decision-making environment. Ambiguity denotes the conditions in which the choice among multiple alternatives is undetermined. However, vagueness states the situations in which sharp and precise boundaries for some domains of interest are not delineated.

- Group 3 (G3) : Random parameters for which the decision maker has no information about the probability distributions. In this case, all the scenarios contained in the scenario set are equally possible to occur.

As deterministic programming is unable to handle uncertain parameters, other types of mathematical models are used to cope with them. The most used methods which take into account uncertainties in the literature are stochastic programming, fuzzy programming and robust programming. In the following subsections, we detail these different programming methods with their advantages and drawbacks.

2.2.2 Stochastic programming

In a stochastic program, it is assumed that the probability densities of the uncertain parameters are known or can be estimated (i.e the uncertain parameters are considered to be in G1). The goal is then to find a feasible solution which maximizes the expected value of the objective function (see Model 2.2).

$$\begin{aligned} \max \quad & \mathrm{E}_s[f_s(x)] \\ s.t. \quad & \\ (a) \quad & \textstyle\sum_{i \in N} a_{i,j} x_i \leq b_j \quad \forall j \in M \\ (b) \quad & x \in \mathbb{X} \subseteq \mathbb{R}^+ \end{aligned} \tag{2.2}$$

For example, in a case where a probability distribution p_s of a discrete scenario set $S = \{s_1, \cdots, s_K\}$ is considered, the *Average* criterion is often used to find a solution. It consists in maximising the average of the evaluations of the objective overall scenarios and can be written as:

$$\max \mathrm{E}[f(x)] = \max \sum_{s \in S} p_s f_s(x) \tag{2.3}$$

A more complete description of stochastic programming can be found in [SDR14].

While providing the best expected value for the objective, this method offers no guarantees in the worst cases as the objective value can be very high in the best cases and compensate for very bad values in the worst cases.

To assess and control the level of risk taken when using a stochastic solution method, the Conditional Value at Risk (CVaR) is often used. This measure has originally been introduced by [RU+00] for financial applications and is defined as follows:

Let X be a random variable, the Conditional Value at Risk at level of probability α ($CVaR_\alpha$) of X is given by

$$\begin{aligned} CVaR_\alpha(X) &= E(X | X \geq VaR_\alpha(X)) \\ Where \quad VaR_\alpha(X) &= inf\{\eta \in R : H_X(\eta) \geq \alpha\} \end{aligned} \tag{2.4}$$

where H represents the cumulative distribution function.

Generally speaking, the Value at Risk (VaR) is the evaluation of the potential loss in the worst case scenario in a given time period associated with the corresponding probability for this worst case to occur, while CVaR is more conservative and quantifies the expected losses that occur beyond the VaR break point.

By minimizing the CVaR in the objective functions of a stochastic model, a DM can control the level of risk taken.

The stochastic approach is the most commonly used in RL design. For example, [SG14] proposed a two-stage stochastic programming approach in order to design an RSC. The conditional value at risk (CVaR) was used as a risk estimator and the return amounts and prices of returned products were considered as two stochastic parameters. Other recent examples of stochastic programming for RL can be found in [AZA17]; [AB14]; [ABA15]; [Hab+17]; [ZU16].

However, stochastic models have two main disadvantages: first, stochastic programs are often hard to solve computationally [SN05]. Second, it can often be difficult to know the exact distribution of probability of the uncertain parameters, and, a too broad estimation can lead to inaccuracies in the solutions.

To overcome this difficulty, fuzzy programming is relatively frequently used [Zad99].

2.2.3 Fuzzy programming

In a fuzzy program, the probability density of the uncertain parameters are not necessarily known (i.e the uncertain parameters are considered to be in G2). Fuzzy programming approaches are used to cope with epistemic uncertainty that deals with lack of knowledge on the parameters. For example, a parameter representing the age of a population can characterize people into "young", "middle age" or "old". These categories are not completely clear and can overlap each other.

As such, the uncertain parameters are represented with fuzzy numbers. Basically, a fuzzy number can be represented as a function whose domain is a specified set and whose range is the interval $[0, 1]$. Each value in the domain is assigned to a specific level of compliance where 0 represents the smallest level, and 1 is the largest level. To illustrate this concept let's consider once again the age of the population. We can assume that all people between 0 and 30 years old are young. However, they aren't all young with the same level. Someone between 0 and 18 is definitely young, then the more the age increases, the less a person is admitted to be young. As such, a function taking as an input the age of a person can be defined to return as an output a level of compliance with "being young" where the ages 0 to 18 are associated to 1 (the largest level of compliance), and where the more the age increases above 18, the more the level of compliance decreases, until reaching 0 (the lowest level of compliance) for instance when the age is above 30. The reader can refer to [DP78]; [DVHDL83] for more information about fuzzy numbers.

Once the fuzzy numbers defined, a fuzzy MIP can then be written as: (see Model 2.5)

$$\begin{array}{ll} \max & f(x) = \sum_i \tilde{p}_i x_i \\ s.t. & \\ (a) & \sum_{i \in N} a_{i,j} x_i \leq b_j \quad \forall j \in M \\ (b) & x \in \mathbb{X} \subseteq \mathbb{R}^+ \end{array} \tag{2.5}$$

Where $\tilde{p_i}$, $\tilde{a_{j,i}}$ and $\tilde{b_j}$ are fuzzy sets in $\mathbb{R}$ and $\tilde{\leq}$ represents the willingness of the DM to permit some violations in the accomplishment of the constraints.

The general model 2.5 includes the special cases where:

1. The objective function is crisp:
$$f(x) = \sum_i p_i x_i$$

2. Some or all constraints are crisp:
$$\sum_{i \in N} a_{j,i} x_i \leq b_j$$

In the literature, there are two main families of fuzzy approaches. In the first family, a defuzzification is first performed (i.e a crisp output is obtained from the aggregated fuzzy set) and deterministic optimization methods are then used to solve the problem. It is especially the case in [Pei+10]; [Pau15].

In the second family, the objective is expressed in the setting of possibility theory [DP88] and credibility theory [Liu04].

A complete description of fuzzy programming and its applications can be found in [Ful98]. This approach is commonly used in RL design, for instance [Sub+15] proposed a fuzzy possibilistic programming model for designing a forward-reverse logistics network with hybrid facilities in the presence of uncertainty on demand quantities and quality of returns as well as the uncertainty of variable costs and random facility disruptions. The fuzzy goal programming model with different priorities was used to solve the developed model. A case study from the lead/acid industry in Turkey was presented. For more examples of fuzzy approach, see [FEP15]; [GPA16]; [Hat+15b]; [Hat+15a]; [NP14]; [Özc16]; [TA18].

Fuzzy programming can be generalized with robust programming (see for instance [GKZ12]) which is the most adapted approach when there is no available information about the uncertain parameters. Indeed, it corresponds to the case where the possibility of scenario s to occur is binary (equal to 1 if scenario s occurs and 0 otherwise).

2.2.4 Robust programming

In a robust optimization setting, no probability for the scenario set is given (i.e the uncertain parameters are considered to be in G3). The value of each parameter may fall within a given closed interval and the set of scenarios is either discreet, or the Cartesian product of these intervals. Robust programming was first introduced by [Soy73]. An overview of robust optimization and its applications can be found in [BTEGN09].

From a practical perspective, robust programming has been often successfully applied in facility location and network design problems (see for instance [BMN11]; [Gab+14]; [ÁM+15]; [PP15]). Furthermore, implementation of RL being a relatively new field of research, there is no efficient probability distributions describing the behavior of the uncertain parameters considered. Thus, in this thesis, we suppose a context of complete ignorance of the DM and define decision models based on robust optimization.

In robust optimization, the goal is to find a reliable solution even when the worst case scenario happens. In this context, the Wald criterion (*maxmin* criterion) is very popular in the literature [Ahu85],[BBC11], and [GYH15].

Let's consider a MIP where the profit coefficients are uncertain. We denote as p_i^s the profit of decision variable $i \in N$ under scenario $s \in \mathbf{S}$. Let $f(x,s) = \sum_{i \in N} p_i^s * x_i$, the Wald criterion consist in solving the following model (2.6):

$$\begin{array}{lll} & \max_{x \in X} \min_{s \in S} f_s(x) & \\ s.t. & & \\ (a) & \sum_{i \in N} a_{i,j} x_i \leq b_j & \forall j \in M \\ (b) & x \in \mathbb{X} \subseteq \mathbb{R}^+ & \end{array} \tag{2.6}$$

Another popular robust criterion is the *minmax regret* criterion [Sav51]. Let's consider a given scenario s, the regret is defined as the loss of profit induced by the occurrence of s compared to the optimal profit made in the best case scenario, i.e. it is the difference or the ratio of the payoffs between the best solution and the chosen solution. In this context, the *minmax regret* criterion minimizes the maximum regret overall scenarios. It can be formalized as follows

$$\begin{array}{ll} & \min_{x \in X} \max_{s \in S} F_s - f_s(x) \\ Or & \min_{x \in X} \max_{s \in S} \frac{f_s(x)}{F_s} \end{array} \tag{2.7}$$

With F_s the total profit of scenario s for the optimal solution

Using the *maxmin* or *minmax regret* criteria, the DM is considered very pessimistic as these criteria only focuses on the worst case scenario and provide no guaranties on the better cases. Moreover, it is necessary to meet the underlying condition that all scenarios are almost possible (ignorance context).

In this context, a refinement of the *maxmin* criterion, namely *Leximin* criterion has been proposed by [Yag97]. In the same way as the *maxmin* criterion, this criterion selects a solution by maximizing the one with the highest minimum profit overall scenarios. However, if multiple solutions exist with the same minimum profit, the criterion moves on to maximizing the second minimum profit, and the third, etc... until one solution dominates the others.

The formal definition of the *Leximin* order is given below (see definition 1):

Definition 1 (*Leximin* order)
Let $f(x) = (f_1(x), ..., f_n(x))$ and $f(y) = (f_1(y), ..., f_n(y))$ be two possible outcomes. The

Leximin order (noted $>_{lex}$) is defined such as:

$$f(x) >_{lex} f(y) \iff \exists k \leq n \text{ such as } \forall i < k,\ f_i(x) = f_i(y) \text{ and } f_k(x) > f_k(y)$$

$$f(x) =_{lex} f(y) \text{ if } f_i(x) = f_i(y)\ \forall i = 1, .., n$$

The *Leximin* criterion is still quite conservative, as a solution with the highest profit in the worst scenario may not offer a lot of opportunities in a better case scenario.

There exist several approaches to cope with the conservatism of robust programming :

1. *The scenario set is adapted.*

   Several methods exist to adapt scenarios sets in order to make robust solution less conservative. Particularly, [BTN98] considered uncertain parameters that are elliptic, thus involving to solve the robust counterparts of the nominal problem in the form of conic quadratic problems. However, this approach leads to nonlinear models, which demand more computational time. In order to overcome these drawbacks, the concept of of "budget of uncertainty" also known as "price of robustness" has been introduced by [BS04]. Using the observation that it is unlikely that all uncertain parameters deviate to the worst case scenario at the same time, or, in other words, that the parameters' uncertainties are not independent, they proposed a model offering a limited number of deviating parameters for each constraint j named Γ_j.

2. *The DM's optimism is taken into account.*

   Several criteria have been proposed for this purpose [GYH15] and Hurwicz-Arrow particularly proposed a decision under ignorance theory [AH72] that specifies the properties that a criterion must satisfy. Two of the oldest and most used criteria are the Hurwicz criterion (H) [Hur51] and the Ordered Weighted Average (OWA) criterion [Yag04]. The Hurwciz criterion [Hur51] consists in modeling the optimism of the DM by making a linear aggregation with the best and the worst evaluation of the objective function overall scenarios (see definition 2). It has often been used to model the behavior of a decision-maker in different contexts (see [KM05],[Lau+10],[Cha+18], [SZW18] ...etc) and has been spread to include imprecise probability theory [JS09]. The OWA criterion is a generalization of the Hurwicz criterion where the optimism of the DM is modelled by a linear aggregation of the ordered evaluations of the objectives overall scenarios (see definition 3).

   Definition 2 (H criterion)

   $$H = (1-\alpha)\min_{s\in S} f_s(x) + \alpha \max_{s\in S} f_s(x)$$

   where $\alpha \in [0,1]$ is called the optimism-pessimism index. Clearly, if $\alpha = 1$ then the problem is solved with max-max criterion; if $\alpha = 0$ then the problem is solved with max-min criterion. Hence, $\alpha \in [0,1]$ controls the relative importance of two extremes min and max.

Definition 3 (OWA criterion)

$$OWA = \sum_{j=1}^{n}(w_j * f_{j,s}(x))$$

were $f_{j,s}(x)$ is the j^{st} best solution and w_j the corresponding weight.

Hurwicz and OWA criteria are compensatory, it means that a good case scenario will soften the effect of a bad case scenario and reciprocally. However, psychological evidences show that a DM often behaves differently regarding if he/she sees uncertainty as a risk or as an opportunity [Gra06] which may influence a lot the choice of the final solution.

Robust programming, while less studied than stochastic or fuzzy programming in the literature for RL design problems, may provide valuable results. For instance, [RBTM13] presented a robust design model for a generic multi-product, multi-echelon CLSC. The uncertainty in demand and the return rate was modelled by a finite set of possible scenarios. The scenario relaxation algorithm was employed to reduce the solution time. Another robust model was studied by [DR+13] who considered a multi-stage, multi-period, capacitated, CLSC design problem with discrete uncertainty. More examples of the use of robust optimization for CLSC design can be found in [PRT11].

2.2.5 Two-stage programming

In two-stage programming, the decision process is conceptually divided into two stages. In the first one, the values for decision variables (y) are chosen before the realization of the scenario is revealed. The values of the second stage decision variable (x) are calculated for the known values of uncertain parameters.

Let Γ be a set of discrete scenarios with $\Gamma = 1...S$, $s \in \Gamma$. The general formulation of two-stage programming in the case of maximization of profit can be written in the following way:

$$\max_{y \in Y}[f^1(y) + g(Q_1(y), ..., Q_S(y))] \tag{2.8}$$

$$\text{Where} \qquad Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma$$

$f^1(y)$ is the evaluation function taking into account scenario-independent variables (or first-stage variables), $f_s^2(x)$ is the evaluation function considering the scenario-dependent variables (or second-stage variables) and g is an aggregation function. For more information about two-stage programming concepts and properties, the reader can refer to [SDR14].

Two-stage programming is widely applied in the field of RL design because it faithfully reproduces the logic of RSC implementation. Indeed, the strategic decisions (for instance facility location) are often considered as the first stage problem and the planning decision (for instance the quantities of flows between facilities) as the second stage one. Indeed, strategic decisions often represent expensive and time-consuming processes contrary to planning decisions which can be easily adapted. In [KO10], the authors particularly proposed a two-stage programming model for a facility location-allocation problem in a paper recycling RSC. Furthermore, the stochastic, fuzzy and robust models presented above can all be adapted with two-stage programming. We propose below some classic two-stage formulation the mostly applied to RL design.

2.2.5.1 Average formulation

In a two-stage average formulation, the aggregation function g is the average of the different profits over all scenarios. Each scenario has an equal weight in the final solution. The objective of a two-stage average formulation can be written as follows:

$$\begin{aligned} & \max_{y \in Y} f^1(y) + \tfrac{1}{S} * \textstyle\sum_s (Q_s(y)) \\ \text{Where} \qquad & Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma \end{aligned} \tag{2.9}$$

This formulation is used in stochastic programming when the probability distribution is uniform.

2.2.5.2 Robust formulation

In a two-stage robust formulation, the aggregation function g is the maximum and the function Q_s is the minimum. In this way, the minimum profit is maximized over all scenarios [Ram+14]:

$$\begin{aligned} & \max_{y \in Y} [f^1(y) + \min_{s \in \Gamma} Q_s(y)] \\ \text{Where} \qquad & Q_s(y) = \max_{x \in X^{y,s}} f_s^2(x) \qquad \forall s \in \Gamma \end{aligned} \tag{2.10}$$

2.2.5.3 Regret Average formulation

The two-stage regret average formulation searches for a optimal solution for each scenario separately and then minimizes the average relative regret overall scenarios compared to the optimal solutions. This formulation is used in [DR+13] and can be written as follows:

$$\begin{aligned} & \max_{y \in Y} \textstyle\sum_{s \in \Gamma} \frac{f^1(y) + Q_s(y)}{F_s} \\ \text{Where} \quad & F_s = \max_{y \in Y} [f^1(y) + Q_s(y)] \quad \forall s \in \Gamma \end{aligned} \tag{2.11}$$

Here, F_s is the total profit of scenario s for the optimal solution.

2.2.6 Taking into account uncertainty in Reverse Logistics

As mentioned in the introduction, uncertainty is one of the most challenging factors when designing RL. Table 2.1 gives information about RL related uncertain parameters and the frequency with which they are found in the literature.

Uncertain parameter	Abbreviation	frequency
Return quantities in a RL network	R	85%
Cost of activities (e.g., transportation, production)	C	45%
Capacity of network facilities/ transportation links	CA	30%
Demand for RL outputs in a RL network	DS	21%
Proportion of returned products/components for different activities in a RL network	PA	18%
Disposal rate of returns in a RL network	DR	11%
Availability of network facilities	AF	10%
Fuzzy goals to represent aspiration levels of multiple objectives	FG	9%
Buying price of returns in a RL network	BP	8%
Selling price of RL outputs to customers in a RL network	SP	8%
Capacity coefficients for holding products/materials in SC facilities	CS	5%
Environmental parameters such as environmental impacts of SC's activities and facilities	EP	2%
Social parameters related to designing logistics networks	PS	2%
Profit of recycling/remanufacturing returned products in RL network	PP	2%
Processing/production time for network facilities	PT	2%

Table 2.1: Uncertain parameters and their frequency in RL literature [GFK17]

When forward and reverse flows are considered at the same time, several studies strongly suggest (see Table 2.2), the most influential factors of uncertainty in RL are admitted to be the initial demand, the demand for reprocessed products, the quantity and the quality of returned products. A summary of the main contributions in 2014-2020 for the CLSC design under uncertainty is presented in Table 2.2. The anterior work was analyzed in the review of [GFK17]. Column 2 corresponds to the uncertain parameters considered in the model, Columns 3 to 5 correspond to the type of model they used to take into account those uncertain parameters, Column 6 reports the solution method employed.

We propose in Table 2.3, an overview of the mots common criteria proposed in the SCM literature to address uncertainty, their advantages and their drawbacks.

Method	Advantages	Drawbacks
Stochastic optimization	Best expected value in average	Need for historical data Often hard to solve computationally
Maxmin	No need for historical data Risk-resistant	No search for opportunities
OWA	No need for historical data Takes into account the DM's optimism	Compensatory No risk control
Hurwicz	No need for historical data Takes into account the DM's optimism	Compensatory No risk control

Table 2.3: Comparison of existing criteria

Article	Uncertainty	S	F	R	Solution method
[AZ13]	R, DR, AF	x			MIP
[AZA17]	D, R	x			MIP
[AB14]	R	x			MIP
[ABA15]	R, C, PA	x			MIP + SAA
[BGH17]	D, R	x			MIP
[Bap+19]	R,R,C	x			MIP
[DGC15]	R, D			x	MIP
[FG19]	All parameters		x		MIP
[FEP15]	R, C, CA		x		MIP
[GNKS19]	D,R,C		x	x	heuristic
[GPA16]	D, C, CA, S		x		improved GA
[Hab+17]	D	x			MIP
[HR18]	R, D, CT	x		x	Bender's decomposition
[Hat+15b]	D, R, C, CA		x		MIP
[Hat+15a]			x		MIP
[JZG16]	R	x			Bender's decomposition
[JZG17]	D, R, C	x			L-shaped method
[KRK16]	R, C	x		x	Bender's decomposition
[KMF15]	R	x			Bender's decomposition
[NP14]	R, D		x		MIP
[Özc16]	D, CA, DR		x		MIP
[Pol+19]	D			x	MIP
[Pra+20]	D,C		x		MIP
[SSE14]	R	x	x	x	Memetic based heuristic
[Sae+19]	R,C,CA			x	MIP
[SG14]	D, BP, SP	x			MIP
[Sub+15]	D, R, C, AF		x		MIP
[STB15]	D, R, C, AF	x	x		MIP
[TA18]	R, D, C		x		MIP
[TAZ20]	D,R,C		x	x	MIP
[YS20]	D,R	x			MIP
[Zha+16]	R, D, C, DS	x	x		MIP + Meta-heuristic
[ZU16]	D	x			MIP
[Zhe+19]	D,R	x			MIP

Table 2.2: An overview of the state-of-the-art

Parameters. R: Product Return quality and/or quantity, D: Demand, C: Cost, CA: Capacities, DR: Disposal Rate, PA: Proportion of returned products for different activities, SP: Selling Price, AF: Availability of Facilities, BP: Buying Price, CT: Carbon Tax, DS: Distances, S: Social Parameters
Type of models. S: Stochastic, F: Fuzzy, R: Robust

As it can be seen in the literature, the models that take uncertainty into account either rely on data about the uncertain parameters, or in a context of complete ignorance of the DM, are risk-oriented and never distinguish hazard from opportunity. However, psychological evidences show that a DM often behaves differently regarding if he/she sees uncertainty as a risk or as an opportunity [Gra06] which may influence a lot the choice of the final solution. We detail this concept in the next section.

2.2.7 Bipolarity of the DM behavior

Bipolarity relates to something which is divided into two opposite sides. In decision making, it can often help to divide positive and negative pieces of information in order to discriminate solutions. Thus, the notion of bipolarity in decisions processes has been present for centuries in our everyday life. One of the most apparent examples we can give to illustrate this point are "pros" and "cons" lists made in order to take a decision when several factors are to be considered. This type of list helps to distinguish the attributes of positive nature or "pros" (representing an advantage compared to the objectives to reach) from the attributes of negative nature or "cons" (with disadvantages, constraints in relation to the achievement of objectives).

On the other hand, the majority of the proposed approaches to take decision under uncertainty in the literature most of the time do not try to emphasize this duality. Indeed, the potential of the alternatives to reach the fixed objectives is often obtained through the evaluation of a common set of attributes all considered in the same way.

Furthermore and as aforementioned, a DM often behaves differently regarding if he/she sees uncertainty as a risk or as an opportunity[Gra06]. We can demonstrate this point with the following example: let's consider a ball hidden in a box. The ball can be either red or white. A game is proposed to a DM in order to guess to color of the ball, the choice of the DM is to play or not to play the game. In a first case, the DM wins 10 euros if he/she guesses correctly and looses nothing otherwise. In this case the bet only offers opportunities to the DM as taking the bet won't let him/her loose anything, and the DM is willing to play. In a second case, the DM wins nothing if he/she guesses correctly but a mistake costs 10 euros. In this case, as only risks are possible when playing the game, the DM won't be willing to participate.

Accounting the fact that uncertainty can be perceived either as a risk or as an opportunity by the DM, [Gra06] studied the concept of bipolar operators. These operators include a neutral value (here denoted as e), above and below which, scores are considered differently. A type of bipolar operator, namely Uninorms has been defined by [YR96]. Based on the definition of a bipolar operator offered by [Gra06], [YR11] proposed a bipolar aggregation using the Uninorms. Originally, it has been defined on [0,1] but in the context of optimization problems, we extend the definition on $\mathbf{R}^+$ as follows:

Definition 4 (Uninorm)
A Uninorm R is a mapping $R : \mathbf{R}^+ \times \mathbf{R}^+ \to \mathbf{R}^+$ having the following properties:

1. $R(a, b) = R(b, a)$ *(Commutative)*
2. $R(a, b) \leq R(c, d)$ *if* $a \leq c$ *and* $b \leq d$ *(Monotonous)*
3. $R(a, R(b, c)) = R(R(a, b), c)$ *(Associative)*
4. *There exists some element $e \in \mathbf{R}^+$, called the identity element, such that for all $x \in \mathbf{R}^+$* $R(x, e) = x$

A Uninorm operates like a t-norm on $[0, e]$, and like a t-conorm on $\overline{[e, +\infty[}$. Thus, considering all scores below e as "bad" scores and all scores above e as "good" scores, we will look at the interval $[0, e]$ as a risky area and the interval $\overline{[e, +\infty[}$ as an opportunistic area. The value e will be representing the optimism level of the DM. We can thus consider that $[0, e]$ is an interval of hazards while $\overline{[e, +\infty[}$ is an interval of opportunities. The threshold e therefore corresponds to the optimism level of the DM.

This type of operators is well known in fuzzy logic literature to generalize the fuzzy *"and"* and fuzzy *"or"*. More recently the theoretical properties of such criteria have been studied for qualitative sequential decision problem were the authors focus on the qualitative aspect of this type of aggregate function [FG20]. However, it has never been used in to solve decision problem under uncertainty in RL, despite the fact that is a very promising concept as it makes it possible to consider uncertainty not only as a risk but also as an opportunity.

In order to fill the gap in the literature, we propose to develop new approaches in order to answer the following questions:

(1) **How does the consideration of the bipolarity of the behavior of the DM regarding zones of risks or opportunities impact the design of RL? How to model this bipolarity in a context of complete ignorance of the DM?**

In addition to the uncertainty, the sustainability of the designed CLSC should also be taken into account. We remind that for a sustainable RSC, three dimensions have to be considered at the same time, i.e. economic, environmental and social, making its design a multi-objective optimisation problem. Therefore, multi-objective solution methods should be used. We discuss the most frequently employed of them for SCM in the next section.

2.3 Multi-objective Optimization

As previously mentioned, when more than one objective is considered in a decision problem, multi-objective optimization is applied in order to find a satisfying solution. In mixed integer linear optimization, the following problem is then considered (see Model 2.12):

$$\begin{array}{ll} \max & f(x) \\ s.t. & \\ (a) & \sum_{i \in N} a_{i,j} x_i \leq b_j \quad \forall j \in M \\ (b) & x \in \mathbb{X} \subseteq \mathbb{R}^+ \end{array} \tag{2.12}$$

With $f = (f_1, ..., f_n)$ the set of objective functions to be maximized where $f_o = \sum_{i \in N} p_{o,i} x_i$, $\forall o \in O = \{0, ..., n\}$.

Let an element $x^* \in X$ be a feasible solution. A vector $z^* = f(x^*) \in \mathbb{R}^k$ is called an objective vector or an outcome. In multi-objective optimization, there does not typically exist a feasible solution that minimizes all objective functions simultaneously. Therefore, attention is paid to Pareto optimal solutions (see Definition 5).

Definition 5 (Pareto Optimality)
A solution $x^* \in X$ is called ***Pareto optimal*** *if and only if there does not exist another solution $x \in X$, such that $f(x) \leq f(x^*)$, and $f_o(x) < f_o(x^*)$ for at least one function.*

More generally, Pareto optimal solutions are the solutions that cannot be improved on one of the objective without degrading at least one of the others. Several possibilities exist to find Pareto optimal solutions. Particularly, according to the optimization-oriented review written by [Esk+15], the solution methods for finding Pareto optimal solutions for multi-objective programs in supply chain management can be classified into 2 categories: the epsilon-constraint method and multi-criteria decision models. The particular properties of each method can be found in [Bra+08].

2.3.1 Epsilon constraint method

The epsilon-constraint method consists in prioritizing a primary objective while expressing other objectives as constraints. It was firstly proposed by [Hai71]. This method is proven to provide Pareto-optimal solutions and so, fixing various values of constraint enables the Pareto front to be approximated. In SCM, this method is well adapted to the extension of a single-objective economic approach to bi-objective models integrating environmental or social criteria. Indeed, by considering the economic model as the primary objective, this approach enables decision makers to measure the financial impact of environmental or social constraints [Esk+15]. Examples of studied papers which used epsilon-constraint method can be found in [BS18]; [CSC18]; [FG18]; [FC+17]; [Mot+18]; [SRG18]; [Sol18].

2.3.2 Multi-Criteria Decision Models (MCDM)

MCDM are used to find the Pareto optimal solution [Esk+15] while considering all conflicting objectives simultaneously. In the area of design of sustainable CLSC, the environmental objective is often conflicting with the social and/or economic objective. Examples of usage of MCDM can be found in [PRT14]; [THN19]. Various solutions methods have been developed in order to solve MCDM, in this manuscript, we particularly focus on the **goal programming** described here below.

2.3.2.1 Goal programming

First, the DM has to set up a priori target values for each objective noted $g_o, \forall o \in O$. The goal programming aims in minimizing the weighted deviations from these values. This method was proposed by [CC77] and is mathematically formulated as:

$$
\begin{array}{lcl}
\min & \sum_o d_o^+ + d_o^- & \\
s.t. & & \\
(a) & \sum_{i\in N} p_{o,i}x_i - d_o^+ + d_o^- = g_o & \forall o \in O \\
(b) & \sum_{i\in N} a_{i,j}x_i \le b_j & \forall j \in M \\
(c) & d_o^+, d_o^-, x_i \ge 0 & \forall i \in N, o \in O
\end{array}
\tag{2.13}
$$

With d_o^+ the positive deviational variable from the o^{th} goal (over-achievement) defined as:

$$d_0^+ = \max(\sum_{i=1}^{n} p_{o,i}x_i - g_o, 0) \tag{2.14}$$

and d_o^- the negative deviational variable from the o^{th} goal (underachievement) defined as:

$$d_o^- = \max(g_o - \sum_{i=1}^{n} p_{o,i}x_i, 0) \tag{2.15}$$

It is worth mentioning that over-achievement and underachievement cannot occur simultaneously. These distances can be adapted depending on the problem. To consider all the objectives in the same order of value, the DM can particularly choose to work with a normalized objective space. We define this concept in the next section.

2.3.2.2 Normalized objective space

To normalize the objective space, we need two specific points namely the *ideal* point and the *nadir* point. The *ideal* point is the one where each objective has its optimal value as a single objective. Usually, this value is not attainable in the case of multi-objective optimisation. We define it as follows:

Definition 6 (Ideal point)

$$f^* = (f_1^*, ..., f_n^*) \ with \ f_o^* = \min_{x\in X}(f_o(x)) \tag{2.16}$$

An example of ideal point is presented in Figure 2.1. Let $n = 2$, we thus have f_1, f_2 the two objective functions considered. The red area represents the space of possible solutions.

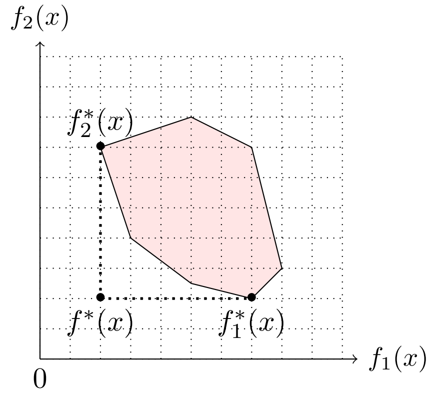


Figure 2.1: Ideal point

The *ideal* point $f^*(x)$ is an unfeasible solution having the coordinates equal to the minimum value of both objective functions.

The *nadir* point will be the point where each objective has its worst value for the optimal solution of another of the objectives. We define it as follows:

Definition 7 (Nadir point)

$$f^{max} = (f_1^{max}, ..., f_n^{max}) \text{ } with \text{ } f_o^{max} = \max_{1 \leq o' \leq n} (f_o(x_{o'}^*)) \tag{2.17}$$

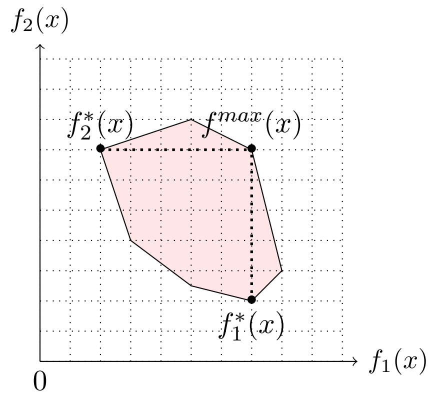


Figure 2.2: Nadir Solution

An example of nadir point is given in Figure 2.2. Let $n = 2$, we thus have f_1, f_2 the two objective functions considered. The red area represent the space of possible solutions. The *nadir* point is a feasible solution having the coordinates equal to the maximum value of each objective functions when the other objective function is optimal.

Now we can define the normalized objectives as follow:

Definition 8 (Normalized objectives)

$D(x) = (D_1(x), ..., D_n(x))$ *is the vector of normalized objectives of solution* x*, with:*

$$D_o(x) = \frac{f_o^*(x) - f_o(x)}{f_o^*(x) - f_o^{max}(x)} \tag{2.18}$$

These normalized objectives are used to consider all the objectives with the same order of value. To consider them in an optimization problem, the vector D must be aggregated. In the next section, we present different aggregation functions that can be used for this purpose.

2.3.2.3 Classic aggregation functions

An aggregation function is a function that serves to measure the achievement of the minimization of unwanted goal deviation variables in the goal programming model. It can be applied either directly on the set of objective functions f_o, $o \in O$ or on the set of normalized objectives D_o, $o \in O$. Here below, we define a set of functions u_o with $o \in O$ representing either f_o or D_o. We introduce some of the most well-known below.

Weighted sum In a Weighted Sum (WS) aggregation, each criteria is given a weight depending on its importance for the DM. Let's consider $\Omega = (\omega_1, ..., \omega_n)$ the set of weight respectively corresponding to the set of functions $u = (u_1, ..., u_n)$. The objective of the multi-objective problem to be solved can be written as:

$$Minimize\ WS(u(x)) = \sum_{o=1,..,n} \omega_o u_o(x)$$

Aggregation based on $\|.\|_1$

Definition 9 ($\|.\|_1$ norm)
Let $u(x) = (u_1(x), ..., u_n(x)) \in \mathbb{R}^n$*. The* $\|.\|_1$ *norm is the norm defined by:*

$$\|u(x)\|_1 = \sum_{o=1}^{n} |u_o(x)|$$

In this approach, all objectives have the same weight, and the goal is to minimize the sum of the distances to the "Ideal" solution. Thus, the objective becomes:

$$Minimize\ \|u(x)\|_1 = \sum_{o=1}^{n} |u_o(x)|$$

This approach assures the best compromising solution in average over all objectives, but offers no guarantee regarding the deviation between the objective values of the solution as one of the distances can be very large and compensated by a smaller one.

Aggregation based on $\|.\|_\infty$

Definition 10 ($\|.\|_\infty$ norm)
Let $u(x) = (u_1(x), ..., u_n(x)) \in \mathbb{R}^n$. The $\|.\|_\infty$ norm is the norm defined by:

$$\|u(x)\|_\infty = \max_{o=1,...,n} |u_o(x)|$$

This approach seeks to minimize the maximum distance to the "Ideal" solution: the DM has a risk-adverse behavior. This approach can be compared to a robust solution method in the context of decision making under uncertainty. The new objective can be written as follows:

$$Minimize\ \|u(x)\|_\infty = \max_{o=1,..,n} |u_o(x)|$$

It is a very conservative approach in the way that it only takes into account the worst objective and may miss opportunities on others.

Aggregation based on Ordered Weighted Average (OWA)

Definition 11 (OWA operator)
The OWA operator [Yag04] is defined as

$$OWA(u(x)) = OWA(u_1(x), ..., u_n(x)) = \sum_{k=1}^{n} \omega_k * r_k \tag{2.19}$$

where r_k is the k-est largest of the $u_o(x)$ and $\Omega = (\omega_1, ..., \omega_n)$ is a set of weight such as $\sum_{k=1}^{n} \omega_k = 1$

By selecting different manifestations for Ω, we can implement different aggregations. Possible operators are:

- Max (when $\omega_1 = 1$ and $\omega_k = 0\ \forall k \neq 1$);
- Min (when $\omega_n = 1$ and $\omega_k = 0\ \forall k \neq n$);
- the simple average (when $\omega_k = \frac{1}{n}\ \forall k = 1...n$);
- Lexicographic maximization, described here below;
- Lexicographic minimization, described here below;
- Gini aggregation, described here below.

Some other aggregations can be obtained with the use of a OWA operator. We define some of them below as they will be used in the models developed in our work.

Lexicographic maximization (*Leximax*) aggregation

Definition 12 (*Leximax* order)
Let $u(x) = (u_1(x), ..., u_n(x))$ and $u(y) = (u_1(y), ..., u_n(y))$ be two possible outcomes. The Leximax order (noted $>_{lex}$) is defined such as: [Yag97]

$$u(x) >_{lex} u(y) \iff \exists k \geq 1 \; such \; as \; \forall o < k, \; u_o(x) = u_o(y) \; and \; u_k(x) > u_k(y)$$

$$u(x) =_{lex} u(y) \; if \; u_o(x) = u_o(y) \; \forall o = 1, .., n$$

Essentially this method compares two solutions with respect to their highest scores to any of the distances to the "Ideal" solution. If they are not equal then it indicates the solution with the lower largest score as being preferred to the other one. If they are equal it then looks at the second largest scores and repeats the process until one is preferred to the other or it runs out of items to compare in which case it considers the two alternatives as tied. Consequently, this approach can be seen as a refinement of the $\|.\|_\infty$ approach where not only the worst distance is minimized but also the second worst, the third worst and so on [OŚ03].

This approach can be approximated with the use of a OWA aggregation operator using the following model [Yag97]:

$$Leximax_{k \in 1...n}(u_k(x)) = min(\sum_{k \in 1...n} \theta_k * \gamma_k)$$

Where γ_k equals the k-est highest $u_o(x)$ and

$$\theta_k = \frac{\epsilon^{n-k}}{(1+\epsilon)^{n+k-1}} \quad \forall k = 1, ..., n$$

with ϵ a very small value.

Lexicographic minimization (*Leximin*) aggregation

Refer to the *Leximin* order definition (Definition 1).

Conversely to the *Leximax* method, this method compares two solutions with respect to their lowest scores to any of the distances to the "utopia" solution. If they are not equal then it indicates the solution with the highest lowest score as being preferred to the other one. If they are equal it then looks at the second lowest scores and repeats the process until one is preferred to the other or it runs out of items to compare in which case it considers the two alternatives as tied.

Once again, this approach can be approximated with the use of an OWA aggregation operator as follows [Yag97]:

$$Leximin_{k\in 1...n}(u_k(x)) = min(\sum_{k\in 1..n} \theta_k * \gamma_k)$$

Where γ_k equals the k-est lowest $u_o(x)$ and

$$\theta_k = \frac{\epsilon^{-k+1}}{(1+\epsilon)^{-k+1}} \quad \forall k = 1, ..., n$$

with ϵ a very small value.

Gini aggregation

Definition 13 (Gini coefficient (G))

$$G(u) = \min \frac{\sum_o \sum_k |u_o(x) - u_k(x)|}{2 * n^2 * \mu(u_o)} \tag{2.20}$$

Where u_o is the value of function o, u_k is the value of function k, n is the number of functions and μ the arithmetic mean of the values of all functions. It measures the inequity between the values on different functions.

To make this objective to be easier integrated in an exact solution method, the formulation of [BF+17] can be used. It uses an approximation of the Gini index with the use of an OWA with particular weights, as shown here below:

$$Minimize\ G(u) = \min \sum_{k=1}^{n} \omega_k^{'}(k * r_k + \sum_{o=1}^{n} d_{o,k}) \tag{2.21}$$

Subject to

$$\begin{array}{ll} r_k + d_{o,k} \geq u_o & \forall o, k \in \{1, ..., n\} \\ d_{o,k} \geq 0 & \forall o, k \in \{1, ..., n\} \end{array} \tag{2.22}$$

with

$$\omega_k' = \omega_k - \omega_{k-1}$$

$$\omega_k = (2(n-k)+1)/n^2 \ \forall \ k \ \in \{1, ..., n\}$$

2.3.3 Taking into account several objectives in sustainable RSC design

As it was mentioned, the question of multi-objective optimisation often raises for the purpose of the design of a sustainable SC. A recent survey presented in [Esk+15] discusses the models developed for taking into account the social and environmental dimensions for RSC and CLSC and published before 2016. We reuse the results presented and complete them with more recent contributions in Table 2.4.

Year	Environmental	Social	Both
1990		[MO90]	
1993			[CCP93]
1999	[BSW99]		
2003	[KBRVW03]		
2005	[HP05],[Hug+05]		
2008	[Erk+08],[GGCJ08],[Min+08] [PVK08],[PRD08],[Net+08]		
2009	[AACRC09],[Boj+09],[GGG09] [MGGJ09],[ZBS09]		[DM09]
2010	[DBPN10],[Gal+10],[GGG10] [GGMG10],[RCP10]		
2011	[CRP11],[GZB11],[Liu+11] [Mel+11],[PVBPN11],[WLS11] [YW11],[Zam+11]		[HG11],[TGÖ11]
2012	[ASP12],[CRP12],[GZB12] [JGK12],[Kos+12],[PR12] [PTR12],[Poz+12]	[PRT12]	[PF+12],[You+12]
2013	[AZ13],[BGB13],[EZN13] [Kan+13],[Lam+13],[Muñ+13] [RF+13],[Sad+13],[XJP13] [YKY13],[ZWT13]		
2014	[BLAP14],[Gov+14],[MEH14] [MTTM14],[SR+14],[HMN14]	[Afs+14]	[DJN14],[SA+14],[Yue+14]
2015	[SR+15],[Gar+15]	[BA15]	[Mot+15],[Mir+15],[TZ15]
2016	[YS16],[CM+16] [Zho+16],[TK16]		[Zha+16],[Mir+16]
2017	[Moh+17],[Zhe17],[MW17] [JS17],[Kad+17]	[ZTMR17]	[FC+17],[PMCB17],[JSO17]
2018	[Bán18],[DYL18],[Ebr18] [Far+18],[Man+18],[YS18] [GA+18a],[WTZ18],[Mem+18] [Doo+18]	[Nem+18],[FFHKM18]	[BS18],[CSC18],[EK+18] [FG18],[SFFHK18],[Sol18] [SRN18],[SRG18],[Mot+18]
2019	[Mar+19],[YG19],[TA19] [FG19],[Gao19]	[Kar+19],[Mey+19]	[NKE19],[LLH19],[THN19]
2020+	[Val+20]		

Table 2.4: Distribution of the papers according to social and environmental considerations and time of publication

We can see from this table that the majority of the papers addressing the sustainable development in the context of RSC design focus on the integration of the environmental dimension alone. Only a few papers consider the integration of the social dimension alone. And in the last years (from 2014) an increasing number of papers consider both dimensions at the same time.

Tables 2.5 and 2.6 present the scope used for the assessment of the environmental and social impacts in the literature. We detail the content of the tables below:

- *Facilities:* The environmental impact of the facilities can be related to the implementation of a new facility, the GHG emissions produced by a facility, the energy consumption...etc.
- *Transport:* One of the largest source of environmental impact in a SC are the transportation flows between facilities [ZTMR17]. Therefore, numerous papers consider this impact when considering the environmental effect of a SC.
- *Product:* The environmental impact is assessed as a function of the product design and reprocessing. It also includes the processing of waste.
- *Work:* The employment is the main social indicator in this category. Some papers consider also the work conditions and workers safety.
- *Societal commitment:* This field regroups all social impacts related to the population's health, education and culture. It is often evaluated with the GDP, the access to healthcare, the development policies...etc
- *Customer issues:* This group regards all impacts affecting the customer, they are various depending on the papers, from the customer's satisfaction level, to the risk of using recycled material.

A numerous amount of the presented papers focus on the added complexity of multi-objective optimisation problems and propose solutions based on metaheuristics to improve their computational time. For instance, [CM+16] propose a multi-objectives simulated annealing algorithm in order to solve a supply chain design problem where the profit maximization and environmental impact minimization are addressed at the same time. In [Mar+19], the same objectives are taken into account (economic and environmental) and the author propose an accelerated Benders decomposition algorithm to solve a CLSC design problem. Other examples can be found in [YG19]; [FG19].

Other papers are specific studies of RSC or CLSC design applied to a particular case. For instance, in [Sol18], a case study for a sustainable closed-loop supply chain specific to the mining industry and particularly to decorative stone quarries in Iran is studied. In [Mir+15], the case of a bio-ethanol supply chain is considered and the three dimensions of sustainability are taken into account in the model. Other examples of case studies can be found in [Mey+19]; [Val+20]; [JSO17].

Among the generic models, only few papers deal with the environmental impact of the facilities, transport and product design and process at the same time. Furthermore, amongst those papers, a fewer number consider the social dimension. For instance in [Mot+18], a multi-objective model for a CLSC design and planning problem under demand uncertainty is presented. The first economic objective is to maximize the net present value. The second objective is to minimize the environmental impact evaluated through LCA methodology. The third objective is social and maximizes the employment based on a GDP metric. However, this model does not account for the negative social impact of layoffs. As such, it can only be applied in cases that do not require layoffs but do require hiring. To fill the gap of the literature, we propose in this manuscript to study a generic multi-objective model for a sustainable CLSC design problem where all the most influential environmental impacts are considered at the same time as the social dimension and particularly the employment. Then, we propose to answer the following research questions:

(2) **How do the economic, environmental and social objectives influence each other?**

(3) **How does the attitude of the DM impact the selection of a compromising solution between the three objectives?**

Finally, few studies in the literature have addressed the equity in decision making in the design of sustainable CLSC. In [Mot+18], the concept of "Social Benefit" is introduced in the social objective. The "Social Benefit" allows maximization of the implementation of facilities in the regions with lower Gross Domestic Product (GDP) with the aim to provide more equitable distribution of facilities overall regions. In the same vein, [CSC18] studied a comprehensive multi-objective model of a biofuel supply chain optimization from coffee crop residues with economic, environmental and social objectives. They consider the balance of job employment in several regions as their social objective. In spite of those studies, equity in sustainable CLSC remains superficial. Furthermore, we found no paper with equity consideration in regards to distribution of environmental pollution.

Therefore, we propose the last research question treated in this thesis:

(4) **How the consideration of environmental and social equity between several locations where the RL network is implemented influences the final solution?**

In the next sections, we present the research realized to address the four questions raised, starting with the first one:

(1) **How does the consideration of the bipolarity of the behavior of the DM regarding zones of risks or opportunities impact the design of RL? How to model this bipolarity in a context of complete ignorance of the DM?**

	Environmental assessment			Social assessment		
Paper	Facilities	Transport	Products	Work	Societal commitment	Customer issues
[AACRC09]	x					
[AZ13]	x		x			
[BLAP14]	x	x	x			
[BA15]					x	
[BSW99]	x					
[CCP93]	x				x	
[CRP11]	x	x				
[DM09]				x	x	x
[DJN14]	x	x	x			
[Erk+08]	x					
[EZN13]	x					
[Gal+10]		x				
[Gov+14]	x	x				
[HG11]			x	x		
[JGK12]	x	x				
[Kan+13]	x	x				
[KBRVW03]	x	x	x			
[Lam+13]	x	x				
[Liu+11]	x	x				
[MO90]						x
[MEH14]	x	x				
[Min+08]	x					
[MTTM14]	x	x				
[Mot+15]				x		
[PVK08]	x					
[PF+12]	x			x		
[PRT12]				x		
[PRD08]		x				
[RCP10]	x	x				
[Sad+13]		x				
[SR+14]		x				
[SR+15]	x					
[SA+14]				x		
[TGÖ11]	x	x		x	x	
[WLS11]	x	x				
[XJP13]		x				
[You+12]				x		
[Yue+14]				x		
[ZWT13]		x				

Table 2.5: Scope for environmental and social assessment (part 1/2)

	Environmental assessment			Social assessment		
Paper	Facilities	Transport	Products	Work	Societal commitment	Customer issues
[Mot+18]	x	x	x	x	x	
[MW17]	x	x				
[CM+16]		x	x			
[Mar+19]	x	x	x			
[Zho+16]	x	x	x			
[FG19]		x				
[Kar+19]						x
[TK16]		x				
[HMN14]		x	x			
[Afs+14]						x
[LLH19]		x	x	x		
[TZ15]		x				x
[Kad+17]			x			
[Far+18]			x			
[GA+18a]	x	x	x			
[Mem+18]	x		x			
[Moh+17]	x	x	x			
[Zhe17]	x	x				
[Bán18]	x		x			
[DYL18]	x					
[Man+18]	x	x				
[Ebr18]	x	x	x			
[WTZ18]	x	x				
[YS18]	x	x				
[ZTMR17]	x		x	x	x	
[FC+17]	x	x	x			x
[SRN18]	x	x				
[SFFHK18]		x	x	x	x	
[SRG18]	x	x	x			x
[THN19]				x		
[BS18]	x	x		x		
[CSC18]	x	x		x	x	
[EK+18]				x		
[FG18]	x	x			x	
[Sol18]	x	x	x			x
[PMCB17]						x
[Nem+18]						x
[FFHKM18]				x	x	

Table 2.6: Scope for environmental and social assessment (part 2/2)

Chapter 3

Reverse Supply Chain design under uncertainty: the R_* criterion

Contents

The model presented in this chapter aims to help managers to better evaluate risks and opportunities while deciding on the design of a RSC in order to manage the reverse flow of end-of-life (EOL) products in an existing supply chain. The goal is to set up the disassembly and recovery facilities and organize the flows between them while seeking to maximize total network profit. We propose a two-stage mixed-integer programming model with multiple periods where the budget available for decisions at each period depends on the outcomes of previous periods. We consider that the demand for EOL products, the quantity of products returned as well as the time required to reprocess these products are uncertain. To incorporate this uncertainty into the decision making process, a discrete set of scenarios is defined. In order to take into account the decision maker's behavior in the areas of risks and opportunities, we propose to use a bipolar criterion to select the final solution. To demonstrate the significance and applicability of the developed model and the relevance of the new criterion, never used before for design problems in logistics, we conduct numerical investigations and do a comparison with classic well-known criteria. The work proposed in this chapter has provided the following publications:

- Zoé Krug, Romain Guillaume, Olga Battaïa "Résolution d'un programme linéaire sous incertitude avec l'Uninorme R_*", ROADEF 2018. *National conference with proceedings*

- Zoé Krug, Olga Battaïa, Romain Guillaume "The use of two-stage approach with R_* criterion to solve a multi-period closed loop supply chain design problem", Logistics Analytic 2018. *International conference without proceedings*

- Romain Guillaume, Olga Battaïa, Zoé Krug "Decision under ignorance: a comparison of existing criteria in a context of linear programming", EDSI 2019. *International conference without proceedings*

- Zoé Krug, Romain Guillaume, Olga Battaïa "A comparison of criteria for decision under ignorance in context of linear programming", IPMU 2020. *International conference with proceedings*

- Zoé Krug, Olga Battaïa, Romain Guillaume "Exploring opportunities in establishing a closed loop supply under uncertainty", International Journal of Production Research 2020

3.1 Proposed solution approach: the R_* criterion

3.1.1 Definition of the R_* criterion

To take the DM perception of risks and opportunities into account, we propose to use a uninorm operator (see definition 4) as an aggregate function to select the final solution. To answer the particular challenges of decision making for RSC design, and consistently with the objective to minimize risks and maximize opportunities, we decided to focus especially on the R_* uninorm which uses a minimum operator for t-norm in the risky area and a maximum for t-conorm in the opportunity area. The formal definition of this criterion is given below:

Let $f_s(x)$ be the evaluation of the objective function for solution x over a scenario $s \in S$,

$$R_*((f_s(x))_{s \in S}, e) = \begin{cases} \min_{s \in S} f_s(x) & \textit{if } \exists \ f_s(x) \leq e \\ \max_{s \in S} f_s(x) & \textit{otherwise} \end{cases} \tag{3.1}$$

R_* specifies that if one of the values of $f_s(x)$ is lower than or equal to e (zone of risk) then the min operator is applied, otherwise the max is applied (zone of opportunity). To provide a better understanding of how this operator aggregates possible solutions, a simple example of resolution is presented. (see Example 1)

Example 1
Let $s_1, s_2 \in S$ be two possible return amount scenarios. Let f be the function of profit that we aim to maximize. We denote $f_{s_1}(x)$ (resp $f_{s_2}(x)$) the profit gained with solution x when s_1 (resp s_2) occurs. The solution space of the problem is shown in Fig.3.1.

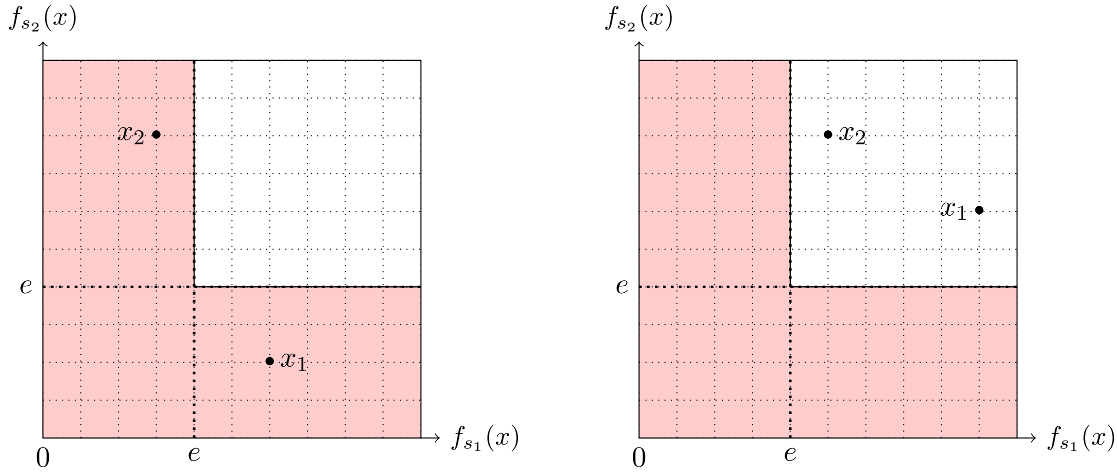


Figure 3.1: R_* criterion solution space

Two solutions x_1 and x_2 are presented in this example, their coordinates give the profit obtained for scenario s_1 and s_2 respectively, e defines the profit expected by the decision maker from the created RSC. Based on this value, the risky area is colored in red oppositely to the opportunistic area kept in white. In the fist case (left figure), both solutions are in the risky area. The R_* operator therefore selects the solution with the highest minimum profit regarding the two scenarios (or robust solution). Here, we have $f_{s_1}(x_1) < f_{s_2}(x_2)$, thus, solution x_2 is selected. In the second case (right figure), both solutions are in the opportunistic area. Hence, the R_* operator selects the highest maximum profit over the two scenarios (or optimistic solution). Here, we have $f_{s_1}(x_1) > f_{s_2}(x_2)$: solution x_1 is selected.

Through its characteristics, R_* criterion allows the DM to choose a threshold of robustness while still letting the possibility for opportunities to be found.

3.1.2 Two-stage MIP formulation for CLSC design problem

In order to integrate R_* criterion in MIP formulation for CLSC design problem, we introduce a new two-stage MIP formulation defined in this section. The uncertainty of reverse flows is modeled with a discrete set of scenarios representing all possible and equally probable cases. Let $\Gamma = 1...S$ be the set of scenarios with $s \in \Gamma$. A two-stage model integrating R_* criterion is defined in the following way. Let $y = y_1, ..., y_n$ be the scenario-independent variables, and $x = x_1, ..., x_n$ the scenario-dependent variables. $f^1(y)$ is thus the evaluation function for the first stage variables and $f^2_s(x)$ for the second stage variables. We apply R_* criterion on both first and second stage variables resulting in the following objective function G for the profit maximization:

$$G = \max_{y \in Y} R_*[f^1(y) + Q_s(y), e] \tag{3.2}$$

The MIP formulation corresponding to this objective is then as follows: let e be a risk threshold, let Z and z be two continuous variables, let Y_s and δ_s be two binary variables.

$$\max Z + z \tag{3.3}$$

$$\begin{array}{llr}
S.t & & \\
(a) & Z \leq f^1(y) + Q_s(y) & \forall s \in \Gamma \\
(b) & Z \leq e & \\
(c) & f^1(y) + Q_s(y) \geq -B * Y_s + e(1 - Y_s) & \forall s \in \Gamma \\
(d) & f^1(y) + Q_s(y) \leq e * Y_s + (1 - Y_s) * B & \forall s \in \Gamma \\
(e) & z \leq (1 - Y_s) * B & \forall s \in \Gamma \\
(f) & \sum_{s=1}^{S} \delta_s = 1 & \\
(g) & z \leq f^1(y) + Q_s(y) + (1 - \delta_s) * B & \forall s \in \Gamma
\end{array}$$

Model (3.3) implies that if the sum of the profit for the first and second stage (or total profit) is lower than or equal to e in any scenario then the min operator is applied, otherwise the max operator is applied. Thus, Z corresponds to a linearization variable for the min operator and z to a linearization variable for the max operator. Constraints (a) and (b) imply that Z is the minimum total profit over all scenarios unless the total profit is higher than e on all scenarios. In that case, the Z value is set to e: the value of the objective will therefore be too high with the value e, but this is irrelevant on the selection of the best solution (as this will then be performed in the opportunistic manner). Constraints (c) and (d) define the value of Y_s as: $Y_s = 1$ if the total profit is lower than e for scenario s and $Y_s = 0$ otherwise. Constraint (e) sets $z = 0$ if the total profit is lower than or equal to e in any scenario. Constraint (f) translates the fact that the best case scenario can only happen once. Constraint (g) implies that if there is no scenario for which the sum of evaluation functions for the first and second stage variables is lower than or equal to e then z is the maximum total profit over all scenarios.

3.2 CLSC location-allocation problem

3.2.1 Description of the CLSC

We consider the case of a Supply Chain for an OEM: it comprises suppliers, production and distribution centers. To establish a CLSC, OEM can turn its distribution centers into Hybrid Distribution/Collection centers (HDC) or fully collection centers to gather EOL products. New facilities may also be implemented: new HDCs to take charge of the flow of EOL products, dismantling centers for deconstruction of EOL products, repair centers, recycling centers for procurement of raw materials and disposal (see Figure 3.2).

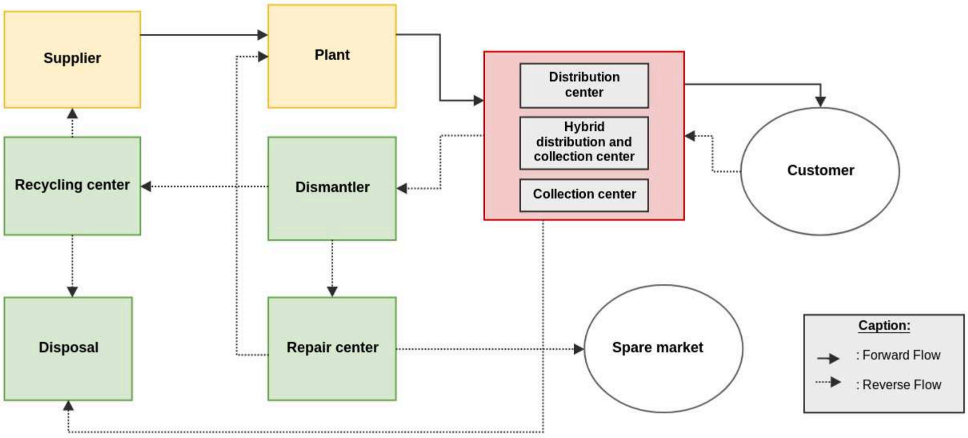


Figure 3.2: CLSC network

To provide a clearer understanding of the different possibilities for the treatment of a EOL product, let consider here an example of an item and the way it can move around the CLSC. After being used by a costumer, a product is returned to a collection center. In the collection center, the quality of the product is assessed to see if it is of good enough quality to be repaired or recycled. If it is, the product is brought to a dismantling center (we assume a predefined percentage of EOL products to be dismantled). Otherwise, the product is put in disposal. Once in the dismantling center, the product is disassembled and another quality assessment is done. The better quality products with potential to be repaired move on to a repair center, and the un-repairable products are brought to a recycling center (here again we assume predefined rates of EOL products to be repaired and recycled). After reprocessing in the repair center, the product can either be sold in the form of spare part, or can be re-used in the plant to be re-manufactured. If reprocessed in the recycling center, extracted recycled material is sold to the supplier while residual material is disposed.

We consider a multi-period horizon where the CLSC can be expanded progressively. The budget for expansion at each period depends on the decisions taken in previous periods. Uncertainty concerns primary and secondary market demand, the quantity of returned products and their reprocessing time are also uncertain. We assume that the quantity of returned products depends on primary market demand: the higher the demand, the higher the quantity of EOL products collected. Thus, a discrete set of scenarios with all equally probable cases is created. To support the DM in selecting the solution corresponding to his/her level of optimism, we use R_* criterion with the two-stage MIP formulation defined in Section 4.

3.2.2 Mathematical Model

	Indexes
$i = 1..I$	Index of suppliers
$j = 1..J$	Index of plants
$l = 1..L$	Index of customers

$c = 1..C$	Index of HDC
$p = 1..P$	Index of dismantlers
$q = 1..Q$	Index of repair centers
$m = 1..M$	Index of spare market customers
$f = 1..F$	Index of disposal sites
$d = 1..D$	Index of recycling centers
$t = 1..T$	Index of time periods
$s = 1..S$	Index of scenarios
	Demand parameters
$D_{l,t,s}$	of consumers l for period t and scenario s
$Dsm_{m,t,s}$	of spare market consumers m for period t and scenario s
$Ds_{i,t,s}$	of suppliers i for period t and scenario s
	Capacity parameters
$CapPlant_j$	Production capacity of plant j
$CapHC_c$	Capacity of HDC c
$Capd_p$	Production capacity of dismantler p
$CapR_q$	Production capacity of repair center q
$CapDec_d$	Production capacity of recycling center d
	Distance parameters
$DisSP_{i,j}$	Between supplier i and plant j
$DisPH_{j,c}$	Between plant j and HDC c
$DisCH_{l,c}$	Between costumer l and HDC c
$DisCoDi_{c,p}$	Between HDC c and dismantler p
$DisCoF_{c,f}$	Between HDC c and disposal f
$DisDiDe_{p,d}$	Between dismantler p and recycling center d
$DisDeDis_{d,f}$	Between recycling center d and disposal f
$DisDeS_{d,i}$	Between recycling center d and supplier i
$DisDiR_{p,q}$	Between dismantler p and repair center q
$DisRSM_{q,m}$	Between repair center q and spare market customer m
$DisRPP_{q,j}$	Between repair center q and plant j
	Time parameters
$Tdismantler_s$	Unit dismantling time
$Trecycle_s$	Unit recycling time
$Trepair_s$	Unit repair time
	Variable cost parameters
Ca_i	Unit cost of buying product at supplier i
Cp_j	Unit production cost at plant j
$Cass_j$	Unit assembling cost at plant j
$Coph_c$	Unit operational cost at HDC c
$Cdis_p$	Unit dismantling cost at dismantling center p
$Crep_q$	Unit repair cost at repair center q
$Cdecr_d$	Unit production cost of raw material at recycling center d
$Ceco_c$	Unit environmental tax for non-reprocessed products
TC	Unit transportation cost for 1 kilometer
	Rate parameters
$R_{t,s}$	Rate of return for period t and scenario s
Re	Repairing rate after dismantling
Rr	Recycling ratio after decomposition
	Unit selling price parameters
SP_l	of product at market zone l
RSP_m	of product at spare market m
Rev_i	of recycled product to the supplier i
	Fixed opening cost parameters
$Cohyb_c$	for HDC c
$CoDism_p$	for dismantling center p
$CoRecy_d$	for recycling center d
$CoDisp_f$	for disposal f
$CoRep_q$	for repair center q

	Fixed operational cost parameters
$CFhyb_{c,t}$	for HDC c in period t
$CFDism_{p,t}$	for dismantling center p in period t
$CFRecy_{d,t}$	for recycling center d in period t
$CFDisp_{f,t}$	for disposal f in period t
$CFRep_{q,t}$	for repair center q in period t
C_t	Budget for opening centers in period t
	Positives variables *(Flow from . to . at period t and scenario s)*
$XSP_{i,j,t,s}$	from supplier i to plant j
$XPH_{j,c,t,s}$	from plant j to hybrid center c
$XCHD_{c,l,t,s}$	from HDC c to customer l
$XCHC_{l,c,t,s}$	from customer l to HDC c
$XCODI_{c,p,t,s}$	from HDC c to dismantler p
$XCOF_{c,f,t,s}$	from HDC c to disposal f
$XDIR_{p,q,t,s}$	from dismantler p to repair center q
$XRSM_{q,m,t,s}$	from repair center q to spare market costumer m
$XDIRE_{p,d,t,s}$	from dismantler p to recycling center d
$XREDIS_{d,f,t,s}$	from recycling center d to disposal f
$XPS_{d,i,t,s}$	from recycling center d to supplier i
$XRPP_{q,j,t,s}$	from repair center q to plant j
$h_{c,l,t,s}$	maximum flow between forward and return from costumer l to HDC center c
	Binary variables
$YCH_{c,t}$	HDC c is opened or not at period t
$YP_{p,t}$	Dismantler p is opened or not at period t
$YD_{d,t}$	Recycling center d is opened or not at period t
$YF_{f,t}$	Disposal f is opened or not at period t
$YQ_{q,t}$	Repair center q is opened or not at period t
$ZYCH_c$	1 if HDC c has been opened, 0 otherwise
ZYP_p	1 if Dismantler p has been opened, 0 otherwise
ZYD_d	1 if Recycling center d has been opened, 0 otherwise
ZYF_f	1 if Disposal f has been opened, 0 otherwise
ZYQ_q	1 if Repair center q has been opened, 0 otherwise
	Additional parameters corresponding to the MIP formulation
B	A big enough value
e_1	Risk threshold
	Additional Variables corresponding to the MIP formulation
δ_s	1 if the best case scenario s occurs, 0 otherwise
z, Z	Variables for the linearization of Model (3.3)

In order to simplify the presentation of the model, we introduce the following expressions:

- *The total income*: it includes all sales revenues over all periods. It is scenario dependent and noted as $Income_s$.

$$\begin{aligned} Income_s \quad &= \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(SP_l * XCHD_{c,l,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(RSP_m * XRSM_{q,m,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(Rev_i * XPS_{d,i,t,s}))) \end{aligned} \tag{3.4}$$

- *The total operational cost*: it includes all production costs, assembling costs, buying costs, dismantling costs and distribution costs of all centers of the chain. It is scenario dependent and noted as $OpCost_s$.

$$\begin{aligned} OpCost_s &= \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{i=1}^{I}(Ca_i * XSP_{i,j,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(Cp_j * XPH_{j,c,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(Cass_j * XPH_{j,c,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(Coph_c * (XCHD_{c,l,t,s} + XCHC_{l,c,t,s})))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(\sum_{c=1}^{C}(Cdis_p * XCODI_{c,p,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(Crep_q * XRSM_{q,m,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{q=1}^{Q}(Crep_q * XRRP_{q,j,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(Cdecr_d * XPS_{d,i,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{c=1}^{C}(Ceco_c * XCOF_{c,f,t,s}))) \end{aligned} \tag{3.5}$$

- *The total fixed cost*: it is the sum of the opening costs of facilities and operational fixed costs for all facilities opened in each period. It is scenario independent and noted as $FixedCost$.

$$\begin{aligned} FixedCost &= \textstyle\sum_{c=1}^{C}(Cohyb_c * ZYCH_c) \\ &+ \textstyle\sum_{p=1}^{P}(CoDism_p * ZYP_p) \\ &+ \textstyle\sum_{d=1}^{D}(CoRecy_d * ZYD_d) \\ &+ \textstyle\sum_{f=1}^{F}(CoDisp_f * ZYF_f) \\ &+ \textstyle\sum_{q=1}^{Q}(CoRep_q * ZYQ_q) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(CFhyb_{c,t} * YCH_{c,t})) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(CFDism_{p,t} * YP_{p,t})) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{d=1}^{D}(CFRecy_{d,t} * YD_{d,t})) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(CFDisp_{f,t} * YF_{f,t})) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{q=1}^{Q}(CFRep_{q,t} * YQ_{q,t})) \end{aligned} \tag{3.6}$$

- *The total transportation cost*: it is the sum of travel costs between connected points of the Supply Chain. It is scenario dependent and noted as $TrtCost_s$.

$$\begin{aligned} TrtCost_s &= \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{i=1}^{I}(TC * DisSP_{i,j} * XSP_{i,j,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{c=1}^{C}(\sum_{j=1}^{J}(TC * DisPH_{j,c} * XPH_{j,c,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{l=1}^{L}(\sum_{c=1}^{C}(TC * DisCH_{l,c} * h_{l,c,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{p=1}^{P}(\sum_{c=1}^{C}(TC * DisCoDi_{c,p} * XCODI_{c,p,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{q=1}^{Q}(\sum_{p=1}^{P}(TC * DisDiR_{p,q} * XDIR_{p,q,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{m=1}^{M}(\sum_{q=1}^{Q}(TC * DisRSM_{q,m} * XRSM_{q,m,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{d=1}^{D}(\sum_{p=1}^{P}(TC * DisDiDe_{p,d} * XDIRE_{p,d,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{D=1}^{D}(TC * DisDeDis_{d,f} * XREDIS_{d,f,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{i=1}^{I}(\sum_{d=1}^{D}(TC * DisDeS_{d,i} * XPS_{d,i,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{j=1}^{J}(\sum_{q=1}^{Q}(TC * DisRPP_{q,j} * XRPP_{q,j,t,s}))) \\ &+ \textstyle\sum_{t=1}^{T}(\sum_{f=1}^{F}(\sum_{c=1}^{C}(TC * DisCoF_{c,f} * XCOF_{c,f,t,s}))) \end{aligned} \tag{3.7}$$

Constraints (1) to (6) verify that the different capacities of all centers are respected.

$$
\begin{array}{lll}
(1) & \sum_{i=1}^{I} XSP_{i,j,t,s} + \sum_{q=1}^{Q} XRPP_{q,j,t,s} \leq CapPlant_j & \forall s \in S, t \in T, j \in J \\
(2) & \sum_{j=1}^{J} XPH_{j,c,t,s} + XCHC_{j,c,t,s} \leq CapHC_c * YCH_{c,t} & \forall s \in S, t \in T, c \in C \\
(3) & \sum_{c=1}^{C} XCODI_{c,p,t,s} * Tdismantler_s \leq Capd_p * YP_{p,t} & \forall s \in S, t \in T, p \in P \\
(4) & \sum_{p=1}^{P} XDIR_{p,q,t,s} * Trepair_s \leq CapR_q * YQ_{q,t} & \forall s \in S, t \in T, q \in Q \\
(5) & \sum_{p=1}^{P} XDIRE_{p,d,t,s} * Trecycle_s \leq CapDec_d * YD_{d,t} & \forall s \in S, t \in T, d \in D \\
(6) & \sum_{d=1}^{D} XREDIS_{d,f,t,s} \leq B * YF_f & \forall s \in S, t \in T, f \in F
\end{array}
$$

Constraints (7) to (9) are used to verify that the demand is never over-satisfied. However, the demand can remain unsatisfied and considered lost in this case.

$$
\begin{array}{lll}
(7) & \sum_{c=1}^{C} (XCHD_{c,l,t,s}) \leq D_{l,t,s} & \forall s \in S, t \in T, l \in L \\
(8) & \sum_{q=1}^{Q} (XRSM_{q,m,t,s}) \leq Dsm_{m,t,s} & \forall s \in S, t \in T, m \in M \\
(9) & \sum_{d=1}^{D} (XPS_{d,i,t,s}) \leq Ds_{i,t,s} & \forall s \in S, t \in T, i \in I
\end{array}
$$

Constraint (10) calculate the quantity of collected EOL products.

$$
(10) \quad \sum_{c=1}^{C} (XCHC_{l,c,t,s}) = R_{t,s} * D_{l,t,s} \quad \forall s \in S, t \in T, l \in L
$$

Constraints (11) and (12) calculate the quantity of the dismantled, repaired and recycled products.

$$
\begin{array}{lll}
(11) & \sum_{c=1}^{C} XCODI_{c,p,t,s} * Re = \sum_{q=1}^{Q} XDIR_{p,q,t,s} & \forall p \in P, s \in S, t \in T \\
(12) & \sum_{p=1}^{P} XDIRE_{p,d,t,s} * Rr = \sum_{i=1}^{I} XPS_{d,i,t,s} & \forall d \in D, s \in S, t \in T
\end{array}
$$

Constraints (13) to (18) are the flow balance constraints.

$$
\begin{array}{ll}
(13) & \sum_{i=1}^{I} (XSP_{i,j,t,s}) + \sum_{q=1}^{Q} (XRPP_{q,j,t,s}) = \sum_{c=1}^{C} (XPH_{j,c,t,s}) \\
& \forall s \in S, t \in T, j \in J \\
(14) & \sum_{j=1}^{J} (XPH_{j,c,t,s}) = \sum_{l=1}^{L} (XCHD_{c,l,t,s}) \\
& \forall s \in S, t \in T, c \in C \\
(15) & \sum_{l=1}^{L} (XCHC_{l,c,t,s}) = \sum_{p=1}^{P} (XCODI_{c,p,t,s}) + \sum_{f=1}^{F} (XCOF_{c,f,t,s}) \\
& \forall s \in S, t \in T, c \in C \\
(16) & \sum_{c=1}^{C} (XCODI_{c,p,t,s}) = \sum_{q=1}^{Q} (XDIR_{p,q,t,s}) + \sum_{d=1}^{D} (XDIRE_{p,d,t,s}) \\
& \forall s \in S, t \in T, p \in P \\
(17) & \sum_{p=1}^{P} (XDIR_{p,q,t,s}) = \sum_{m=1}^{M} (XRSM_{q,m,t,s}) + \sum_{j=1}^{J} (XRPP_{q,j,t,s}) \\
& \forall s \in S, t \in T, q \in Q \\
(18) & \sum_{p=1}^{P} (XDIRE_{p,d,t,s}) = \sum_{f=1}^{F} (XREDIS_{d,f,t,s}) + \sum_{i=1}^{I} (XPS_{d,i,t,s}) \\
& \forall s \in S, t \in T, d \in D
\end{array}
$$

Constraint (19) restricts the maximum number of opened centers for a period depending on the available budget.

$$
\begin{aligned}
(19)\quad & \textstyle\sum_{c=1}^{C}((YCH_{c,t} - YCH_{c,t-1}) * Cohyb_c) + \sum_{p=1}^{P}((YP_{p,t} - YP_{p,t-1}) * CoDism_p) \\
& + \textstyle\sum_{d=1}^{D}((YD_{d,t} - YD_{d,t-1}) * CoRecy_d) + \sum_{f=1}^{F}((YF_{f,t} - YF_{f,t-1}) * CoDisp_f) \\
& + \textstyle\sum_{q=1}^{Q}((YQ_{q,t} - YQ_{q,t-1}) * CoRep_q) \leq C_t \forall t \in T
\end{aligned}
$$

Constraint (20) updates the budget regarding the number of opened centers in the previous period.

$$
\begin{aligned}
(20)\quad & C_t = C_1 - \textstyle\sum_{c=1}^{C}(YCH_{c,t-1} * Cohyb_c) \\
& - \textstyle\sum_{p=1}^{P}(YP_{p,t-1} * CoDism_p) - \sum_{d=1}^{D}(YD_{d,t-1} * CoRecy_d) \\
& + \textstyle\sum_{f=1}^{F}(YF_{f,t-1} * CoDisp_f) - \sum_{q=1}^{Q}(YQ_{q,t-1} * CoRep_q) \qquad \forall t \in T
\end{aligned}
$$

Constraints (21) to (25) calculate the fixed opening costs.

$$
\begin{array}{lll}
(21) & ZYCH_c \geq (1/T) * \sum_{t=1}^{T} YCH_{c,t} & \forall c \in C \\
(22) & ZYQ_q \geq (1/T) * \sum_{t=1}^{T} YQ_{q,t} & \forall q \in Q \\
(23) & ZYD_d \geq (1/T) * \sum_{t=1}^{T} YD_{d,t} & \forall d \in D \\
(24) & ZYP_p \geq (1/T) * \sum_{t=1}^{T} YP_{p,t} & \forall p \in P \\
(25) & ZYF_f \geq (1/T) * \sum_{t=1}^{T} YF_{f,t} & \forall f \in F
\end{array}
$$

Constraints (26) to (30) forbid to close opened centers.

$$
\begin{array}{lll}
(26) & YCH_{c,t+1} \geq YCH_{c,t} & \forall c \in C, t \in T \\
(27) & YQ_{q,t+1} \geq YQ_{q,t} & \forall q \in Q, t \in T \\
(28) & YD_{d,t+1} \geq YD_{d,t} & \forall d \in D, t \in T \\
(29) & YP_{p,t+1} \geq YP_{p,t} & \forall p \in P, t \in T \\
(30) & YF_{f,t+1} \geq YF_{f,t} & \forall f \in F, t \in T
\end{array}
$$

Constraints (31) and (32) are used in order to limit the transportation costs to unidirectional among forward and reverse flows depending on the maximum number of products transported between.

$$
\begin{array}{lll}
(31) & h_{c,l,t,s} \geq XCHD_{c,l,t,s} & \forall c \in C, l \in L, s \in S, t \in T \\
(32) & h_{c,l,t,s} \geq XCHC_{l,c,t,s} & \forall c \in C, l \in L, s \in S, t \in T
\end{array}
$$

Finally, the additional constraints corresponding to the expression of model 3.3 are taken into account in (A) to (G).

$$\begin{array}{lll}(A) & Z \leq TotalProfit_s & \forall s \in S \\ (B) & Z \leq e_1 & \\ (C) & TotalProfit_s \geq -B * Y_s + e_1(1 - Y_s) & \forall s \in S \\ (D) & TotalProfit_s \leq e_1 * Y_s + (1 - Y_s) * B & \forall s \in S \\ (E) & z \leq (1 - Y_s) * B & \forall s \in S \\ (F) & \sum_{s=1}^{S} \delta_s = 1 & \\ (G) & z \leq TotalProfit_s + (1 - \delta_s) * B & \forall s \in S \end{array}$$

3.2.3 Numerical investigation

To illustrate the behaviour of the model and the usefulness of the proposed solution methodology, an explicatory numerical investigation has been performed. The obtained results are reported in this section. The data used was adapted from the study presented in [Sub+15] where a lead/acid battery CLSC network design under uncertainty was considered for a Turkish industry. The model of [Sub+15] differs from ours since it does not include dismantling centers and only considers one type of center for both recycling and repair, they also only consider three outcomes for the reprocessed EOL products: 1) re-selling them as spare parts, 2) re-manufacturing them in the plant, 3) putting them in disposal. They do not consider the re-selling of recycled material to the supplier. Apart from those points, both models consider the flows of products in forward and reverse directions. We adapted the data by adding the lacking distances and costs for the dismantlers and repair centers with the same order of value as those used for the other centers. 10 time periods were considered with 10 suppliers and plants, 10 potential locations for establishing the HDC centers and 10 customers and spare market customers. The number of potential locations for establishing repair centers, or recycling centers, or disposal centers is 10. The maximum number of opened centers is limited by the available budget. Other parameters are reported in Table 3.1. The transportation costs are defined per product and per 1 kilometer.

Parameters	Range of value	Parameters	Range of value
CapPlant	[28000,56000]	Ca	[0.5,4]
CapHC	[5250,20000]	Cp	[25,65]
Capd	[28000,56000]	Cass	[0.3,0.8]
CapR	[28000,56000]	Coph	[2,5]
CapDec	[28000,56000]	Cdis	[10,12]
Distances	[0,500]	Crep	[7,9]
SP	[40,60]	Cdecr	[0.47,1]
RSP	[5,15]	TC	0.003
Rev	[5,7]	Cohyb	[6000,23000]
Re	70%	Codism	[40000,60000]
Rr	90%	CoRecy	[40000,60000]
CFRep	100	CoDisp	[40000,60000]
CFDisp	100	CoRep	[40000,60000]
CFRecy	100	CFhyb	100
CFDism	100		

Table 3.1: Nominal data of the model

In the study of [Sub+15], 3 uncertain parameters (initial demand, returned fraction of demand and disposal rate) were considered, while we consider 7 uncertain parameters (inital demand, spare market demand, demand for recycled products, return rate, reprocessing time of EOL products at dismantler, repair center and recycling center). Indeed, we felt like these 7 parameters better represent the variety of uncertainties that are often present in reverse logistics decision. For each uncertain parameter, we consider two possible scenarios of realization given as follows: for uncertain demand of customers at primary D: low level ([1500,1800]) or high level ([2200, 2500]) and secondary markets, spare market Dsm: low level ([350,500]) or high level ([1200,1750]), supplier secondary demand Ds: low level ([250, 400]), high level ([1000,1250]) and for the uncertain return rate of products from consumers R: low level (10% in the first period + 2% per period), high level (40% in the first period + 5% per period) as well as for the uncertain reprocessing time of products $Tdismantler$, $Trecycle$, $Trepair$: long time ([5,6]) or short time ([1,2]). We selected the "low" and "high" level of each uncertain parameter in accordance to the study of [Sub+15], the "high" level corresponding to a high range of the values used in their work and the "low" level corresponding to a low range of the values used in their work. We consider the uncertain parameters to be independent and we create eight different scenarios (s_1-s_8), each of them is presented in Table 3.2. Then, for each scenario, one value for each parameter is randomly selected with the use of a uniform distribution [1] from the intervals presented above. The scenario remains unchanged for the 10 considered periods, i.e. for 10 periods in a scenario with a high demand, 10 values drawn from the high demand range are selected. In total, 50 different problem instances were generated. Each problem instance was solved through the process presented in Figure 3.3.

Γ	DE	Dsm	Ds	R	Tdismantler	Trecycle	Trepair
s_1	low	low	low	low	long	long	long
s_2	low	low	low	low	short	short	short
s_3	low	low	low	high	long	long	long
s_4	high	high	high	low	long	long	long
s_5	low	low	low	high	short	short	short
s_6	high	high	high	low	short	short	short
s_7	high	high	high	high	long	long	long
s_8	high	high	high	high	short	short	short

Table 3.2: Uncertain parameters for eight different scenarios

At the first step, the problem is solved as described in Section 3.2.2. Then, the values of the scenario independent variables are recorded. The model is then solved for each scenario separately considering the defined scenario independent variables, in order to find the values of the scenario dependent variables for the maximization of the profit.

The numerical investigation was conducted with IBM-ILOG CPLEX 12.6.3 on an Intel Core 2.60 gigahertz machine with 15 gigabyte RAM. The objective was to compare R_* criterion with the three approaches mentioned in Section 2.2:

1. The robust approach with the objective to maximize the worst-case scenario.

[1] The uniform distribution was selected over a normal distribution or a mean value because it better illustrates the lack of information of the decision maker about the behavior of the uncertain parameters.

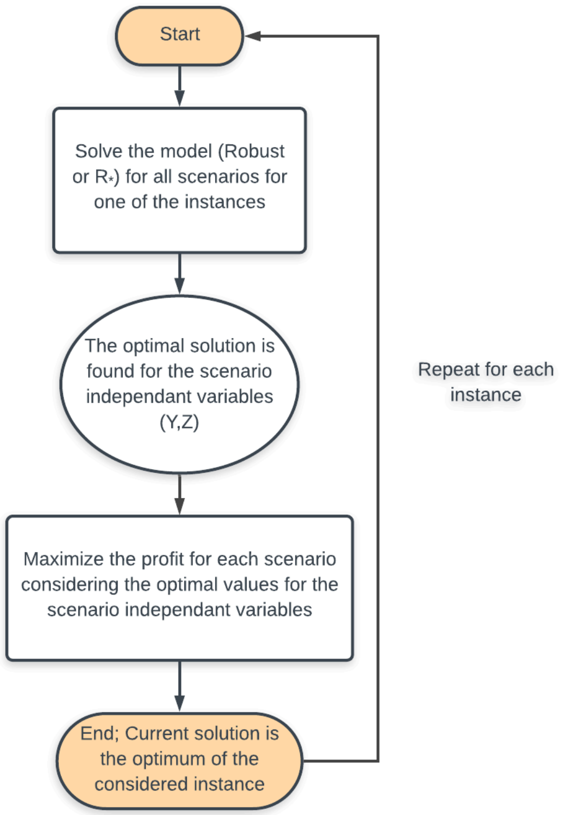


Figure 3.3: Resolution process

2. The average approach with the objective to maximize the average over all scenarios with a uniform probability distribution.

3. The average regret approach with the objective to maximize the average of the regret over all scenarios with a uniform probability distribution.

The average solution times for the models tested for the case of 2 (s_1 and s_8) and 8 scenarios are reported in Table 3.3. The results show that while for 2 scenarios the solution times for robust and R_* models are quite similar, for 8 scenarios it is approximately twice longer for R_*.

Model	Number of scenarios	Average solution time(s)
Robust	2	1 623
Average	2	177
R_*	2	1 714
Robust	8	15 900
Average	8	2 077
R_*	8	33 217

Table 3.3: Solution time regarding models and number of scenarios

3.2.4 Analysis of Results and discussion

3.2.4.1 Explorative study of the impact of possible contexts on the performance of the CLSC

The results obtained for 8 scenarios (reported in Table 3.4) showed the existence of clusters of similar scenarios. The scenarios belonging to the same cluster are indicated by the same colour in Table 3.4. The values of e are calculated as a percentage of the value of the "MaxMin" solution. The payoff values reported are the $TotalProfit$ made by the CLSC when scenario s_1 to s_8 occur. The following observations can be made.

Model	s_1(€)	s_2(€)	s_3(€)	s_4(€)	s_5(€)	s_6(€)	s_7(€)	s_8(€)
Robust	3 319 100	3 404 364	1 363 587	5 315 179	3 063 511	5 479 111	1 125 648	6 453 565
Average	3 418 763	3 508 855	1 320 371	5 368 389	3 167 903	5 596 203	879 353	6 524 019
R_*, e=99%	3 351 986	3 412 147	1 316 274	5 327 129	3 101 006	5 492 417	1 125 453	6 496 221
R_*, e=85%	3 349 895	3 418 813	1 331 187	5 296 488	3 084 977	5 526 364	962 056	6 506 497

Table 3.4: Total profits for all combinations of scenarios and models (reveal clusters in the results)

Observation 1. Scenario s_8 (in green) is the best case scenario with maximal $TotalProfit_s$. It corresponds to the scenario where demands (DE, Dsm and DS) and return rate of EOL products (R) are high and the reprocessing times of products ($Tdismantler$, $Trepair$ and $Trecycle$) are short. In this situation, we can assume that the company is able to respond to the high demands due to the high flow of EOL products coming back from the consumers in addition with a high reprocessing capacity due to the short times of reprocessing EOL products. Therefore, the number of reprocessed products sold is high and generates considerable profit for the company.

Observation 2. Scenario s_3 and s_7 (in red) are the worst case scenarios with minimal $TotalProfit_s$. They correspond to the cases where the rate of return (R) is high, but the reprocessing times of EOL products ($Tdismantler$, $Trepair$ and $Trecycle$) are long. The number of reprocessed products sold is low and thus generates less profit than in the other cases.

Observation 3. Scenario s_4 and s_6 (in blue) are "medium high" scenarios, and correspond to the situation where demands (DE, Dsm and Ds) are high, but return rate (R) is low. In this case, because of the low rate of return, the company doesn't need a lot of reprocessing facilities to process all the EOL product, thus, the reprocessing times have no impact on the profit. All the reprocessed product are sold, creating profit, but a part of the demand is lost as the flow of reprocessed product is not high enough to respond to the high demand.

Observation 4. Scenario s_1, s_2 and s_5 (in orange) are "medium low" scenarios. They represent the case where the demand is low, and where either the return rate is high and the reprocessing time of EOL products is short, or the return rate is low and the reprocessing time of EOL products is long, or the return rate is low and the reprocessing time of EOL products is short. In those cases, the company is able to reprocess all the returned EOL products without additional costs generated from products put in disposal. However, at the same time, the company is unable to resell all the reprocessed products as the demand is low, and so no considerable profit is possible.

On the basis of these results, the set of scenarios was reduced to 4, keeping only one scenario of each group (i.e. s_1, s_6, s_7 and s_8). This setting requires less computational time and provides the same level of managerial insights. In the next sections, we compare the performances of three models (robust, average, R_*) for these 4 scenarios and for all possible pairs of them.

3.2.4.2 *Robust* model vs R_*

The robust model is the one conceptually closest to R_* since it considers a set of equally possible scenarios. In order to compare their behaviour, the value of risk threshold e was set up to the value of "MaxMin" criterion minus 1% or 3%. The obtained results for 4 scenarios are presented in Table 3.5, where column 1 shows the model used, the values reported are the $TotalProfit$ made by the CLSC when scenario s_1 to s_8 occur. They are colored in green when the R_* solution brings an improvement compared to the Robust solution and in red otherwise. The standard deviation σ (i.e the square root of the variance) among the scenarios is given in the last column.

Model	s_1	s_6	s_7	s_8	σ
Robust	3 334 384	5 244 279	1 253 605	6 218 444	1 903 483
R_*, e=99%	3 330 883	5 239 336	1 250 748	6 231 859	1 905 423
R_*, e=97%	3 331 035	5 238 529	1 229 414	6 248 992	1 918 007

Table 3.5: Compared $TotalProfit_s$ between Robust and R_* for the case of 4 scenarios

The obtained results show that R_* may provide better opportunities to the decision maker at price of low risks, especially for the case of $e = 99\%$ of the robust value.

When taking more risks (lowering the value of e) the DM invests more in the implementation of new centers at each period. Thus, if a good case scenario happens (for instance high demand, high returns and short reprocessing time of OEL products), the CLSC is able to collect and reprocess more products resulting in better total profit. Contrariwise, if a bad case scenario happens, the additional investment made by the DM won't be profitable.

To deepen the analysis, we compare the results obtained for each pair of 4 scenarios reported in Table 3.6. The values reported are the relative percentage of the best $TotalProfit$ made by the CLSC in each scenario, depending on the solution method.

The following observations can be made on the obtained results.

Observation 1. The R_* model is efficient in comparison to the robust model where both scenarios are not too pessimistic, i.e. opportunities are possible on at least one of the scenarios

Model	s_1	s_8	σ
Robust	100%	73,36%	475 179
R_*, e= 99%	98,96%	90,97%	1 047 111
R_*, e= 97%	97,05%	100%	1 365 222
Model	s_6	s_8	σ
Robust	100%	88,52%	2 619
R_*, e=99%	99,08%	95,93%	261 659
R_*, e=97%	97,28%	100%	440 992
Model	s_1	s_6	σ
Robust	100%	98,10%	974 108
R_*, e=99%	98,97%	99,63%	1031 542
R_*, e=97%	97,13%	100%	1 080 937
Model	s_8	s_7	σ
Robust	99,43%	100%	2 402 857
R_*, e= 99%	99,84%	99,07%	2 421 540
R_*, e= 97%	100%	97,47%	2 436 837
Model	s_1	s_7	σ
Robust	99,68%	100%	1 042 445
R_*, e=99%	99,83%	99,13%	1 050 470
R_*, e=97%	100%	97,19%	1 065 418
Model	s_6	s_7	σ
Robust	99,51%	100%	2 011 897
R_*, e=99%	99,85%	98,58%	2 024 368
R_*, e=97%	100%	96,63%	2 040 881

Table 3.6: Comparison of profit obtained with Robust and R_* for the case of 2 scenarios

(see for instance s_1 versus s_8 or s_6 versus s_8.) By allowing a relatively low degradation for the worst case scenario, a significant improvement can be found for the best case. Decreasing e leads to better opportunities, but also to more important losses, however, the gain is superior to the loss in the considered setting. From a practical point of view, when taking more risks, the DM invests more in the implementation of new centers, therefore when scenario s_8 happens, the CLSC is able to reprocess more EOL products and thus to better respond to the demand which brings more profit to the company. At the contrary, when scenario s_1 or s_6 happens, either the demand is low, or the flow of returned products is low, or the reprocessing capacity of the CLSC is low. In all these cases, the CLSC is unable to make a considerable profit. Nevertheless, taking a little risk and implementing more new centers helps to keep a satisfying level of profit compared to a robust approach.

Observation 2. When the models are compared on the best case scenario (s_8) with the worst case one (s_7), or on two middle case scenarios (s_1 and s_6), the opportunities are still possible but the DM has to be very careful about the level of risk to take. Indeed, when we consider the case where the best case scenario (s_8) is faced with the worst case one (s_7), taking more risks in the investment of new centers may bring more profit if s_8 happens, as the CLSC will be able to better respond to the demand. However, this profit is not always compensated by the loss occurred if s_7 happens. When we consider the situation where the two middle cases (s_1 and s_6) are confronted to each other, the room for opportunities is thin in both scenario, as the CLSC may encounter difficulties to respond to the demand. Thus, implementing new centers may lead to better opportunities in one of the two cases but does not necessarily worth the risk in the other case.

Observation 3. Finally, R_* model cannot help to find new opportunities unless by taking much higher risks where both scenarios are not optimistic (the worst case scenario (s_7) and either s_1 or s_6). For such a situation, the robustness should be preferred in order to limit the losses. Here, from a production perspective, taking more risks and thus implementing new centers will probably not lead to more opportunities. Indeed, when the worst case scenario (s_7) happens, the costs generated by the implementation of new centers are not compensated by the reprocessing more EOL products. When one of the middle case scenarios happens (s_1 or s_6) the CLSC is unable to make a considerable profit because of either low demand, a low flow of returned products, or a low reprocessing capacity. Thus, taking risk and implementing more centers than with a robust solution will not provide substantially better profit in this case.

In conclusion, the solutions found with R_* criterion show a greater number of implemented reverse centers compared to the robust solution. Taking more risk is synonym to investing more for the implementation of new centers at the beginning of each period, and thus being able to reprocess and sell more products when a good case scenario happens. When the two scenarios are not too pessimistic, a good case scenario is very likely to occur. Consequently, choosing a solution where more reverse centers are opened will lead to a good probability of increased profit compared to a safer solution where less centers are opened. On the contrary, if all possible scenarios are quite pessimistic, the risk taken by the investment for implementation of additional centers compared to the robust solution will probably not result in a better profit.

3.2.4.3 *Average* and *Regret Average* models vs R_*

Since the stochastic models are the most used in the literature for the CLSC problem, it seems legitimate to compare them with our model even if they do not take uncertain parameters into account in the same way (a stochastic model considers a distribution of probability (here uniform) for the scenarios. The results obtained for the case of 4 scenarios are presented in Table 3.7. The comparison of scenarios two by two showed the same results, we do not present them here. The table is organized in the same way as previously, with a new column "*Av*" for the mean value over all scenarios. There is also new Column "*Reg*" corresponding to the value of the sum of regret over all scenarios. The risk threshold e is still equal to the value of "MaxMin" criterion minus 0% (i.e. the robust solution), or -1% and -3%.

Model	s_1	s_6	s_7	s_8	*Av*	*Reg*	σ
Average	3 374 146	5 287 225	1 190 523	6 262 269	4 028 541	1 102 861	1 940 129
Regret	3 374 215	5 287 219	1 190 381	6 262 349	4 028 541	1 102 861	1 942 797
R_*, e=100%	3 334 384	5 244 279	1 253 605	6 218 444	4 012 678	1 166 311	1 903 483
R_*, e=99%	3 330 883	5 239 336	1 250 748	6 231 859	4 013 207	1 164 197	1 905 423
R_*, e=97%	3 331 035	5 238 539	1 229 414	6 248 992	4 011 992	1 169 054	1 918 007

Table 3.7: Comparison of the profits found with the two stochastic models and R_*

It can be observed that the solutions given by the two stochastic models are almost equivalent. For this reason, only gaps between R_* model and average model are reported. Positive gaps are in green and negative ones are in red. The solutions given by R_* are more robust than the stochastic solutions and opportunities can still be found, even if they are less important than in comparison with the robust model. The mean of $TotalProfit_s$ over all scenarios is in the same order of values for all models. Regarding the regret value for each scenario and for each model, the two stochastic models have both the lowest regret. The value of the regret seems to increase while the value of e decreases. However, the regret stays in the same magnitude for all models.

These results show that R_* model allows more robustness by controlling the worst case scenario and still considering opportunities as the best case is comparable with stochastic solutions. Thus, R_* offers a compromise between the "MaxMin" solution which is too conservative and a stochastic solution which is not robust enough.

3.2.4.4 Variance analysis

Figure 3.4 reports the standard deviation for all tested 50 problem instances of the case of 4 scenarios for average model, robust model and R_* model for two values of e. The deviation of the regret average model is not reported because of its quasi equivalence to the average model.

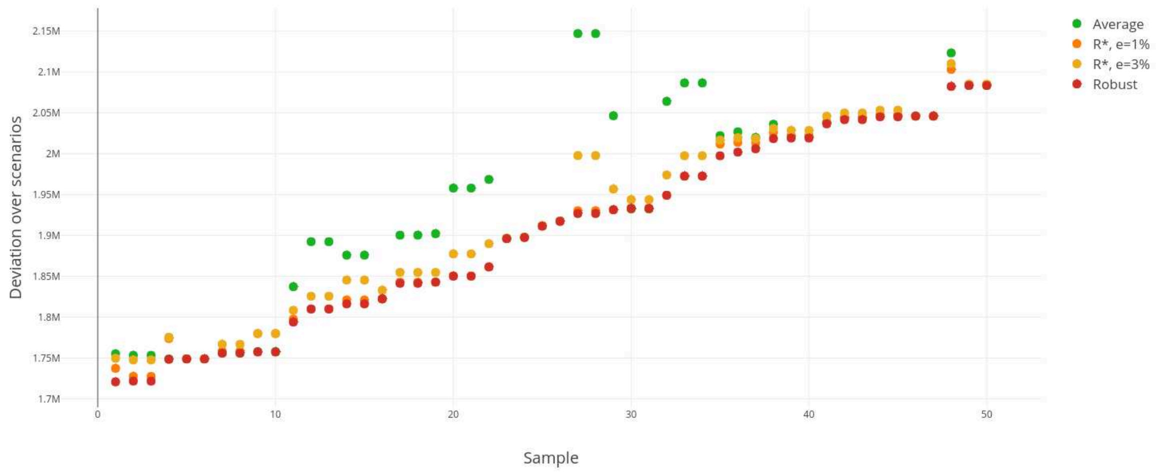


Figure 3.4: Standard deviation provided by the tested models

It can be seen that the variances of robust and R_* models are very close while the deviation of the average model is relatively dispersed.

Figure 3.5 shows the value obtained for the best case scenario by the tested models for all 50 problem instances. Robust model provides the minimal value. R_* model is sensible to the value of e: while it decreases, the value for the best case scenario improves. The values

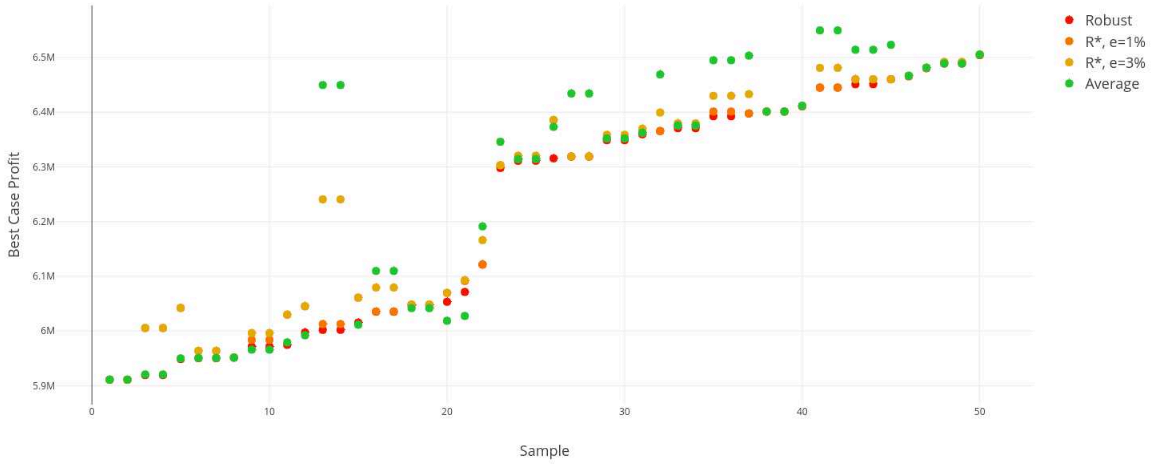


Figure 3.5: The value for the best case scenario provided by the tested models

returned by R_* criterion are always higher than with the Robust model, confirming the fact that R_* criterion allows to better explore opportunities. Finally, average model is not constant in providing a good value, thus, it does not guarantee the maximization of opportunities, but it is largely the best one for 18 instances from 50 (i.e. in about 36% of the cases).

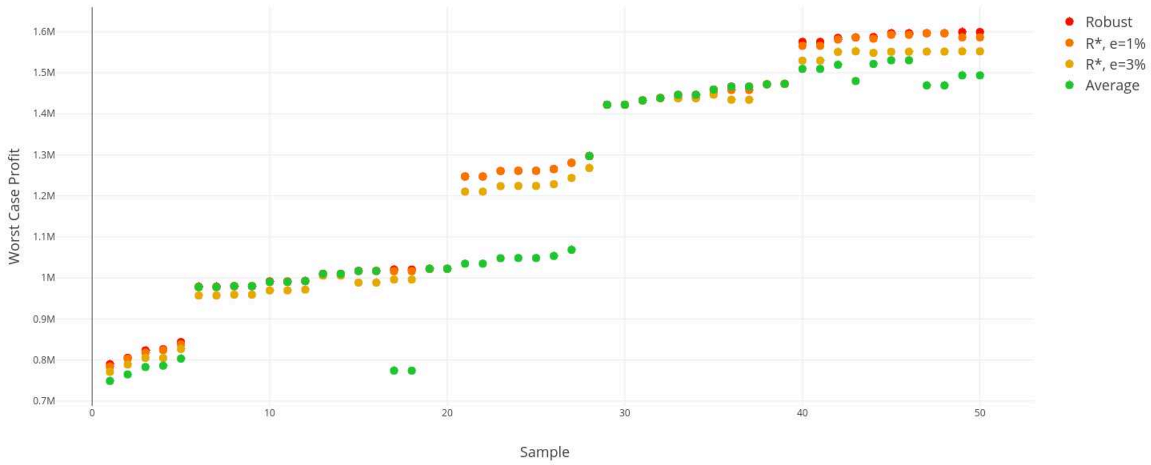


Figure 3.6: The value for the worst case scenario provided by the tested models

Figure 3.6 shows the value obtained for the worst case scenario by the tested models for all 50 problem instances. Here, unsurprisingly, the robust model provides the best value. R_* model is again sensible to the value of e: the profit decreases when the value of e decreases, nevertheless it remains very close to the value found with the Robust criterion. Average model is again inconstant, it could provide a value as good as the robust model or to be largely worse (16 instances from 50 i.e. about 32%). Thus, it does not allow the control of the risk taken by the DM.

When the two figures are considered at the same time, we can see that the R_* criterion offers a compromise between a robust solution with no opportunities or an average solution with no control over the robustness.

From the realized analysis we can conclude the following.

If e is superior or equal to the value of the robust solution, model R_* will give the equivalent solution. The closer the value of e to the value of the robust model, the closer the solution obtained with R_* is to the robust solution and the smaller is the standard deviation of the profits for different scenarios as well as the gap between the solution's best and worst scenarios. The average and regret average models are the ones with the greatest average over scenarios, but have the worst "worst case scenarios".

3.3 Conclusion

Establishing CLSC is an essential challenge when shifting from linear to circular economy. A successful CLSC design relies on appropriate modeling of uncertainty in terms of risk, but also opportunities. In this study, we suggest a new modeling approach using R_* to take DM optimism into account in both hazard and opportunity zones. This approach can be used to set up reverse facilities and connect them to an existing forward supply chain. The CLSC can be expanded gradually on the basis of the decisions made in previous periods. The proposed approach is compared to robust and stochastic models in an extensive numerical investigation. The results obtained show that the use of R_* criterion makes it possible to better explore the opportunity zone without loosing control over robustness.

Indeed, it provides the DM with greater control on the investment she/he is willing to make to open new reverse centers, bringing more profit in a good case scenario while still controlling the losses when a bad case scenario occurs. Particularly, we show that in the case where the initial demand is high, the rate of return is high and the reprocessing time of EOL products is short (s_8) versus the case where the demand and the return are low and the reprocessing time is long (s_1), the solution found with R_* criterion allows up to 36% more profit that the robust solution in the fist case for only 3% of losses in the second case.

This study reveals many new research paths. One of those research path lies in examining the case of a discrete set of scenarios with imprecise probabilities or of a continuous set of scenarios. The proposed model can also be extended by considering not only the best and worst case scenarios but all scenarios in between. For instance, a Leximax criterion can be applied in order to rank solutions with the same best and worst case scenarios. We propose to study this last point in the next chapter.

Chapter 4

Reverse Supply Chain design under uncertainty: the $LexiR_*$ criterion

Contents

In this chapter, we propose to improve the R_* criterion presented in the previous chapter and we develop a lexicographic approach for the consideration of existing scenarios. We propose two methods to compute the optimal solution for lexicographic R_* criterion: the first method is in the form of an algorithm, the second one is in the form of a Mixed-Integer Program (MIP). The performance of the developed approaches is demonstrated for a reverse facility location problem. The work proposed in this chapter has provided the following publications:

- Zoé Krug, Romain Guillaume, Olga Battaïa "Lexicographic R_* Criterion For Decision Making Under Uncertainty in Reverse Logistics", MIM 2019. *International conference with proceedings*

- Zoé Krug, Olga Battaïa, Romain Guillaume "Résolution d'un problème de décision sous incertitude avec le $lexiR_*$", ROADEF 2020. *National conference with proceedings*

- Zoé Krug, Romain Guillaume, Olga Battaïa "Design of Reverse Supply Chains under Uncertainty: the Lexicographic R_* criterion for exploring opportunities", *submitted to an international peer-review journal*

4.1 Proposed solution approach: the $LexiR_*$ criterion

Originally, R_* only pays attention to the best and worst cases profits and oversees all cases in between: two solutions with the same best case profit and the same worst case profit are considered equivalent even if they give different profits for other scenarios. This comparison scenario by scenario can be realized with $LexiR_*$ criterion which uses a lexicographic minimum (*leximin*) in the risky area and a lexicographic maximum (*leximax*) in the opportunistic area. *Leximin* operator selects a solution by maximizing the one with the highest minimum profit overall scenarios. If multiple solutions exist with the same minimum profit, the criterion is applied to maximize the second minimum profit, then the third, etc... until one solution dominates the others. *Leximax* operator works in the same manner but maximizing the highest profit, then the second highest profit, then the third, etc...([Ogr97]; [OŚ03]).

Refer to the formal definitions of *leximax* (see definition 12) and *leximin* (see definition 1).

The $LexiR_*$ criterion can be written formally as:
Be $S^- = \{s \in S | f_s(x) \leq e\}$ and $S^+ = S \setminus S^-$:

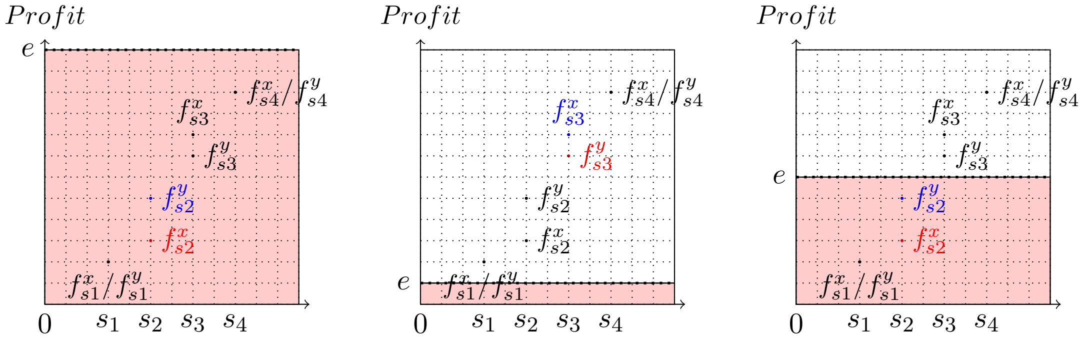
$$LexiR_*((f_s(x))_{s \in S}, e) =$$

$$\begin{cases} Leximin_{s \in S^-} f_s(x) \\ Then \\ Leximax_{s \in S^+} f_s(x) \end{cases} \tag{4.1}$$

An example of resolution with $LexiR_*$ criterion is presented in Example 2.

Example 2
Let $S = \{s_1, s_2, s_3, s_4\}$ be a discrete set of scenarios and f represent the profit obtained for each scenario. Let us consider two solutions x and y which provide the following profits for 4 considered scenarios: $f_s^x = (2, 3, 8, 10)$ and $f_s^y = (2, 5, 7, 10)$. We can observe that solutions x and y are considered equal by the R_* criterion since they offer the same best case profit and worst case profit. However, they are distinguished with $LexiR_*$ criterion. We consider 3 different cases of the DM optimism reflected by the risk threshold e.

1. *Case 1: The DM expects the profit $e = 12$ (see Fig.4.1 (a)). All possible profit values for*



(a) Case 1: $e = 12$

(b) Case 2: $e = 1$

(c) Case 3: $e = 6$

Figure 4.1: Resolution with $LexiR_*$ criterion

considered scenarios are in the risky area for both solutions. Based on this observation and in accordance with the definition of $LexiR_*$ approach, leximin criterion is applied to select the best solution. First, the worst case scenario (here s_1) is considered. We have $f^x_{s1} = f^y_{s2}$, therefore x and y are not differentiated. Then the second worst case scenario is considered (here s_2). We have $f^y_{s2} > f^x_{s2}$, therefore solution y is preferred to x by leximin.

2. *Case 2: The DM expects the profit equal to $e = 1$ (see Fig.4.1 (b)). All possible profit values for considered scenarios are in the opportunistic area for both solutions. Based on this observation and in accordance with the definition of $LexiR_*$ approach, leximax criterion is thus applied to select the final solution. For the best case scenario (here $_s4$), we have $f^x_{s4} = f^y_{s4}$, therefore x and y are not differentiated. For the second best case scenario (here s_3), we have $f^x_{s3} > f^y_{s3}$, therefore solution x is preferred to y.*

3. *Case 3: The DM expects the profit $e = 6$ (see Fig.4.1 (c)). Two profit values are in the opportunistic area and two in the risky area for both solutions. Based on this observation and in accordance with the definition of $LexiR_*$ approach, firstly, the risky values are compared with leximin criterion, as in Case 1. Therefore, solution y is selected.*

We propose two methods to compute the optimal solution for lexicographic R_* criterion : the first method is in the form of an algorithm, the second one is in the form of a Mixed-Integer Program (MIP).

4.1.1 Lexicographic R_* Algorithm

In this section, we present the formal mathematical formulation for $LexiR_*$ approach for RSC design according to its definition in the previous section.

First, $LexiR_*$ criterion is applied taking into account all possible scenarios. The obtained values of profit found at this step for all scenarios are compared to the threshold e. If all of them are above the threshold, then the algorithm continues with the application of *leximax*

Notation	Description	Notation	Description
R_k	Linearization of min	Y_s	Binary variable
r_k	Linearization of max	δ_s^k	Binary variable
k	Number of iteration	γ_s^k	Binary variable
e	Risk threshold	M	Big value

Table 4.1: Algorithm Notations

criterion to select the final solution. Otherwise, if for some scenarios, the objective value found is below e, the worst case scenario is expressed as a constraint for further resolution. The R_* criterion is then re-applied on the reduced set of scenarios taking into account a new constraint for the worst case. It means that among all solutions having this value of the profit in the worst case, we are looking for solutions providing the best opportunities in all other cases. As before, if the objective value found is above e, a *leximax* criterion is applied to select the final solution and on the contrary if it is below e, it is recorded and then the second worst case scenario is expressed as a constraint. This process continues until all scenarios have been treated.

Algorithm 1.

- *Step.0*
  $k \leftarrow 0$
  $k' \leftarrow 0$
  $N \leftarrow \{s_1, ..., s_n\}$

- *Step.1*
  Solve Model (4.2)

$$\max R_k + r_k \tag{4.2}$$

$$\begin{array}{lcl}
S.t & & \\
(a) & R_k \leq f_s((x,y)) & \forall s \in N, \\
(b) & R_k \leq e & \\
(c) & f_s((x,y)) \geq -M * Y_s + e(1 - Y_s) & \forall s \in N \\
(d) & f_s((x,y)) \leq e * Y_s + (1 - Y_s)M & \forall s \in N \\
(e) & r_k \leq (1 - Y_s)M & \forall s \in N \\
(f) & \sum_{s=1}^{S} \delta_s^k = 1 & \\
(g) & r_k \leq f_s((x,y)) + (1 - \delta_s^k)M & \forall s \in N
\end{array}$$

- *Step.2*
  If $R_k + r_k \leq e$
  then $R_k = R_k^*$, k=k+1 and go to *Step.3*.
  Otherwise,
  define $R_k = e$, $r_1 = r_k^*$, $k' = 2$ and go to *Step.5*

- *Step.3:*
  Solve Model (4.3)

$$
\begin{array}{lcl}
 & \max R_k + r_k & \\
S.t & & \\
(a) & R_i \leq f_s((x,y)) + M(1-\gamma_s^i) & \forall s \in N, i \in 1..k \\
(b) & \sum_{s=1}^{S} \gamma_s^i = S - i & \forall i \in 1..k \\
(c) & R_k \leq e & \\
(d) & f_s((x,y)) \geq -M * Y_s + e(1-Y_s) & \forall s \in N \\
(e) & f_s((x,y)) \leq e * Y_s + (1-Y_s)M & \forall s \in N \\
(f) & r_k \leq (1-Y_s)M & \forall s \in N \\
(g) & \sum_{s=1}^{S} \delta_s^k = 1 & \\
(h) & r_k \leq f_s((x,y)) + (1-\delta_s^k) * M & \forall s \in N
\end{array}
\tag{4.3}
$$

- *Step.4:*
  If $S-k=0$ then go to Step.7
  Otherwise:
  If $R_k \leq e$, then $R_k = R_k^*$, $k = k+1$ and return to Step.3
  If $R_k + r_k > e$, then $R_k = e, r_1 = r_k^*$ define $k' = 2$ and go to Step.5

- *Step.5:*
  Solve Model (4.4)

$$
\begin{array}{lcl}
 & \max r_{k'} & \\
S.t & & \\
(a) & R_i \leq f_s((x,y)) + M(1-\gamma_s^i) & \forall s \in N, \forall i \in 1..k \\
(b) & \sum_{s=1}^{S} \gamma_s^i = S - i, & \forall i \in 1..k \\
(c) & r_i \leq f_s((x,y)) + M(1-\delta_s^i) & \forall s \in N, \forall i \in 1..k' \\
(d) & \sum_{s=1}^{S} \delta_s^{k'} = k' &
\end{array}
\tag{4.4}
$$

- *Step.6:*
  If $S-k-k'-1=0$ then go to Step.7
  Otherwise $r_{k'} = r_{k'}^*$, $k' = k'+1$, and go to Step.5

- *Step.7:*
  Stop.

The steps of Algorithm 1 can be detailed in the following manner:

Step 0: We define k as the number of iterations performed in the risky area, k' as the number of iterations performed in the opportunistic area and $N = s_1, ..., s_n$ is the discrete set of scenarios considered. At the start of the algorithm, k and k' are initialized by 0.

Step 1: The decision problem is solved using R_* criterion through the resolution of Model 4.2 (only the best and worst case scenario are taken into account). This model is a MIP. Constraints (b) to (e) differentiate the case where the robust solution is selected (i.e there exist no possible solution for which all objective values are above e overall scenarios) and the case where the opportunistic solution is selected (otherwise). In the former case, constraints (a) help to maximize the minimum objective value. In the latter case, constraints (f) and (g) help to maximize the maximum objective value.

Step 2: The objective value found at Step 1 is analysed if it lower than e, then k is implemented and the process goes to Step 3. If it is higher than e, then k' is implemented and the process goes to Step 5.

Step 3: Model 4.3 is used in order to maximize the second worst profit, then the third and so on depending of the number k of iterations previously solved.

Step 4: This step checks if the value of the objective found through Model 4.3 is lower or higher than e. If this objective value is lower, and if the number k of iteration is lower than the number of scenario (namely S), then k is implemented and Model 4.3 is solved one more time. If $S = k$, then all scenarios have been treated and Algorithm proceeds to Step 7. Otherwise, if the objective value is higher than e, k' is implemented and Algorithm goes to Step 5.

Step 5: Model 4.4 is used to maximize the maximum profit, then the second one and so on depending on the number of iterations k' previously performed.

Step 6: This Step checks if all scenarios have been treated, if not, Step 5 is repeated. Otherwise, the algorithm goes to Step 7.

Step 7: The algorithm stops.

4.1.2 Lexicographic R_* MIP: approximated method

Algorithm 1 offers an exact resolution for the application of $LexiR_*$ approach. However, it includes the resolution of 3 different MIP that can require relatively long solution time. If the solution time is relatively limited, the following approximate compact method in the form of a single MIP can be used instead to implement $LexiR_*$ approach. We denote it as MIP-$LexiR_*$. Its resolution provides an approximated solution and cannot guarantee the optimum, but the solution time is reduced significantly.

All notations needed for the description of MIP-$LexiR_*$ are defined in Table 4.2.

Let $\omega_k = (\omega_1, ..., \omega_n)$ be a vector of weights with $\omega_1 > \omega_2 > .... > \omega_n$. We denote s,s' two indexes representing scenarios $\in N$ with $s \neq s'$. K is a vector of the same size of N and $k \in K$ is an index helping to browse all scenarios, S is the number of scenarios.

The proposed MIP is detailed in Model 4.5.

Notation	Description	Notation	Description
R_k	Linearization of min	Y_s	Binary variable
r_k	Linearization of max	$\delta_{s,s'}$	Binary variable
k	Number of iteration	γ_s^k	Binary variable
A_k	Binary variable	μ_k	Binary variable
$C_{s,k}$	Binary variable	$D_{s,k}$	Binary variable
e	Risk threshold	M	Big value

Table 4.2: MIP Notations

$$\max \textstyle\sum_k (\omega_k * (R_k + r_k)) \tag{4.5}$$

$$\begin{array}{llr}
S.t & & \\
(a) & R_k \leq f_s((x,y)) + M * (1 - \gamma_s^k) & \forall s \in N, k \in K \\
(b) & R_k \leq e & \forall k \in K \\
(c) & \sum_{s=1}^{S} \gamma_s^k = S - k + 1 & \forall k \in K \\
& & \\
(d) & f_s((x,y)) \geq -M * (1 - Y_s) + e * Y_s & \forall s \in N \\
(e) & f_s((x,y)) \leq e * (1 - Y_s) + Y_s * M & \forall s \in N \\
& & \\
(f) & f_s((x,y)) \leq f'_s((x,y)) + M * \delta_{s,s'} & \forall s, s' \in N \\
(g) & f'_s((x,y)) - M * (1 - \delta_{s,s'}) \leq f_s((x,y)) & \forall s, s' \in N \\
& & \\
(h) & r_k \leq A_k * M & \forall k \in K \\
(i) & \sum_{s'=1}^{S} \delta_{s,s'} \leq k + (1 - C_{s,k}) * M & \forall s \in N, k \in K \\
(j) & \sum_{s'=1}^{S} \delta_{s,s'} \geq k - (1 - C_{s,k}) * M & \forall s \in N, k \in K \\
(k) & D_{s,k} \leq Y_s & \forall s \in N, k \in K \\
(l) & D_{s,k} \leq C_{s,k} & \forall s \in N, k \in K \\
(m) & A_k \leq \sum_{s=1}^{S} D_{s,k} & \forall k \in K \\
(n) & \sum_s \mu_{s,k} = \sum_{i=1}^{k} A_i & \forall k \in K \\
(o) & r_k \leq f_s((x,y)) + (1 - \mu_{s,k}) * M & \forall s \in N, k \in K
\end{array}$$

Constraints (a), complementary with constraint (c) are the linearization of the minimum profit, then second minimum profit, then third and so on as long as the minimum profit is lower than e. Otherwise, the value for R_k is set to e in constraint (b).

Constraints (d) and (e) define the following:

$$Y_s = \begin{cases} 0 & if\ f_s(x) \leq e \\ 1 & if\ f_s(x) > e \end{cases}$$

Constraints (f) and (g) define the following:

$$\delta_{s,s'} = \begin{cases} 0 & \textit{if } f_s(x) \leq f'_s(x) \\ 1 & \textit{Otherwise} \end{cases}$$

The sum on s of variable $\delta_{s,s'}$ represents the number of scenarios above and below $f_s(x)$ for each k. This helps us to define constraints (i) and (j) in order to give the following information:

$$C_{s,k} = \begin{cases} 1 & \textit{if } \sum_s \delta_{s,s'} = k \\ 0 & \textit{Otherwise} \end{cases}$$

Constraint (k) and (l) are then used to define:

$$D_{s,k} = \begin{cases} 1 & \textit{if } Y_s = 1 \textit{ and } C_{s,k} = 1 \\ 0 & \textit{Otherwise} \end{cases}$$

It should be noted that $D_{s,k}$ is only activated if $k - st$ profit $f_s(x)$ is higher than e.

Constraint (m) defines

$$A_k = \begin{cases} 1 & \textit{if } \sum_s D_{s,k} = 1 \\ 0 & \textit{Otherwise} \end{cases}$$

It should be noted that A_k is only activated is $k - st$ profit $F(x, s)$ is higher than e. This is used to set the value of r_k to 0 is profit $F(x, s)$ is lower than e in constraint (h).

Then constraint (n) is used to count how many times variable A_k has been activated: the number of times where profit $f_s(x)$ has been higher than e using variable $\mu_{s,k}$.

Constraint (o) is the linearization of the maximum profit, then second maximum profit and so on as long as it is higher than e due to variable $\mu_{s,k}$

4.2 RSC design problem

In this section, we present the framework used in order to study the developed $LexiR_*$ approach to a design problem of RSC. This framework has been chosen as very generic in order to cover various situations that can appear in different industrial contexts. In order to facilitate the understanding of the solution approaches, the structure of the RSC has been simplified. Therefore, the attention is given to the decision making process and not to the organizational details of the RSC. This simplification is only made for seek of illustration, the proposed approach can be applied to the design problem of any RSC independently of the industrial context and its complexity. The only mandatory condition is to be able to collect enough information about the RSC in order to define the corresponding optimization problem. Another limitation is the centralized decision making process: all decisions about all facilities are taken by a centralized decision maker who is a single person or a group of persons capable of reaching a consensus and acting for the common objective of maximizing the total profit.

4.2.1 Description of the RSC

The context of the decision making is the following. A third party logistic company is willing to design a new RSC. The goal is to decide which new facilities (collection centers, re-manufacturing centers and disposal centers) have to be installed and where as well as the organization of the transportation flows between them in order to maximize the total profit gained from the RSC. Figure 4.2 shows the structure of the RSC under design. Three parameters are considered uncertain, namely the quantity of returned EOL products by the customers, the quantity of demand for re-manufactured products and the reprocessing time of EOL products.

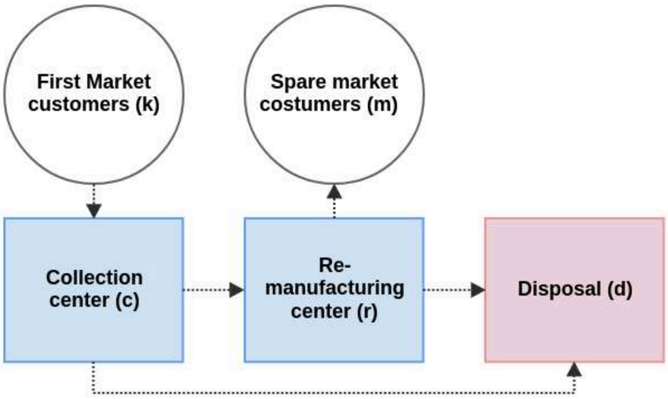


Figure 4.2: Reverse Supply Chain under design

4.2.2 Mathematical Model

This optimization problem is formulated through the following mathematical model. The indexes, parameters and variables of the problem are defined as follows:

	Indexes
$k = 1..K$	Index of customers
$m = 1..M$	Index of spare markets
$c = 1..C$	Index of collection centers
$r = 1..R$	Index of re-manufacturing centers
$d = 1..D$	Index of disposal sites
$s = 1..S$	Index of scenarios

	Demand
$D_{m,s}$	of spare market m for scenario s
	Capacity
$CapC_c$	of collection center c
$CapR_r$	of re-manufacturing center r
	Distance between...
$DKC_{k,c}$	customer k and collection center c
$DCR_{c,r}$	collection center c and re-manufacturing center r
$DCD_{c,d}$	collection center c and disposal d
$DRD_{r,d}$	re-manufacturing center r and disposal d
$DRM_{r,m}$	re-manufacturing center r and spare market m
	Time parameters
$Tremanu_s$	Unit dismantling time
	Unit operational cost
$Coph_c$	at collection center c
$Cdis_p$	at re-manufacturing center p
$Ceco$	tax for non-reprocessed products
TC	transportation cost for 1 kilometer
	Rate parameters
$R_{k,s}$	Quantity of return for scenario s and costumer k
Rr	Re-manufacturing rate after collection
Rd	Disposal rate after re-manufacturing
	Unit selling price parameters
RSP_m	of product at spare market m
	Fixed opening cost parameters
CFC_c	for collection center c
CFR_r	for re-manufacturing center r
CFD_d	for disposal d
	Positives variables *(Flow from . to . for s)*
$XKC_{k,c,s}$	customer k to collection center c
$XCR_{c,r,s}$	collection center c to re-manufacturing center r
$XCD_{c,d,s}$	collection center c to disposal d
$XRD_{r,d,s}$	re-manufacturing center r to disposal d
$XRM_{r,m,s}$	re-manufacturing center r to spare market m
	Binary variables
YC_c	collection center c is opened or not
YR_r	re-manufacturing center r is opened or not
YD_d	Disposal d is opened or not

To make the model more readable, some expressions are defined below.

The total income: it includes all sales revenues. It is scenario dependent and can be formulated as:

$$Income_s \quad = \sum_{m=1}^{M}(\sum_{r=1}^{R}(RSP_m * XRM_{r,m,s}))) \tag{4.6}$$

The total operational cost: it includes all production costs, assembling costs, buying costs, dismantling costs or distribution costs from/to all centers of the chain. It is scenario dependent and can be defined as follows:

$$\begin{aligned} OpCost_s \quad &= \sum_{k=1}^{K}(\sum_{c=1}^{C}(Coph_c * XKC_{k,c,s})) \\ &+ \sum_{c=1}^{C}(\sum_{r=1}^{R}(Cdis_r * XCR_{c,r,s})) \\ &+ \sum_{f=1}^{F}(\sum_{c=1}^{C}(Ceco * (XRD_{r,d,s} + XCD_{c,d,s})))) \end{aligned} \tag{4.7}$$

The total fixed cost: it is the sum of the set-up costs of facilities:

$$\begin{aligned} FixedCost &= \textstyle\sum_{c=1}^{C}(CFC_c * YC_c) \\ &+ \textstyle\sum_{p=1}^{P}(CFR_r * YR_r) \\ &+ \textstyle\sum_{d=1}^{D}(CFD_d * YD_d) \end{aligned} \tag{4.8}$$

The total transportation costs: it is the sum of travel costs between connected points of the Supply Chain. It is scenario dependent and can be written as:

$$\begin{aligned} TrtCost_s &= \textstyle\sum_{k=1}^{K}(\sum_{c=1}^{C}(TC * DKC_{k,c} * XKC_{k,c,s})) \\ &+ \textstyle\sum_{r=1}^{R}(\sum_{c=1}^{C}(TC * DCR_{c,r} * XCR_{c,r,s})) \\ &+ \textstyle\sum_{d=1}^{D}(\sum_{c=1}^{C}(TC * DCD_{c,d} * XCD_{c,d,s})) \\ &+ \textstyle\sum_{r=1}^{R}(\sum_{d=1}^{D}(TC * DRD_{r,d} * XRD_{r,d,s})) \\ &+ \textstyle\sum_{r=1}^{R}(\sum_{d=1}^{D}(TC * DRSM_{r,m} * XRM_{r,m,s})) \end{aligned} \tag{4.9}$$

The objective is to maximize the total profit calculated as:

$$TotalProfit_s = Income_s - OpCost_s - FixedCost - TrtCost_s \tag{4.10}$$

The constraints are given by:

$$\begin{array}{lll}
(1) & \sum_{k=1}^{K} XKC_{k,c,s} \leq CapC_c * YC_c & \forall c \in C, s \in S \\
(2) & \sum_{c=1}^{C} XCR_{c,r,s} * Tremanu_s \leq CapR_r * YR_r & \forall r \in R, s \in S \\
(3) & \sum_{c=1}^{C} XCD_{c,d,s} + \sum_{r=1}^{R} XRD_{r,d,s} \leq B * YF_f & \forall d \in D, s \in S \\
(4) & \sum_{r=1}^{R} XRM_{r,m,s} \leq D_{m,s} & \forall m \in M, s \in S \\
(5) & \sum_{c=1}^{C} XKC_{k,c,s} \leq R_{k,s} & \forall k \in K, s \in S \\
(6) & \sum_{k=1}^{K} XKC_{k,c,s} * Rr = \sum_{r=1}^{R} XCR_{c,r,s} & \forall c \in C, s \in S \\
(7) & \sum_{c=1}^{C} XCR_{c,r,s} * Rd = \sum_{d=1}^{D} XRD_{r,d,t,s} & \forall r \in R, s \in S \\
(8) & \sum_{k=1}^{K} XKC_{k,c,s} = \sum_{r=1}^{R} XCR_{c,r,s} + \sum_{d=1}^{D} XCD_{c,d,s} & \forall c \in C, s \in S \\
(9) & \sum_{c=1}^{C} XCR_{c,r,s} = \sum_{d=1}^{D} XRD_{r,d,s} + \sum_{m=1}^{M} XRM_{r,m,s} & \forall r \in R, s \in S
\end{array}$$

Constraints (1) to (3) are capacity constraints characterizing the number of product each center is able to process a each period. Constraint (4) certifies that the production do not exceed the demand. Unsatisfied demand is considered lost. Constraint (5) confirms that the quantity of collected EOL products cannot be superior to the quantity of returned products from the consumer. Constraints (6) and (7) calculate the quantity of dismantled, repaired and recycled products according to the predefined rates *Rr* and *Rd.* Constraints (8) and (9) check the balance of the flows between centers.

4.2.3 Numerical Investigation

For our numerical experiments, this model has been initiated with the following data. We consider 10 possible locations for each type of center (collection, re-manufacturing and disposal), 10 first market consumers and 10 spare market consumers. The distances between centers are comprised between 1 and 500 kilometers. The related parameters are defined in Table 4.3. Other parameters used: $Ceco$=1, TC=1, Rd=80%, Rr=80%.

Parameter	Value
$CapC$	[55000, 107000, 190000, 58000, 100000, 200000, 90000, 150000, 170000, 121200]
$CapR$	[56100, 50500, 47060, 28000, 29100, 53500, 31000, 56100, 38000, 42100]
$Coph$	[3, 2, 5, 2, 1, 4, 5, 6, 1, 3]
$Cdis$	[2, 2, 6, 8, 7, 4, 5, 3, 1, 2]
RSP	[100, 150, 200, 320, 140, 210, 220, 110, 100, 150]
CFC	[10000, 20000, 60000, 90000, 70000, 80000, 15000, 12000, 17000, 18000]
CFR	[40000, 60000, 50000, 45000, 55000, 47000, 57000, 42000, 52000, 40000]
CFD	[42000, 52000, 40000, 50500, 40000, 60000, 50000, 40000, 55000, 40000]

Table 4.3: Deterministic Parameters

Three parameters are considered uncertain, namely the quantity of returned EOL products by the customers, the quantity of demand for re-manufactured products and the reprocessing time of EOL products. Their values are not known at the moment of the decision making and are estimated by experts. Each parameter has its "high" and "low" estimation. For example, the quantity of returned EOL products R by each of 10 customers is within the interval of [12000,17500] if the level of return is low and this returned quantity is considered within the interval [22000, 27500] if the return is high. The same is for the demand for re-manufactured products D for second market actors: it is within the interval [12000,17500] if the demand is low or within the interval [55000, 65500] if the demand is high, finally the remanufacturing time depends on the quality of the returned products, it is long if the quality is low, i.e. $Tremanu$ is within the interval [7,8] and short if the quality is high, i.e. within the interval [1,2]. According to those levels, four scenarios are defined and presented in Table 4.4.

Parameter	s_1	s_2	s_3	s_4
D	high	low	high	high
R	low	low	high	high
$Tremanu$	short	long	long	short

Table 4.4: Scenarios

Then, one value for each parameter is randomly selected from the intervals presented above. In this way, 20 different problem instances have been generated. Their resolution was conducted with IBM-ILOG CPLEX 12.6.3 on an Intel Core 2.60 gigahertz machine with 15 gigabyte RAM.

4.2.4 Analysis of results and discussion

The analysis of the results of the resolution of 20 problem instances is presented in four parts. First, we compare the results obtained with R_* and robust optimization. The former one has never been used before for design of RSC, and the latter one is the approach the most frequently used in the literature for design of RSC when historical data is not available to build future scenarios. Second, we compare the results obtained with R_* and $LexiR_*$ criteria in order to show how $LexiR_*$ criterion improves the results. Third, the results obtained with *Leximin*, $LexiR_*$ and *Leximax* criteria are compared. Finally, the performances of exact and approximate algorithms for $LexiR_*$ are discussed.

4.2.4.1 Comparison between R_* and robust approach

Table 4.5 reports the average values obtained from 20 solved problem instances.The first column indicates the approach used for resolution. The second column provides the value of e for R_* criterion as a maximal percentage of losses in comparison to the value provided by the robust method in the worst case. This method allows us to analyze which percentage of the profit the decision maker must accept to loose in order to access some opportunities. For example, $e = -1\%$ means that the decision maker expects a profit equal at least to 2765524*0.99, i.e. she/he accepts to loose 1% of the value in the worst case to gain 44% of the robust value in the best case. The results of the profit for each scenario are presented in Columns 3 to 6. They are in relative percentage of the robust solution and are colored in green when R_* criterion brings an improvement compared to the robust model and in red when it brings a deterioration.

Model	e	s_1(€)	s_2(€)	s_3(€)	s_4(€)
Robust	-	2920516	2765524	2987654	3206202
R_*	0%	2920516	2765524	2987654	3206202
R_*	-1%	+4.31%	-0.98%	+19.16%	+44.17%
R_*	-2%	+0.15%	-1.82%	-3.43%	+70.17%
R_*	-3%	+11.67%	-2.92%	+16.95%	+85.97%
R_*	-4%	+6.87%	-3.70%	+3.84%	+110.35%
R_*	-5%	+5.51%	-4.78%	+21.74%	+135.72%
R_*	-20%	+5.73%	-14.94%	+38.25%	+160.94%

Table 4.5: Comparison of the profits obtained with R_* and robust approaches

Table 4.5 shows that R_* criterion returns the robust solution if the value e is equal to the "MinMax" solution or above. It illustrates that R_* is a generalization of the robust criterion since it behaves in the same way when e is equal to the value of the robust solution. However, if some losses in the worst case can be accepted by the decision maker, better opportunities can be found for other scenarios. At the same time, as the level of losses can be chosen by the decision maker, this approach is able to protect the DM from taking high risks. The more the value of e decreases, i.e. the more the DM is willing to take risks, the more the profit in the worst case scenario declines, but the profit in the best case scenario shows a considerable improvement and the payoff is much more important than the losses. The two middle case scenarios can either be improved or degraded depending on the case. This is observed since the final solution is chosen on the best case value if the opportunities are available. With $LexiR_*$ approach the decision maker can choose a solution taking into account its performance for all scenarios. This is shown in the next section.

These results show that with the choice of value for e, the DM can control the robustness of the solution while exploring the zone of opportunities. In the case of the design of RSC, the readiness for opportunities follows to opening more collection and recycling centers, i.e. more returned products can be treated if the return level is high and remanufacturing is profitable. If the decision is made with the use of a robust approach, the RSC can be under-sized inducing a loss of opportunities.

4.2.4.2 Comparison between R_* and $LexiR_*$ approach

Table 4.6 presents the average results obtained for the same 20 problem instances as in the previous section and is built in the same way as Table 4.5. The presented results still provide relative percentage of difference from the robust solution.

Model	e	s_1(€)	s_2(€)	s_3(€)	s_4(€)
Robust	-	2920516	2765524	2987654	3206202
R_*	0%	2920516	2765524	2987654	3206202
$LexiR_*$	0%	+69.50%	0%	+149.16%	+133.84%
R_*	-5%	+5.51%	-4.78%	+21.74%	+135.72%
$LexiR_*$	-5%	+61.57%	-4.78%	+150.66%	+135.72%
R_*	-20%	+5.73%	-14.94%	+38.25%	+160.94%
$LexiR_*$	-20%	+51.87%	-14.94%	+177.18%	+160.94%

Table 4.6: Comparison of the profits obtained with R_* and $LexiR_*$ approaches

When $e = 0\%$, the profit found with $LexiR_*$ and R_* criteria in the worst case scenario is the same (i.e. the "MinMax" solution). However, it is improved substantially on all other cases with $LexiR_*$ criterion. Then, when e decreases, the values of the profit in the worst case scenario (s_2) and in the best case scenario (s_4) are the same with R_* and $LexiR_*$ criteria, but are greatly improved with $LexiR_*$ criterion on the two middle cases scenarios (s_1 and s_3).

These results show that, when using the $LexiR_*$ approach, the DM can find new opportunities even if he doesn't take more risks compared to the robust approach. Furthermore, if he is willing to take some risks, he still has the same control over these risks as when using the R_* criterion, and the opportunities are better explored, particularly on the middle cases scenarios.

4.2.4.3 Comparison between Leximin, $LexiR_*$ and Leximax criteria

Table 4.7 presents the average results obtained for the same 20 problem instances as in previous section with the use of *Leximin*, $LexiR_*$ and *Leximax*. The table is built in the same way as Table 4.5 and 4.6. The presented results provide relative percentage of difference from the *Leximin* solution. They are colored in green when $LexiR_*$ or *Leximax* criteria bring an improvement in comparison with the *Leximin* solution for each scenario and in red when they bring a deterioration.

Model	e	s_1(€)	s_2(€)	s_3(€)	s_4(€)
Leximin	-	5345165	2765524	6922933	6969008
$LexiR_*$	+20%	-1.86%	0%	+0.07%	0%
$LexiR_*$	+5%	-3.67%	0%	+0.96%	+1.04%
$LexiR_*$	0%	-7.39%	0%	+7.53%	+7.58%
$LexiR_*$	-5%	-11.28%	-4.78%	+8.17%	+8.45%
$LexiR_*$	-20%	-16.24%	-14.94%	+19.62%	+20.05%
Leximax	-	-18.58%	-66.07%	+19.62%	+20.05%

Table 4.7: Results obtained with *Leximin*, $LexiR_*$ and *Leximax*

The following observations can be made:

- The higher the value of e, the closer the results obtained with the corresponding $LexiR_*$ to the results obtained with *Leximin*.

- If e decreases, but is still equal to or above the robust "MinMax" solution, the $LexiR_*$ model improves the three best case scenarios compared to the robust solution and the two best case scenarios compared to *Leximin* criterion. In this case, applying the $LexiR_*$ helps the DM to find new opportunities without taking any risks compared to the robust method. It also allows to find new opportunities in comparison to *Leximin* criterion, but in this case, some risks must be taken on the third best case scenario.

- The more e decreases in comparison to the "MinMax" solution, the worse are the results for the worst case scenario, however, more opportunities are revealed in the two best case scenarios. The use of $LexiR_*$ provides more opportunities in every case than the use of R_* criterion.

- When the value of e is very low (close to 0), i.e. the DM is very opportunistic and ready to take really high risks to find the best opportunities, the results obtained with $LexiR_*$ criterion are very close to the results obtained with *Leximax* criterion.

- The use of $LexiR_*$ approach follows to better results for the two middle case scenarios compared to the use of R_*. Therefore, the risks taken by the DM are better controlled.

To give a better view of the amplitude of the solutions, we present in Fig 4.3 the values of the profit for each scenario depending on the value of e. Each color represents a scenario:

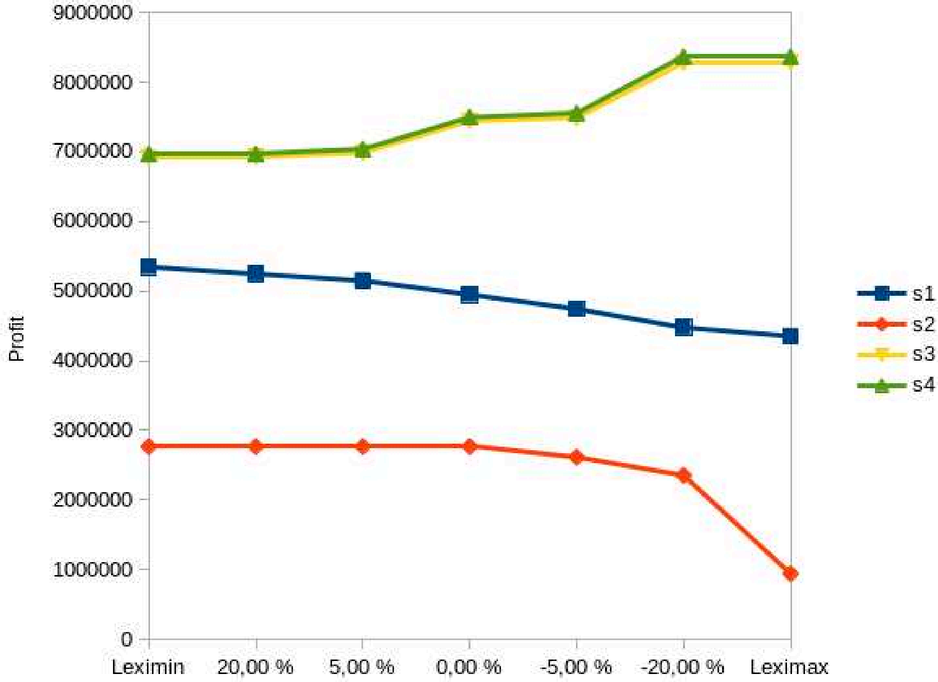


Figure 4.3: Amplitude of profits for 4 scenarios depending on e

the worst case scenario (s_2) is colored in red while the best case scenario (s_3) is colored in yellow.

We can see from this figure that *Leximin* criterion has the smallest amplitude between the scenarios contrary to *Leximax* criterion which has the highest one. $LexiR_*$ criterion's amplitude depends on the value of e: the higher the value of e the less important is the amplitude between the scenarios. It shows that the use of e offers to the decsion maker the possibility to control the level of the taken risks, to not worsten too much the results in the worst case scenario and at the same time improve the profits due to the opportunities found for the best case scenario.

4.2.5 Comparison of $LexiR_*$ algorithm and $LexiR_*$ MIP

In this section, the advantages and drawbacks of the two proposed methods are discussed. The criteria of comparison are: the solution time required and the quality of the obtained solution. Table 4.8 shows the solution times for both $LexiR_*$ algorithm and $LexiR_*$ MIP for different numbers of scenarios. The scenarios have been randomly generated for the purpose of the experiment. Each instance has been solved with both methods for 10 different values of e (also randomly generated).

When four scenarios are considered, the two methods are able to solve the problem quite

Number of scenarios	$LexiR_*$ Algorithm	$LexiR_*$ MIP
4	5.28	4.54
8	547.29	35.35
16	2222.19	300.40
32	17000.28	1454.73
64	85271.36	12839.46

Table 4.8: Comparison of solution times (in seconds) between $LexiR_*$ algorithm and $LexiR_*$ MIP

fast and in comparable amount of time (see Table 4.8). Then, if we increase the number of scenarios, the solution time extends. The solution time of the $LexiR_*$ MIP increases significantly slower than the one of the $LexiR_*$ algorithm. On the other hand, the $LexiR_*$ MIP being an approximate solution method, it does not always allow to find the exact optimum. Furthermore, the $LexiR_*$ algorithm is solved by iterations, and the number of iterations is the same than the number of scenarios considered. Each iteration takes approximately the same time to solve. For instance, when 32 scenario are solved, the total solution time of the algorithm is 17000.28 seconds. Therefore, it is approximately $17000.26 \div 32 \approx 531$ seconds for each iteration. The DM can choose to stop the resolution at any iteration. In this case, the found solution will be optimized for the first x considered scenarios and approximate the other ones.

To illustrate this point, we compared the results found for the optimal solution when 32 scenarios are considered with the results obtained when the Algorithm is stopped at the 4th, 8th, 16th and 24th iterations. We analyzed the deviation from the optimal solution depending on the number of iteration solved. We also compared with the results found with the $LexiR_*$ MIP.

The results are presented in Table 4.9, they show that the MIP gives a very good approximation of the optimal solution: only 2 scenarios deviates slightly from the optimum. When the model is solved with the algorithm stopped at the 24th, 16th, 8th, or 4th iterations, the following observations can be made:

- The more the number of iterations solved is high, the more the found solution is close to the optimal
- As previously explained in Section 4.1.1, the $LexiR_*$ algorithm first optimizes the worst cases scenarios with a *Leximin* before moving on to the best cases scenarios with a *Leximax*. Thus, as long as the value of e is higher than the profit of the scenario considered, the DM is risk adverse and opportunities are not revealed. As so, if the number of iterations solved is lower than the number of scenarios in the risky area, opportunities cannot be found. We can see this effect in our case, when the algorithm is stopped at 4 or 8 iterations: only the worst cases scenarios are optimized and the better cases scenarios can deviate up to 27% from the optimum.
- If the number of iterations solved is high enough for scenarios in the opportunity area

to be considered, then opportunities are revealed on the best cases.

Model	$LexiR_*$ Algorithm					$LexiR_*$ MIP
Number of iterations	32	24	16	8	4	-
Scenario	Profit(€)	Deviation	Deviation	Deviation	Deviation	Deviation
s_1	2427710	0,00%	0,00%	0,00%	0,00%	0,00%
s_2	2610029	0,00%	0,00%	0,00%	0,00%	0,00%
s_3	2651913	0,00%	0,00%	0,00%	0,00%	0,00%
s_4	2683295	0,00%	0,00%	0,00%	0,00%	0,00%
s_5	2700265	0,00%	0,00%	0,00%	−0,01%	0,00%
s_6	2782584	0,00%	0,00%	0,00%	−2,96%	0,00%
s_7	2787666	0,00%	0,00%	0,00%	−3,14%	0,00%
s_8	2845463	0,00%	0,00%	0,00%	−5,11%	0,00%
s_9	2948545	0,00%	0,00%	0,00%	−8,42%	0,00%
s_{10}	2950168	0,00%	0,00%	−0,05%	−8,47%	−0,05%
s_{11}	2950906	0,00%	0,00%	−0,08%	−8,50%	0,00%
s_{12}	3013577	0,00%	0,00%	−2,16%	−10,40%	0,00%
s_{13}	3077298	0,00%	0,00%	−4,18%	−9,58%	−0,63%
s_{14}	3120285	0,00%	0,00%	−5,50%	−10,66%	0,00%
s_{15}	3175696	0,00%	0,00%	−7,15%	−10,40%	0,00%
s_{16}	3265788	0,00%	0,00%	−9,71%	−10,12%	0,00%
s_{17}	3297803	0,00%	0,00%	−10,59%	−10,69%	0,00%
s_{18}	3395708	0,00%	0,00%	−13,16%	−13,10%	0,00%
s_{19}	3398593	0,00%	0,00%	−13,17%	−11,33%	0,00%
s_{20}	3519252	0,00%	0,00%	−14,51%	−14,06%	0,00%
s_{21}	3533295	0,00%	0,00%	−13,12%	−12,66%	0,00%
s_{22}	3582553	0,00%	0,00%	−12,90%	−13,50%	0,00%
s_{23}	3764976	0,00%	0,00%	−16,46%	−17,12%	0,00%
s_{24}	4080441	0,00%	−4,70%	−22,17%	−23,44%	0,00%
s_{25}	4335246	0,00%	−5,88%	−23,93%	−27,77%	0,00%
s_{26}	4427709	−0,12%	−1,87%	−25,49%	−26,32%	0,00%
s_{27}	4427710	−0,10%	−0,21%	−24,65%	−25,52%	0,00%
s_{28}	4427710	−0,09%	−0,21%	−24,50%	−25,12%	0,00%
s_{29}	4427714	−0,08%	−0,01%	−23,49%	−20,66%	0,00%
s_{30}	4472278	0,00%	0,00%	−22,59%	−21,16%	0,00%
s_{31}	4487614	0,00%	0,00%	−20,93%	−14,11%	0,00%
s_{32}	4518240	0,00%	0,00%	−14,32%	−12,66%	0,00%

Table 4.9: Comparison of results $LexiR_*$ Algorithm versus MIP for 32 scenarios

Therefore, we can conclude that: if the DM is willing to solve the problem with an exact method and if the budget of the computational time is not an issue, he/she should use the $LexiR_*$ algorithm to solve it. If the DM would prefer a more rapid solution, even if this one is not optimal, he/she can either use the $LexiR_*$ MIP or the $LexiR_*$ Algorithm and interrupt it at a satisfying number of iterations.

4.3 Conclusion

In order to help the decision makers to design a successful RSC under uncertainty, we suggest a new bipolar criterion, namely $LexiR_*$, able to differentiate risks from opportunities depending on the optimism of the decision maker. We compare this criterion with classic criteria from the literature to show its advantages and how it helps the decision maker to seize new opportunities when creating a RSC. In particular, we show that the $LexiR_*$ criterion better explores opportunities compared to a classic robust solution approach, while still allowing the decision makers to control the level of risk to be taken.

We develop two solution methods to apply this criterion. The first one is in the form of an algorithm and another is in the form of a MIP. We analyse the solution time for both $LexiR_*$ algotitthm and $LexiR_*$ MIP and show that the $LexiR_*$ algotitthm takes a significantly longer time, but allows to find an exact solution, contrary to $LexiR_*$ MIP that offers only an approximate solution but obtained in shorter time.

From the methodological point of view, the further research will be oriented to the generalization of $LexiR_*$ criterion to a continuous set of scenarios. From Supply Chain perspective, a generalized study aiming to connect forward and reverse supply chains will be performed in the context of design of a Closed-Loop Supply Chain. In addition to the economic performance of such supply chains, their environmental and social performances should be evaluated as well, in order to reach a sustainable solution for the created CLSC. Furthermore, we would like to address the concept of equity between several locations where the CLSC is implemented, and particularly the social equity and environmental equity in order to fairly split the employment and pollution emissions between the regions concerned. The last Chapter focuses on these two last points, but at first, we consider this problem in the deterministic context in order to increase progressively the complexity of the analysis.

Chapter 5

Sustainable Closed-Loop Supply Chain Design with Equity Considerations

Contents

In this chapter, we study the design of a sustainable CLSC where the economic, environmental and social dimensions are taken into account. We propose a multi-objective model including one objective for each dimension.

The studied CLSC design problem is based on the framework presented in Section 3.2. Some adaptations have been made to simplify its formulation as well as study some new features:

- First, the uncertainty on the parameters is not considered anymore in the decision making process. Indeed, for simplification purpose, and because of the inclusion of two new dimensions (environmental and social) and induced complexity, we decided to consider the deterministic setting first.

- The second adaptation regards the capacity of the implemented facilities. In the previous model (Section 3.2), each facility had a predefined capacity. In the new model, the capacities of the implemented centers can be of three types: small, medium or large. Therefore, each time the DM makes the decision of implementing a new facility, she/he can choose the type of capacity the most suited to the situation. Naturally, the cost for implementing a facility will vary depending on its size.

- The last adaptation concerns the locations of the implemented centers. In the first model (See Section 3.2), each facility had a predefined location on which it could be implemented or not. In the new model presented here, there is a choice of different potential regions for implementing new recovery facilities with each region having an initial level of pollution and unemployment. Facility location decisions impact on the final level of pollution and unemployment in each region. This adaptation will help to analyze the relation between the distribution of the centers on the different locations and the scores of the environmental and social impacts.

To provide sustainability in the considered locations, we seek to deliver overall environmental and social equity in all locations, so that no area is left out. Equity is defined in the Cambridge Dictionary as "the situation in which everyone is treated fairly and equally". In our case, we are particularly interested in considering environmental equity and social equity: we minimize the environmental impact in the more polluted areas and maximize the social impact in the areas with the highest unemployment rate. Few studies in the literature have addressed the equity in decision making in the design of sustainable CLSC. For instance, [Mot+18] presented a generic model of sustainable CLSC with a TBL approach in the form a multi-objective MIP. They introduced the concept of "Social Benefit" as their social objective. The "Social Benefit" allows maximization of the implementation of facilities in the regions with lower Gross Domestic Product (GDP) with the aim to provide more equitable distribution of facilities over all regions. In the same vein, [CSC18] studied a comprehensive multi-objective model of a biofuel supply chain optimization from coffee crop residues with economic, environmental and social objectives. They consider the balance of job employment in several regions as their social objective. In spite of those studies, equity in sustainable CLSC remains superficial. Furthermore, we found no paper with equity consideration in regards to distribution of environmental pollution.

In order to choose the model for equity in both environmental and social objectives, we used the results of the study of [MS94] which reported on the 20 equity measures most commonly used to analyze equity in facility location problems. We chose to use the Gini coefficient (noted G).

The Gini coefficient satisfies the principle of Pareto-optimality which implies that if the coefficient improves, then none of the groups being affected will be worsen. In our model, we propose to use the Gini coefficient as an objective, rather than as a simple analytic tool (see Section 2.3.2.3). In order to maximize the equity, we seek to minimize the Gini coefficient for both environmental and social impacts.

We afterwards solve the model using a goal programming method to analyze the impact of equity on the profitability of the CLSC and find the best compromise between the three objectives.

Therefore the following research questions are answered in this chapter:

(2) **How do the economic, environmental and social objectives influence each other?**

(3) **How does the attitude of the DM impact the selection of a compromising solution between the three objectives?**

(4) **How the consideration of equity between several locations influences the final solution?**

5.1 Mathematical model

The mathematical modelling of the problem stated above is given in this section:

5.1.1 Index, Parameters and Variables

The list of all index, parameters and variables is given below:

	Indexes
$i = 1..I$	Index of suppliers
$j = 1..J$	Index of plants
$l = 1..L$	Index of customers
$c = 1..C$	Index of HDC
$p = 1..P$	Index of dismantlers
$q = 1..Q$	Index of repair centers
$m = 1..M$	Index of spare market customers
$f = 1..F$	Index of disposal sites
$d = 1..D$	Index of recycling centers
$t = 1..T$	Index of time periods
$loc = 1...LOC$	Index of regions
$cap = 1...CAP$	Index of capacities
	Demand *of ... at period t*
$D_{l,t}$	consumers l
$Dsm_{m,t}$	spare market m
$Ds_{i,t}$	suppliers i
	Capacities
Cap_{cap}	of new center
$CapPlant_j$	of plant j
$VCAP_t$	brough by the creation of one variable job at period t
	Distance *between ... and ...*
$DisSP_{i,j}$	supplier i and plant j
$DisPH_{j,c}$	plant j and HDC c
$DisCH_{l,c}$	costumer l and HDC c
$DisCoDi_{c,p}$	HDC c and dismantler p

$DisCoF_{c,f}$	HDC c and disposal f
$DisDiDe_{p,d}$	dismantler p and recycler d
$DisDeDis_{d,f}$	recycler d and disposal f
$DisDeS_{d,i}$	recycler d and supplier i
$DisDiR_{p,q}$	dismantler p and repair q
$DisRSM_{q,m}$	repair q and spare market m
$DisRPP_{q,j}$	repair q and plant j
	Time parameters
$Tdismantler$	Unit dismantling time
$Trecycle$	Unit recycling time
$Trepair$	Unit repair time
	Unit cost of ...
Ca_i	Buying at supplier i
Cp_j	Production at plant j
$Cass_j$	Assembling at plant j
$Coph_c$	Operation at HDC c
$Cdis_p$	Dismantling at dismantler p
$Crep_q$	Repair at repair center q
$Cdecr_d$	Recycling at recycler d
$Ceco_c$	disposed EOL
TC	Transportation for 1 kilometer
	Rate *of ...*
R_t	Returned EOL at period t
Re	Repairing after dismantling
Rr	Recycling after decomposition
P_{loc}	Pollution at location loc
U_{loc}	Unemployment at location loc
	Unit selling price *of ...*
SP_l	product at market zone l
RSP_m	product at spare market m
Rev_i	recycled product to supplier i
	Opening cost at location loc**, capacity** cap
$Cohyb_{c,loc,cap}$	for HDC c
$CoDism_{p,loc,cap}$	for dismantling center p
$CoRecy_{d,loc,cap}$	for recycling center d
$CoDisp_{f,loc,cap}$	for disposal f
$CoRep_{q,loc,cap}$	for repair center q
	EI of ... at location loc**, capacity** cap
$EIHDC_{c,loc,cap}$	establishing HDC c
$EIDis_{p,loc,cap}$	establishing dismantler p
$EIRep_{q,loc,cap}$	establishing repair centre q
$EIRec_{d,loc,cap}$	establishing recycler d
$EIDisp_{f,loc,cap}$	establishing disposal f
TE	EI of transporting 1 product for 1 km
	EI of processing at location loc**, capacity** cap
$PICHD_{c,l}$	in HDC c in the forward way
$PIPH_{j,c}$	in plant j to be distributed in HDC c
$PICODI_{c,p}$	at HDC c to be dismantled a p
$PIRSM_{q,m}$	at repair center q to be resold a m
$PIRPP_{q,j}$	at repair center q to be utilized at j
$PIPS_{d,i}$	at recycling center d to be resold at i
$PIDIR_{p,q}$	at dismantling center p to be repaired at q
$PIDIRE_{p,d}$	at dismantling center p to be recycled at d
DI	EI of disposing of 1 unit of product

	Fixed cost at location loc, capacity cap
$CFhyb_{c,t,loc,cap}$	for HDC c in period t
$CFDism_{p,t,loc,cap}$	for dismantling center p in period t
$CFRecy_{d,t,loc,cap}$	for recycling center d in period t
$CFDisp_{f,t,loc,cap}$	for disposal f in period t
$CFRep_{q,t,loc,cap}$	for repair center q in period t
C_t	Budget for opening centers in period t
	Salaries at period t and location loc
$FJS_{t,loc}$	for one fixed job
$VJS_{t,loc}$	for one variable job
	Number of fixed jobs at... at location loc
$FJCH_{c,t,loc,cap}$	HCD center c of capacity cap
$FJP_{p,t,loc,cap}$	dismantler p of capacity cap
$FJD_{d,t,loc,cap}$	recycler d of capacity cap
$FJF_{f,t,loc,cap}$	disposal f of capacity cap
$FJQ_{q,t,loc,cap}$	repair center q of capacity cap
	Number of variable jobs at . at period t
$VJCH_{c,t,loc}$	HDC c at location loc
$VJP_{p,t,loc}$	Dismantler p at location loc
$VJD_{d,t,loc}$	Recycling center d at location loc
$VJQ_{q,t,loc}$	Repair center q at location loc
	Positives variables *(Flow from . to . at period t)*
$XSP_{i,j,t}$	from supplier i to plant j
$XPH_{j,c,t}$	from plant j to HDC c
$XCHD_{c,l,t}$	from HDC c to customer l
$XCHC_{l,c,t}$	from customer l to HDC c
$XCODI_{c,p,t}$	from HDC c to dismantler p
$XCOF_{c,f,t}$	from HDC c to disposal f
$XDIR_{p,q,t}$	from dismantler p to repair center q
$XRSM_{q,m,t}$	from repair center q to spare market costumer m
$XDIRE_{p,d,t}$	from dismantler p to recycling center d
$XREDIS_{d,f,t}$	from recycling center d to disposal f
$XPS_{d,i,t}$	from recycling center d to supplier i
$XRPP_{q,j,t}$	from repair center q to plant j
$h_{c,l,t}$	Variable helping to linearize the objective function
	Binary variables
$YCH_{c,t,loc,cap}$	HDC c is opened or not at period t at location loc and capacity cap
$YP_{p,t,loc,cap}$	Dismantler p is opened or not at period t at location loc and capacity cap
$YD_{d,t,loc,cap}$	Recycling center d is opened or not at period t at location loc and capacity cap
$YF_{f,t,loc}$	Disposal f is opened or not at period t at location loc
$YQ_{q,t,loc,cap}$	Repair center q is opened or not at period t at location loc and capacity cap
$ZYCH_{c,loc,cap}$	1 if HDC c has been opened at location loc, 0 otherwise
$ZYP_{p,loc,cap}$	1 if Dismantler p has been opened at location loc and capacity cap, 0 otherwise
$ZYD_{d,loc,cap}$	1 if Recycling center d has been opened at location loc and capacity cap, 0 otherwise
$ZYF_{f,loc,cap}$	1 if Disposal f has been opened at location loc and capacity cap, 0 otherwise
$ZYQ_{q,loc,cap}$	1 if Repair center q has been opened at location loc and capacity cap, 0 otherwise

5.1.2 Objectives

In this section we detail the mathematical formulation of the three objectives related to the three dimensions of sustainability.

5.1.2.1 Economic Objective

In the same way as in in Section 3.2, the profit is given by the incomes of the CLSC minus its costs.

The revenues are simply calculated by all the benefits from the sales of products (equation 5.1):

$$\begin{aligned} Income &= \sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{c=1}^{C} (SP_l * XCHD_{c,l,t}) \\ &+ \sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{q=1}^{Q} (RSP_m * XRSM_{q,m,t}) \\ &+ \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{d=1}^{D} (Rev_i * XPS_{d,i,t}) \end{aligned} \tag{5.1}$$

The costs comes from several sources:

- The costs from the implementation and maintenance of new facilities namely $FixedCosts$ (equation 5.2).

$$\begin{aligned} FixedCost &= \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{c=1}^{C} (Cohyb_c * ZYCH_{c,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{p=1}^{P} (CoDism_{p,loc,cap} * ZYP_{p,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{d=1}^{D} (CoRecy_{d,loc,cap} * ZYD_{d,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{f=1}^{F} (CoDisp_{f,loc,cap} * ZYF_{f,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{q=1}^{Q} (CoRep_{q,loc,cap} * ZYQ_{q,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{t=1}^{T} \sum_{c=1}^{C} (CFhyb_{c,t,loc,cap} * YCH_{c,t,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{t=1}^{T} \sum_{p=1}^{P} (CFDism_{p,t,loc,cap} * YP_{p,t,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{t=1}^{T} \sum_{d=1}^{D} (CFRecy_{d,t,loc,cap} * YD_{d,t,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{t=1}^{T} \sum_{f=1}^{F} (CFDisp_{f,t,loc,cap} * YF_{f,t,loc,cap}) \\ &+ \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{t=1}^{T} \sum_{q=1}^{Q} (CFRep_{q,t,loc,cap} * YQ_{q,t,loc,cap}) \end{aligned} \tag{5.2}$$

- The operational costs from the production in each facility, the eco-tax from products put in disposal and the salaries of the employees namely $OpCost$ (equation 5.3).

$$\begin{aligned} OpCost \quad &= \textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I}(Ca_i * XSP_{i,j,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{j=1}^{J}(Cp_j * XPH_{j,c,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{j=1}^{J}(Cass_j * XPH_{j,c,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{c=1}^{C}(Coph_c * (XCHD_{c,l,t} + XCHC_{l,c,t})) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{c=1}^{C}(Cdis_p * XCODI_{c,p,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{q=1}^{Q}(Crep_q * XRSM_{q,m,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{q=1}^{Q}(Crep_q * XRRP_{q,j,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{d=1}^{D}(Cdecr_d * XPS_{d,i,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{c=1}^{C}(Ceco_c * XCOF_{c,f,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{cap=1}^{CAP}\sum_{c=1}^{C}(FJS_{t,loc} * FJCH_{c,t,loc,cap}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{cap=1}^{CAP}\sum_{p=1}^{P}(FJS_{t,loc} * FJP_{p,t,loc,cap}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{cap=1}^{CAP}\sum_{d=1}^{D}(FJS_{t,loc} * FJD_{d,t,loc,cap}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{cap=1}^{CAP}\sum_{f=1}^{F}(FJS_{t,loc} * FJF_{f,t,loc,cap}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{cap=1}^{CAP}\sum_{q=1}^{Q}(FJS_{t,loc} * FJQ_{q,t,loc,cap}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{c=1}^{C}(VJS_{t,loc} * VJCH_{c,t,loc}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{p=1}^{P}(VJS_{t,loc} * VJP_{p,t,loc}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{d=1}^{D}(VJS_{t,loc} * VJD_{d,t,loc}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{loc=1}^{LOC}\sum_{q=1}^{Q}(VJS_{t,loc} * VJQ_{q,t,loc}) \end{aligned} \tag{5.3}$$

- The costs from transportation namely $TrtCosts$ (equation 5.4).

$$\begin{aligned} TrtCost \quad = TC* \quad &[\textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I}(DisSP_{i,j} * XSP_{i,j,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{j=1}^{J}(DisPH_{j,c} * XPH_{j,c,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{c=1}^{C}(DisCH_{l,c} * h_{l,c,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{c=1}^{C}(DisCoDi_{c,p} * XCODI_{c,p,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P}(DisDiR_{p,q} * XDIR_{p,q,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{q=1}^{Q}(DisRSM_{q,m} * XRSM_{q,m,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{p=1}^{P}(DisDiDe_{p,d} * XDIRE_{p,d,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{D=1}^{D}(DisDeDis_{d,f} * XREDIS_{d,f,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{d=1}^{D}(DisDeS_{d,i} * XPS_{d,i,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{q=1}^{Q}(DisRPP_{q,j} * XRPP_{q,j,t}) \\ &+ \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{c=1}^{C}(DisCoF_{c,f} * XCOF_{c,f,t})] \end{aligned} \tag{5.4}$$

In the rest of the paper, we will refer to the sum of all costs as $TotalCosts$ defined as $TotalProfit = Income - TotalCosts$.

The economic objective noted hereafter as $Z1$ is defined as follows:

$$Z1 = Maximize(TotalProfit) \tag{5.5}$$

5.1.2.2 Environmental Objective

The environmental objective is to establish new facilities with equitable environmental impact over all regions. The environmental impact, denoted hereafter as EI, is calculated taking into account the facilities location, processing of products in each facility, transportation, and impact of creating waste (see Section 1.3.1):

$$EI_{loc} = FacilitiesLocation_{loc} + OpImpact + TrtEmission + DisposalImpact \tag{5.6}$$

With:

- *FacilitiesLocation*: it is the impact of facility establishment, i.e. the impact generated by the construction of a new facility calculated with the emissions and energy consumption of materials used during the construction. It depends on the regions where facilities are built, as we consider that establishing a facility in different regions can lead to different impacts (equation 5.7).

$$\begin{aligned} FacilitiesLocation_{loc} &= \textstyle\sum_{cap=1}^{CAP} \sum_{c=1}^{C} (ZYCH_{c,loc,cap} * EIHDC_{c,loc,cap}) \\ &+ \textstyle\sum_{cap=1}^{CAP} \sum_{p=1}^{P} (ZYP_{p,loc,cap} * EIDis_{p,loc,cap}) \\ &+ \textstyle\sum_{cap=1}^{CAP} \sum_{d=1}^{D} (ZYD_{d,loc,cap} * EIRep_{d,loc,cap}) \\ &+ \textstyle\sum_{cap=1}^{CAP} \sum_{f=1}^{F} (ZYF_{f,loc,cap} * EIRec_{f,loc,cap}) \\ &+ \textstyle\sum_{cap=1}^{CAP} \sum_{q=1}^{Q} (ZYQ_{q,loc,cap} * EIDisp_{q,loc,cap}) \end{aligned} \tag{5.7}$$

- *OpImpact*: It is the impact generated by the production of one product in each facility and includes various factors such as the energy consumption, the emitted carbon dioxide, the water and soil pollution...etc (equation 5.8).

$$\begin{aligned} OpImpact &= \textstyle\sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{i=1}^{I} (PIP_{i,j} * XSP_{i,j,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{c=1}^{C} \sum_{j=1}^{J} (PIPH_{j,c} * XPH_{j,c,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{l=1}^{L} \sum_{c=1}^{C} (PICHD_{c,l} * XCHD_{c,l,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{c=1}^{C} (PICODI_{c,p} * XCODI_{c,p,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{m=1}^{M} \sum_{q=1}^{Q} (PIRSM_{q,m} * XRSM_{q,m,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{q=1}^{Q} (PIRPP_{q,j} * XRRP_{q,j,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{d=1}^{D} (PIPS_{d,i} * XPS_{d,i,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{d=1}^{D} (PIDIR_{p,q} * XDIR_{p,q,t}) \\ &+ \textstyle\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{d=1}^{D} (PIDIRE_{p,d} * XDIRE_{p,d,t}) \end{aligned} \tag{5.8}$$

- *TrtEmission*: it is the impact of transportation between facilities. We remind that this impact integrates all emissions of carbon dioxide related to the transportation network and is inherent to the number and length of the trips, the type of transportation as well as the amount of products transported. It is considered in the literature as the most influential environmental impact(equation 5.9).

$$\begin{aligned} TrtEmission \quad = TE* \quad & [\textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I}(DisSP_{i,j} * XSP_{i,j,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{c=1}^{C}\sum_{j=1}^{J}(DisPH_{j,c} * XPH_{j,c,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{c=1}^{C}(DisCH_{l,c} * h_{l,c,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{c=1}^{C}(DisCoDi_{c,p} * XCODI_{c,p,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{q=1}^{Q}\sum_{p=1}^{P}(DisDiR_{p,q} * XDIR_{p,q,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{m=1}^{M}\sum_{q=1}^{Q}(DisRSM_{q,m} * XRSM_{q,m,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{p=1}^{P}(DisDiDe_{p,d} * XDIRE_{p,d,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{D=1}^{D}(DisDeDis_{d,f} * XREDIS_{d,f,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{d=1}^{D}(DisDeS_{d,i} * XPS_{d,i,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{q=1}^{Q}(DisRPP_{q,j} * XRPP_{q,j,t}) \\ & + \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{c=1}^{C}(DisCoF_{c,f} * XCOF_{c,f,t})] \end{aligned} \tag{5.9}$$

- *DisposalImpact*: it is the impact of disposing of waste, calculated for one unit of product in terms of emissions and soil pollution. (equation 5.10)

$$\begin{aligned} DisposalImpact \quad & = DI * \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{d=1}^{D}(XREDIS_{d,f,t}) \\ & + DI * \textstyle\sum_{t=1}^{T}\sum_{f=1}^{F}\sum_{c=1}^{C}(XCOF_{c,f,t}) \end{aligned} \tag{5.10}$$

To maximize the environmental equity among regions, we use the Gini index in the objective function. As all regions do not have the same initial rate of pollution, the pollution rate P in each location before the implementation of the CLSC is modelled. The mathematical expression of the environmental objective noted Z_2 considering Gini Index is as follows:

$$Z_2 = \min \frac{\sum_{loc}\sum_{loc2}|P * EI_{loc} - P * EI_{loc2}|}{2 * LOC^2 * \mu(P * EI_{loc})} \tag{5.11}$$

where μ represents the mean. To make Z_2 easier to solve computationally, we use the formulation of [BF+17] which proposed a linear program for the formulation of Gini Index as follows:

$$Z_2 = \min \sum_{loc=1}^{LOC} \omega'_{loc}(loc * r2_{loc} + \sum_{loc2=1}^{LOC} b2_{loc2,loc}) \tag{5.12}$$

Subject to

$$\begin{aligned} & r2_{loc} + b2_{loc2,loc} \geq P * EI_{loc2} && \forall loc, loc2 \in LOC \\ & b2_{loc2,loc} \geq 0 && \forall loc, loc2 \in LOC \end{aligned} \tag{5.13}$$

with

$$\omega'_{loc} = \omega_{loc} - \omega_{loc-1}$$
$$\omega_{loc} = (2(LOC - loc) + 1)/LOC^2 \ \forall \ loc \ \in LOC$$

5.1.2.3 Social Objective

In the same spirit as for the environmental objective, we seek to provide equitable distribution of social benefits between the regions with regard to the social impact of the CLSC. As previously mentioned, the literature acknowledges the difficulty to quantify the social impact of a CLSC. In this context, we choose to follow the literature and consider the job creation as a social impact. More particularly, and in the same way as [SFFHK18], we differentiate permanent ongoing jobs and casual jobs, respectively referred to hereafter as fixed and variable jobs. As stated by [SFFHK18], fixed jobs are represented by the establishment of a facility while variable jobs are represented by a short term fluctuation in quantity of products processed in the facility in each time period. An increasing quantity of products represents increased employment of casual workers and vice-versa. We consider that the social impact of the fixed jobs is more important important than (casual) variable jobs as fixed jobs provide more sustainable and secure long-term employment. Each region starts with a certain unemployment rate U. We denote the social impact with SI_{loc} and we define it as:

$$\begin{aligned}
SI_{loc} \ &= \textstyle\sum_{t=1}^{T} \sum_{cap=1}^{CAP} \sum_{c=1}^{C} (FJCH_{c,t,loc,cap} * YCH_{c,t,loc,cap}) \\
&+ \textstyle\sum_{t=1}^{T} \sum_{cap=1}^{CAP} \sum_{p=1}^{P} (FJP_{p,t,loc,cap} * YP_{p,t,loc,cap}) \\
&+ \textstyle\sum_{t=1}^{T} \sum_{cap=1}^{CAP} \sum_{d=1}^{D} (FJD_{d,t,loc,cap} * YD_{d,t,loc,cap}) \\
&+ \textstyle\sum_{t=1}^{T} \sum_{cap=1}^{CAP} \sum_{f=1}^{F} (FJF_{f,t,loc,cap} * YF_{f,t,loc,cap}) \\
&+ \textstyle\sum_{t=1}^{T} \sum_{cap=1}^{CAP} \sum_{q=1}^{Q} (FJQ_{q,t,loc,cap} * YQ_{q,t,loc,cap}) \\
&+ \textstyle\sum_{t=2}^{T} \sum_{cap=1}^{CAP} \sum_{c=1}^{C} \sum_{l=1}^{L} \sum_{p=1}^{P} (VJCH_{c,t,loc} * (\Delta XCHD_{c,l,t} + \Delta XCODI_{c,p,t})) \\
&+ \textstyle\sum_{t=2}^{T} \sum_{cap=1}^{CAP} \sum_{p=1}^{P} \sum_{q=1}^{Q} \sum_{d=1}^{D} (VJP_{p,t,loc} * (\Delta XDIR_{p,q,t} + \Delta XDIRE_{p,d,t})) \\
&+ \textstyle\sum_{t=2}^{T} \sum_{cap=1}^{CAP} \sum_{d=1}^{D} \sum_{f=1}^{F} \sum_{i=1}^{I} (VJD_{d,t,loc} * (\Delta XREDIS_{d,f,t} + \Delta XPS_{d,i,t})) \\
&+ \textstyle\sum_{t=2}^{T} \sum_{cap=1}^{CAP} \sum_{q=1}^{Q} \sum_{m=1}^{M} \sum_{j=1}^{J} (VJQ_{q,t,loc} * (\Delta XRSM_{q,m,t} + \Delta XRPP_{q,j,t}))
\end{aligned} \tag{5.14}$$

With:

$$\begin{aligned}
\Delta XCHD_{c,l,t} &= XCHD_{c,l,t} - XCHD_{c,l,t-1} \\
\Delta XCODI_{c,p,t} &= XCODI_{c,p,t} - XCODI_{c,p,t-1} \\
\Delta XDIR_{p,q,t} &= XDIR_{p,q,t} - XDIR_{p,q,t-1} \\
\Delta XDIRE_{p,d,t} &= XDIRE_{p,d,t} - XDIRE_{p,d,t-1} \\
\Delta XREDIS_{d,f,t} &= XREDIS_{d,f,t} - XREDIS_{d,f,t-1} \\
\Delta XPS_{d,i,t} &= XPS_{d,i,t} - XPS_{d,i,t-1} \\
\Delta XRSM_{q,m,t} &= XRSM_{q,m,t} - XRSM_{q,m,t-1} \\
\Delta XRPP_{q,j,t} &= XRPP_{q,j,t} - XRPP_{q,j,t-1}
\end{aligned} \tag{5.15}$$

The expression of the social objective with Gini Index is noted Z_3 and defined as follows:

$$Z_3 = \min \frac{\sum_{loc}\sum_{loc2}|U * SI_{loc} - U * SI_{loc2}|}{2 * LOC^2 * \mu(U * SI_{loc})} \tag{5.16}$$

where μ represents the mean. In the same way as for the second objective, we use the linear formulation of [BF+17]:

$$Z_3 = \min \sum_{loc=1}^{LOC} \omega'_{loc}(loc * r3_{loc} + \sum_{loc2=1}^{LOC} b3_{loc2,loc}) \tag{5.17}$$

Subject to

$$\begin{array}{ll} r3_{loc} + b3_{loc2,loc} \geq U * SI_{loc2} & \forall loc, loc2 \in [LOC] \\ b3_{loc2,loc} \geq 0 & \forall loc, loc2 \in [LOC] \end{array} \tag{5.18}$$

with

$$\omega'_{loc} = \omega_{loc} - \omega_{loc-1}$$

$$\omega_{loc} = (2(LOC - loc) + 1)/LOC^2 \ \forall \ loc \ \in LOC$$

5.1.3 Constraints

Constraints (1) to (6) verify that the different capacities of all centers are respected.

$$\begin{array}{lll}
(1) & \sum_{i=1}^{I} XSP_{i,j,t} + \sum_{q=1}^{Q} XRPP_{q,j,t} \leq CapPlant_j & \forall \ t, j \\
(2) & \sum_{j=1}^{J} XPH_{j,c,t} + XCHC_{j,c,t} \leq Cap_{cap} * YCH_{c,t,loc,cap} & \forall \ loc, cap, t, c \\
(3) & \sum_{c=1}^{C} XCODI_{c,p,t} * Tdismantler \leq Cap_{cap} * YP_{p,t,loc,cap} & \forall \ loc, cap, t, p \\
(4) & \sum_{p=1}^{P} XDIR_{p,q,t} * Trepair \leq Cap_{cap} * YQ_{q,t,loc,cap} & \forall \ loc, cap, t, q \\
(5) & \sum_{p=1}^{P} XDIRE_{p,d,t} * Trecycle \leq Cap_{cap} * YD_{d,t,loc,cap} & \forall \ loc, cap, t, d \\
(6) & \sum_{d=1}^{D} XREDIS_{d,f,t} \leq B * YF_{f,t,loc} & \forall \ loc, t, f
\end{array}$$

Constraints (7) to (9) are used to verify that the demand is never over-satisfied. However, the demand can remain unsatisfied and is considered lost in this case.

$$\begin{array}{lll}
(7) & \sum_{c=1}^{C}(XCHD_{c,l,t}) \leq D_{l,t} & \forall t \in T, l \in L \\
(8) & \sum_{q=1}^{Q}(XRSM_{q,m,t}) \leq Dsm_{m,t} & \forall t \in T, m \in M \\
(9) & \sum_{d=1}^{D}(XPS_{d,i,t}) \leq Ds_{i,t} & \forall t \in T, i \in I
\end{array}$$

Constraint (10) calculates the quantity of collected EOL products.

$$\begin{array}{lll}
(10) & \sum_{c=1}^{C}(XCHC_{l,c,t}) = R_t * D_{l,t} & \forall t \in T, l \in L
\end{array}$$

Constraints (11) and (12) calculate the quantity of dismantled, repaired and recycled products.

$$(11) \quad \sum_{c=1}^{C} XCODI_{c,p,t} * Re = \sum_{q=1}^{Q} XDIR_{p,q,t} \quad \forall p \in P, t \in T$$
$$(12) \quad \sum_{p=1}^{P} XDIRE_{p,d,t} * Rr = \sum_{i=1}^{I} XPS_{d,i,t} \quad \forall d \in D, t \in T$$

Constraints (13) to (18) are the flow balance constraints.

$$(13) \quad \sum_{i=1}^{I} XSP_{i,j,t} + \sum_{q=1}^{Q} XRPP_{q,j,t} = \sum_{c=1}^{C} XPH_{j,c,t} \quad \forall t \in T, j \in J$$
$$(14) \quad \sum_{j=1}^{J} XPH_{j,c,t} = \sum_{l=1}^{L} XCHD_{c,l,t} \quad \forall t \in T, c \in C$$
$$(15) \quad \sum_{l=1}^{L} XCHC_{l,c,t} = \sum_{p=1}^{P} XCODI_{c,p,t} + \sum_{f=1}^{F} XCOF_{c,f,t} \quad \forall t \in T, c \in C$$
$$(16) \quad \sum_{c=1}^{C} XCODI_{c,p,t} = \sum_{q=1}^{Q} XDIR_{p,q,t} + \sum_{d=1}^{D} XDIRE_{p,d,t} \quad \forall t \in T, p \in P$$
$$(17) \quad \sum_{p=1}^{P} XDIR_{p,q,t} = \sum_{m=1}^{M} XRSM_{q,m,t} + \sum_{j=1}^{J} XRPP_{q,j,t} \quad \forall t \in T, q \in Q$$
$$(18) \quad \sum_{p=1}^{P} XDIRE_{p,d,t} = \sum_{f=1}^{F} XREDIS_{d,f,t} + \sum_{i=1}^{I} XPS_{d,i,t} \quad \forall t \in T, d \in D$$

Constraint (19) restricts the maximum number of opened centers for a period depending on the available budget.

$$\begin{aligned}(19) \quad & \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{c=1}^{C} ((YCH_{c,t,loc,cap} - YCH_{c,t-1,loc,cap}) * Cohyb_{c,cap}) \\ & + \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{p=1}^{P} ((YP_{p,t,loc,cap} - YP_{p,t-1,loc,cap}) * CoDism_{p,cap}) \\ & + \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{d=1}^{D} ((YD_{d,t,loc,cap} - YD_{d,t-1,loc,cap}) * CoRecy_{d,cap}) \\ & + \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{f=1}^{F} ((YF_{f,t,loc,cap} - YF_{f,t-1,loc,cap}) * CoDisp_{f,cap}) \\ & + \sum_{loc=1}^{LOC} \sum_{cap=1}^{CAP} \sum_{q=1}^{Q} ((YQ_{q,t,loc,cap} - YQ_{q,t-1,loc,cap}) * CoRep_{q,cap}) \leq C_t \quad \forall t \in T\end{aligned}$$

Constraint (20) updates the budget regarding the number of opened centers in the previous period.

$$\begin{aligned}(20) \quad & C_t = C_1 - \sum_{cap=1}^{CAP} \sum_{loc=1}^{LOC} \sum_{c=1}^{C} (YCH_{c,t-1,loc,cap} * Cohyb_{c,cap}) \\ & - \sum_{cap=1}^{CAP} \sum_{loc=1}^{LOC} \sum_{p=1}^{P} (YP_{p,t-1,loc,cap} * CoDism_{p,cap}) \\ & - \sum_{cap=1}^{CAP} \sum_{loc=1}^{LOC} \sum_{d=1}^{D} (YD_{d,t-1,loc,cap} * CoRecy_{d,cap}) \\ & - \sum_{cap=1}^{CAP} \sum_{loc=1}^{LOC} \sum_{f=1}^{F} (YF_{f,t-1,loc,cap} * CoDisp_{f,cap}) \\ & - \sum_{cap=1}^{CAP} \sum_{loc=1}^{LOC} \sum_{q=1}^{Q} (YQ_{q,t-1,loc,cap} * CoRep_{q,cap}) \quad \forall t \in T\end{aligned}$$

Constraints (21) to (25) calculate the fixed opening costs.

$$(21) \quad ZYCH_{c,loc,cap} \geq (1/T) * \sum_{t=1}^{T} YCH_{c,t,loc,cap} \quad \forall cap \in CAP, loc \in LOC, c \in C$$
$$(22) \quad ZYQ_{q,loc,cap} \geq (1/T) * \sum_{t=1}^{T} YQ_{q,t,loc,cap} \quad \forall cap \in CAP, loc \in LOC, q \in Q$$
$$(23) \quad ZYD_{d,loc,cap} \geq (1/T) * \sum_{t=1}^{T} YD_{d,t,loc,cap} \quad \forall cap \in CAP, loc \in LOC, d \in D$$
$$(24) \quad ZYP_{p,loc,cap} \geq (1/T) * \sum_{t=1}^{T} YP_{p,t,loc,cap} \quad \forall cap \in CAP, loc \in LOC, p \in P$$
$$(25) \quad ZYF_{f,loc,cap} \geq (1/T) * \sum_{t=1}^{T} YF_{f,t,loc,cap} \quad \forall cap \in CAP, loc \in LOC, f \in F$$

Constraints (26) to (30) forbid to close opened centers.

$$
\begin{array}{lll}
(26) & YCH_{c,t+1,loc,cap} \geq YCH_{c,t,loc,cap} & \forall cap \in CAP, loc \in LOC, c \in C, t \in T \\
(27) & YQ_{q,t+1,loc,cap} \geq YQ_{q,t,loc,cap} & \forall cap \in CAP, loc \in LOC, q \in Q, t \in T \\
(28) & YD_{d,t+1,loc,cap} \geq YD_{d,t,loc,cap} & \forall cap \in CAP, loc \in LOC, d \in D, t \in T \\
(29) & YP_{p,t+1,loc,cap} \geq YP_{p,t,loc,cap} & \forall cap \in CAP, loc \in LOC, p \in P, t \in T \\
(30) & YF_{f,t+1,loc,cap} \geq YF_{f,t,loc,cap} & \forall cap \in CAP, loc \in LOC, f \in F, t \in T
\end{array}
$$

Constraints (31) and (32) are used in order to limit the transportation costs to unidirectional among forward and reverse flows depending on the maximum number of products transported between.

$$
\begin{array}{lll}
(31) & h_{c,l,t} \geq XCHD_{c,l,t} & \forall c \in C, l \in L, t \in T \\
(32) & h_{c,l,t} \geq XCHC_{l,c,t} & \forall c \in C, l \in L, t \in T
\end{array}
$$

5.2 Proposed solution approaches

We focus on a Multi-Criteria Decision Model (MCDA) for the resolution of the problem in order to search for the Pareto optimal solutions.In particular, we used a goal programming solution method which consists of setting a priori target values for each objective, and minimizing weighted deviations from these values.

According to definitions 2.16, 2.17 and 2.18, we denote $Z^* = (Z_1^*, Z_2^*, Z_3^*)$ the ideal solution and $Z^{max} = (Z_1^{max}, Z_2^{max}, Z_3^{max})$ the nadir solution. The deviation from solution x to the ideal solution is thus defined as $D = (D_1, D_2, D_3)$ with:

$$D1 = \frac{Z_1^* - Z_1}{Z_1^* - Z_1^{max}}$$

$$D2 = \frac{Z_2^* - Z_2}{Z_2^* - Z_2^{max}}$$

$$D3 = \frac{Z_3^* - Z_3}{Z_3^* - Z_3^{max}}$$

In order to find a satisfying compromising solution for all objectives, we seek to minimize the three deviations.

At this end, we first use classic aggregation functions defined in 2.3.2.3 to solve the problem: in particular, the aggregation based on the $||.||_1$ norm, the aggregation based on the $||.||_\infty$ norm and the *Leximin* aggregation.

Each approach has its particular benefits. However, none of them integrates the sensibility of the DM to the risk aversion in decision making process. We address this issue by introducing two new goal programming approaches based on bipolar aggregation operators and particularly Uninorms and conduct a comparison of all approaches.

5.2.1 Uninorm R_* approach

In the first proposed solution method, we apply R_* uninorm as it has been defined in previous chapters. This results in OPT_{R_*} solution method defined as follows:

Let D_o be the evaluation of the deviation o for solution x,

$$OPT_{R_*}(D_o, e) = \begin{cases} \min \max_{o \in |n|} D_o & \textbf{if } \exists\ D_o \geq e \\ \min \min_{o \in |n|} D_o & \textbf{otherwise} \end{cases} \tag{5.19}$$

In other words, we consider here that e is the relative deviation from the utopia value that the DM is ready to accept for each objective. The behavior of the DM will not result in the same chosen final solution if one of the deviations is larger than e or if all of them are smaller. The solution method works in the following way:

- if $D_o \leq e\ \forall\ o \in O$ then the DM's acceptance threshold is satisfied. Thus, the DM will look for the solution that brings the greatest opportunity, that is to say the solution for which the minimum deviation over all objectives is minimal.
- if $\exists$ *o such as* $D_o \geq e$ then the DM's acceptance threshold is not satisfied. Thus, the DM will select the solution that offers the lowest maximum deviation among all objectives.

It can be written in a form of a MIP [KGB18] of the following form:

$$\min Z + z \tag{5.20}$$

$$\begin{array}{lcl}
S.t & & \\
(a) & Z \geq D_o & \forall o \in O \\
(b) & Z \geq e & \\
(c) & D_o \leq -B * Y_o + e(1 - Y_o) & \forall o \in O \\
(d) & D_o \leq e * Y_o + (1 - Y_o) * B & \forall o \in O \\
(e) & z \geq (1 - Y_o) * B & \forall o \in O \\
(f) & \sum_{s=1}^{S} \delta_o = 1 & \\
(g) & z \geq D_o + (1 - \delta_o) * B & \forall o \in O \\
With & & \\
& Y_o, \delta_o \in \{0, 1\} \text{ and } B \text{ a very large number} &
\end{array}$$

To provide further understanding of the method we present an example below: (see Figure 5.1). Let X and Y be two possible solutions of the multi-objective problem. X_1 (resp X_2,

X_3) is the value of deviation D_1 (resp D_2, D_3) for solution X, and the same goes for Y. In the first case (i.e. the figure on the left - Figure 5.1), the value of e is set to 0.3. None of the solutions observe the DM threshold (i.e. the values of the deviations D_2 and D_3 are higher than e). In that case, a *minmax* is applied and solution Y is chosen. In the second case (the figure in the middle, Figure 5.1), the value of e is set to 0.8. Solution Y observes the DM threshold (D_1,D_2 and D_3 values are all below e) contrary to solution X for which the value of D_3 is above e. In this case, solution Y is chosen. In the last case (the figure on the right in Figure 5.1), the value of e is set to 0.9 and thus both solutions are in the opportunity area. In that case, the final solution is the one with the minimum deviation over all deviations. This is solution X.

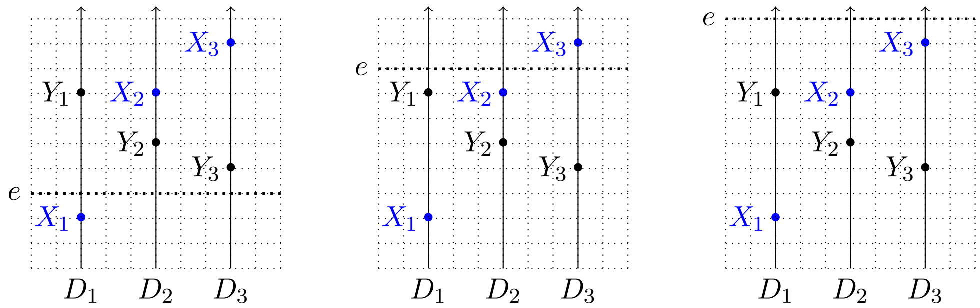


Figure 5.1: Examples of resolution for OPT_{R_*} solution method

5.2.2 Hybrid approach

The second proposed approach (noted OPT_{HYB}) is an hybrid one between the *Leximin* approach (see definition 1) and the R_* approach. Indeed, it is a bipolar approach in the sense that we consider that, as long as the acceptable threshold for environmental equity and social equity is observed, the DM is satisfied and the main goal is to maximize the profit. On the contrary, if one or several objectives do not satisfy the acceptable threshold, the DM chooses a compromise by selecting the solution with the lowest maximum deviation among all criteria, and applies a *Leximin* solution method. The formulation of OPT_{HYB} is given as:

$$OPT_{HYB}(D_0, e) = \begin{cases} leximin_{o\in|n|} D_o & if\ \exists\ o \in O\ such\ as\ D_o \geq e \\ \min D_1 & otherwise \end{cases} \quad (5.21)$$

Here again, we present an example of resolution in Figure 5.2). Let X and Y be two possible solutions of the multi-objective problem. X_1 (resp X_2, X_3) is the value of deviation D_1 (resp D_2, D_3) for solution X, and the same goes for Y. In the first case (i.e. the figure on the left - Figure 5.2), the value of e is set to 0.3. None of the solutions observe the DM threshold (i.e. the values of the deviations D_2 and D_3 are higher than e). In that case, a *Leximin* solution method is applied and solution Y is chosen. In the second case (the figure in the middle, Fugure 5.2), the value of e is set to 0.6. Y_2 and Y_3 are lower than e, thus solution Y is considered to be in the opportunity area. As for solution X, it still does not observe the DM threshold. In that case, solution Y is chosen. In the last case (the figure on the right in Figure 5.2), the value of e is set to 0.9 and thus both solutions are in the opportunity area. In that case, the final solution is the one with the maximum profit (i.e. minimum deviation for D_1). This is solution X.

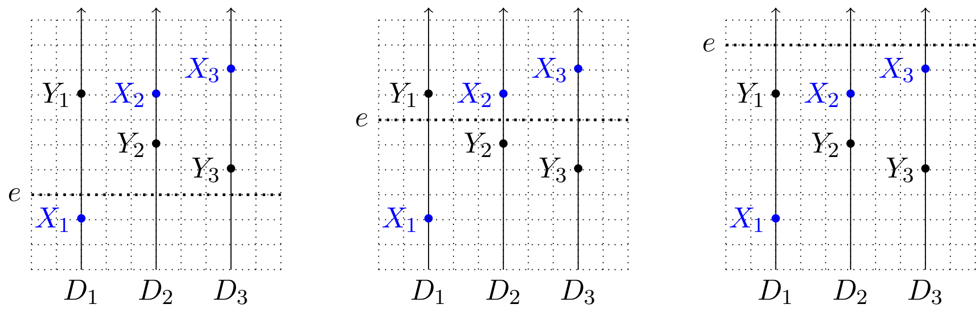


Figure 5.2: Examples of resolution for OPT_{HYB} solution method

This multi-criteria optimization approach makes it possible to define the most important criterion for the DM (in this case, profit). Then, as long as the other criteria have satisfying values, the mutli-objective problem becomes a single objective problem with constraints on the values of the less important criteria. On the contrary, if the secondary criteria do not have satisfying values, we keep the three dimensional problem and choose a satisfactory compromise solution for all criteria (primary and secondary).

5.3 Numerical investigation

As mentioned in the introduction, the quantification of the several environmental and social impacts is a complex process. In this study, we particularly used three types of recognized sources: public databases (www.bilans-ges.ademe.fr, air.plumelabs.com, www.insee.fr, data.oecd.org, co2.myclimate.org), official reports and cases study of CLSC from the literature (see Table 2.4). The final data adapted for the numerical study is presented in Table 5.1.

We consider 10 possible locations for each new center. Each new center has three possibilities of capacity sizes (small, medium, or large). We generate 10 different problem instances based on the presented data in Table 5.1 and the analysis of the results is made on the average values of 10 instances.

The model is solved with Gurobi 7.5.1 on a Intel(R) Xeon(R) CPU E5-2698 server with 500 Go RAM. Considering the long solution time, we decided to stop the resolution when the

Parameter	Value	Parameter	Value
$D_{l,t}$	U(40,300)	$EIDis_{p,loc,cap}$	U(10,50)
$Dsm_{m,t}$	U(32,240)	$EIRep_{q,loc,cap}$	U(10,50)
$Ds_{i,t}$	U(24,180)	$EIRec_{d,loc,cap}$	U(10,50)
Cap_{cap}	U(680000,840000)	$EIDisp_{f,loc,cap}$	U(10,50)
$CapPlant_j$	U(400000,480000)	TE	0.0148
$Distances$	U(5,1500)	$PIPH_{j,c}$	U(2.1,2.3)
$Tdismantler$	U(1,5)	$PICODI_{c,p}$	U(0.7,1.3)
$Trecycle$	U(1,5)	$PIRSM_{q,m}$	U(0.7,1.1)
$Trepair$	U(1,5)	$PIRPP_{q,j}$	U(0.7,1.1)
Ca_i	U(1.1,1.3)	$PIPS_{d,i}$	U(0.7,1.1)
Cp_j	U(2.1,2.4)	$PIDIR_{p,q}$	U(0.7,1.1)
$Cass_j$	U(0.7,0.9)	$PIDIRE_{p,d}$	U(0.7,1.1)
$Coph_c$	U(0.06,0.09)	P_{loc}	(0.2,0.38)
$Cdis_p$	U(0.07,0.09)	DI	U(0.5,0.8)
$Crep_q$	U(0.07,0.09)	$CFhyb_{c,t,loc,cap}$	50,100,150
$Cdecr_d$	U(0.07,0.09)	$CFDism_{p,t,loc,cap}$	50,100,150
$Ceco_c$	U(0.2,0.4)	$CFRecy_{d,t,loc,cap}$	50,100,150
TC	0.0120	$CFDisp_{f,t,loc,cap}$	50,100,150
R_t	0.8	$CFRep_{q,t,loc,cap}$	50,100,150
Re	0.8	$FJS_{t,loc}$	U(15,16)
Rr	0.4	$VJS_{t,loc}$	U(16.5,17.5)
U_{loc}	(0,2)	$FJCH_{c,t,loc,cap}$	U(0.2,3)
SP_l	U(500,900)	$FJP_{p,t,loc,cap}$	U(0.2,3)
RSP_m	U(400,720)	$FJD_{d,t,loc,cap}$	U(0.2,3)
Rev_i	U(300,540)	$FJF_{f,t,loc,cap}$	U(0.2,3)
$Cohyb_{c,loc,cap}$	U(125,170)	$FJQ_{q,t,loc,cap}$	U(0.2,3)
$CoDism_{p,loc,cap}$	U(30,60)	$VJCH_{c,t,loc}$	U(0.04,2)
$CoRecy_{d,loc,cap}$	U(4000,6000)	$VJP_{p,t,loc}$	U(0.04,2)
$CoDisp_{f,loc,cap}$	U(100,150)	$VJD_{d,t,loc}$	U(0.04,2)
$CoRep_{q,loc,cap}$	U(30,60)	$VJQ_{q,t,loc}$	U(0.04,2)
$EIHDC_{c,loc,cap}$	U(10,50)		

Table 5.1: Data for the numerical experiment

reached GAP is equal to 10%. Accounting this accommodation, the average solution time for obtaining the payoff table values is of 2.5 hours.

5.3.1 Analysis of results and discussion

The results were obtained through the following process / steps :

1. Firstly, the model is solved in a mono-objective mode for each of the three considered objectives. Each time one objective is optimized, the value of other 2 objectives are

recorded.

2. The mono-objective resolution is used to build a payoff table presented in Table 5.2 where the Ideal solution is in green coloured font and the Nadir solution is in red coloured font.

	max Z_1	min Z_2	min Z_3
Z_1	10 952 201	75 679	380
Z_2	90 006	23 092	2 916
Z_3	3 464 054	31 650	0
	90 006	75 679	2 916

Table 5.2: Payoff table

From these results, we can make the following assumptions:

- The total profit seems negatively correlated with the environmental equity: Indeed, the more the environmental equity is satisfied, the less the CLSC has opportunities to make profit.
- The total profit does not seem to be correlated with the social equity: When the profit is optimal from the economic point of view, social equity has a good score. But if social equity is optimal, then the total profit is significantly reduced.
- The environmental equity and the social equity do not seem to be correlated: the worst value for the social equity corresponds to the best value for the environmental equity, but on the other hand the worst value for the environmental equity allows to have a good score as regards social equity.

On the basis of the obtained results (Table 5.2), the following values are given to the deviations D_1, D_2 and D_3:

$$D_1 = \frac{10952201 - Z_1}{10952201 - 90006} = \frac{10952201 - Z_1}{10862195}$$

$$D_2 = \frac{23092 - Z_2}{23092 - 75679} = \frac{23092 - Z_2}{-52587}$$

$$D_3 = \frac{0 - Z_3}{0 - 2916} = \frac{-Z_3}{-2916}$$

These deviations are used in the computational experiment. Table 5.3 summaries the results obtained with the developed goal programming approaches. Here again, we used Gurobi 7.5.1 on a Intel(R) Xeon(R) CPU E5-2698 server with 500 Go RAM to solve the model. The average solution time for the goal programming methods is of 30 minutes. Column 1 indicates the solution approach. Column 2 gives the values of e when OPT_{R_*} or OPT_{HYB}

methods are used. Columns 3 to 5 respectively provide the values for the 3 objectives Z_1, Z_2 and Z_3. Columns 6 to 8 indicate the values for $D_o \forall o \in O$ i.e., the deviation from the "utopia" solution for each objective. Finally, Columns 9 to 11 give information about the total sum of the deviations, including the minimum deviation and the maximum deviation for all objectives.

Approach	e	Z_1	Z_2	Z_3	D_1	D_2	D_3	$\sum_o D_o$	$\max_o D_o$	$\min_o D_o$
$\lVert\cdot\rVert_1$	-	8 087 811	48936	0	0.26	0.49	0.07	0.957	0.49	0.07
$\lVert\cdot\rVert_\infty$	-	6 901 363	42703	1087					0.37	0.37
Leximin	-	6 900 260	42708	874	0.37	0.37	0.3	1.04	0.37	0.3
OPT_{R_*}	0.4	7 715 718	44126	1166	0.29	0.4	0.4	1.09	0.4	0.29
OPT_{R_*}	0.5	5 423 986	49384	84	0.5	0.5	0	1	0.5	0
OPT_{R_*}	0.6	4 458 632	54687	0	0.59	0.6	0	1.19	0.6	0
OPT_{HYB}	0.3	6 900 260	42708	874	0.37	0.37	0.3	1.04	0.37	0.3
OPT_{HYB}	0.4	7 320 971	44126	1166	0.33	0.4	0.4	1.13	0.4	0.33
OPT_{HYB}	0.5	8 720 668	49385	1456	0.2	0.5	0.5	1.2	0.5	0.2
OPT_{HYB}	0.6	9 788 484	54644	1613	0.1	0.6	0.55	1.25	0.6	0.1

Table 5.3: Results

These results make possible the following observations:

- As expected, Approach $\lVert.\rVert_1$ leads to the minimum total deviation for all objectives. On the other hand, the maximum deviation value is 0.49 for environmental equity which is significantly far from the best value obtained with other approaches i.e. 0.3. Thus the final solution may not be equally satisfactory for all objectives.

- Approach $\lVert.\rVert_\infty$ leads both to the smallest highest deviation and to the highest minimum deviation. This means that the results obtained for all objectives are not very far from the optimum but not very close at the same time. All objectives are equally satisfactory, but some opportunities are missed.

- *Leximin* approach improves the results of $\lVert.\rVert_\infty$ approach, particularly on the social equity. For almost the same profit and almost the same environmental impact as for $\lVert.\rVert_\infty$, the social objective is improved by 14%. However, since several different solutions are possible with comparable values of objectives, the DM cannot control her/his preferences between such solutions.

- OPT_{R_*} approach provides the possibility to the DM to choose the desired level of fulfilment for each objective. If this level is met, then it is possible to explore the opportunities in the solution space. The impact of value of e can be seen in comparison to the values of D_o obtained with other methods. Since the maximum of the minimum deviations is 0.37, if e is smaller than 0.37, the same solution as with $\lVert.\rVert_\infty$ method will be obtained, since the desired level of fulfillment is not attainable for one of the objectives, in our case the environmental one. However, if e is higher than 0.37, new opportunities can be found. For instance, when e is equal to 0.5, the values of environmental and economic objectives are slightly worsened in comparison to the $\|.\|_\infty$ solution, but new opportunities are found on the social aspect as it achieves its optimal value in this case.

However, this method does not allow a choice of which objective function the DM would prefer in finding new opportunities. Here, we can illustrate this effect by looking at the results when $e = 0.4$ and $e = 0.5$, as opportunities are not found for the same objectives for the two values. Indeed, when $e = 0.4$ opportunities are found for objective Z_1 and when $e = 0.5$ opportunities are found for objective Z_3. This lack of control can be fixed with OPT_{HYB} criterion.

- Indeed, considering the fact that the DM is mostly willing to explore the opportunities for the economic objective, i.e. the total profit, the OPT_{HYB} approach is designed in a way to make it possible to choose an acceptable level for the other two objectives and then maximize the value of the economic objective only. As a consequence, this method provides the best results for objective Z_1. Then, the more the value of e increases, the more the total profit is improved. When e is equal to 0.6, the total profit is almost optimal compared to the "Ideal" solution. The hybrid method can be adapted to prioritize any of the objectives that is the most important for the DM.

To further deepen these observations and provide the DM with practical managerial insights, we analyzed for each solution the number of opened centers (all types included) and the distribution of the implemented centers over all locations. On the basis of this analysis, the following additional observations can be made:

The solution showing the highest number of new centers implemented was obtained with the OPT_{HYB} method and $e \geq 0.5$. On the other hand, the solution with the lowest number of opened centers is that obtained with $\|.\|_\infty$. More generally, to obtain a higher profit it is necessary to open more centers. Indeed, it seems consistent to expect that if more centers are opened, the CLSC will be able to collect and reprocess larger quantities of EOL products for the purpose of recapturing or creating value. Larger quantities of retrieved raw materials from EOL products reduce the need in raw materials and increase the efficiency of resource consumption (e.g. metals, ores, copper).

On the contrary, the opening of dismantling, recycling, repair and disposal centers implementations seems to be related to environmental equity. Indeed, in the solution achieving the highest environmental equity (namely $\|.\|_\infty$, *Leximin* and OPT_{HYB} when $e = 0.3$), not all types of centers are implemented in every location. The most polluted regions are only provided with HDC centers and other types of centers are implemented in the less polluted regions. On the contrary, in the solutions with the lowest environmental equity (OPT_{R_*} when $e = 0.6$ and OPT_{HYB} when $e = 0.6$), all types of centers are implemented in every locations.

5.4 Conclusion and future research directions

Establishing CLSC is an essential challenge to meet the current need for cleaner production, waste reduction, cost-savings, profitability, sustainability, reduction in climate change, and social responsibility. In order to be sustainable, a CLSC must consider at the same time three dimensions: economy (e.g.profits, waste reduction), environment (e.g. reduced natural resource consumption and environmental protection) and society (e.g. corporate social responsibility and fairness and social equity).

In this chapter, we propose several criteria to take into account the DM's attitude, perspective and behavior and compare them through a numerical experiment. The results show that the use of OPT_{R_*} criterion makes it possible to better explore the opportunity zone without losing control over the level of fulfilment of other criteria. OPT_{HYB} criterion can be further used in order to select a priority objective and maximize the opportunities for this one while keeping a satisfactory level of fulfilment of the other two objectives.

We also show that the solutions leading to the best profits are the solutions where the DM makes the decision of opening more centers in the reverse part of the CLSC. In addition, the solutions leading to the best social equity are the solutions where the centers are distributed in the different regions regarding the employment rate of each region. Finally, the type of center implemented in each region has an impact on the environmental equity.

This study reveals many possible future research directions. The main one lies in including uncertainty in the model as all the information about the parameters to be taken into account when implementing a new CLSC is not always easily predictable or available.

Conclusion and perspectives

In the current context of climate and environmental crisis (60% decrease in wildlife over the last 40 years and 90% of land impacted by human activity in 2050 if nothing changes [GA+18b]), many institutional actors (e.g. G7, European commission, IPCC ...) promote the development of circular economy. The goal is to reduce the waste accumulated in landfills and to save raw materials due to the reprocessing of the end-of-life products. New types of production chains must be designed in order to be able to implement this new type of organization, in the form of RSC or CLSC. The design of such systems is complex for many reasons, two of them were addressed in this thesis [AAVW18]: 1. Many factors of uncertainty are involved in the decision making process. 2. Several objectives must be considered simultaneously (in addition to profit maximization) in order to make these systems sustainable.

In the first part of the manuscript (i.e chapter 3 and 4), we focus on the first challenge. The uncertainty involved in the decision-making when designing RSC or CLSC comes from various sources (product demand, volume of returns, fractions of parts recovered for the various product recovery processes, etc.). Mathematical models of decision-making under uncertainty have already been proposed in the literature but they are most of the time based on probability distributions about the uncertain parameters (stochastic models). However, given the relative recentness of the RSC and CLSC in practice, such an approach seems to be not reliable and compromised. Other existing models often propose a conservative risk aversion approach (robust models) which only takes into account the worst possible case and neglects the opportunities present in the others cases. To the best of our knowledge, none of the existing approaches take into account the psychological fact that a decision maker subjected to uncertainty does not necessarily make the same decision depending on whether he considers the uncertainty as a risk or as an opportunity. In this manuscript, we propose to use two new criteria (namely R_* and $lexiR_*$) allowing to take into account the bipolarity of the behavior of the DM in a context of complete ignorance about the uncertain parameters of the designed RSC or CLSC. These criteria are based on the concept of uninorms and use a risk threshold chosen by the DM. Below this threshold, the DM is careful about taken risks and above this threshold, the DM is open for searching opportunities. We study how such an approach impacts the design of a CLSC for an OEM where reverse facilities are connected to an existing forward supply chain gradually over several time periods and the design of a RSC for a third party logistic company.

We compare R_* and $LexiR_*$ criteria with classic criteria from the literature in order to show their advantages and their ability to help the decision maker better explore opportunities. In particular, we show that they better explore the opportunities compared to a classic robust approach, while allowing decision-makers to control the level of risk to be taken. We propose two methods of implementation for the $lexiR_*$ criterion, one in the form of an algorithm and the other in the form of a MIP and we analyse the solution times for both methods. We show that the $lexiR_*$ algorithm takes a much longer time to solve but allows to find an exact solution. At the contrary, the $lexiR_*$ MIP only offers an approximation of the optimal solution but in a much shorter time.

In the second part of the manuscript (i.e chapter 5), we focus on the sustainability of CLSC where three dimensions should be taken into account at the same time: economic (e.g. benefits), environmental (e.g reduced consumption of natural resources and environmental protection) and social (e.g. corporate social responsibility). We propose several mathematical models (namely OPT_{R_*} and OPT_{HYB}) to take into account the DM's attitude, perspective and behavior and compare them through a numerical experiment. Furthermore, we propose a CLSC design model where equity is considered in both the environmental and social objectives. The results show that the use of OPT_{R_*} criterion makes it possible to better explore the opportunity zone without losing control over the level of fulfilment of other criteria compared to other classic aggregation functions. Furthermore, we show that OPT_{HYB} criterion can be used in order to select a priority objective and maximize the opportunities according to it while keeping a satisfactory level of fulfilment for other two objectives. The results also show that the solutions leading to the best profits are the solutions where the DM make the decision of opening more centers in the reverse part of the CLSC.

These studies reveals many possible futures research directions.

First, it will be interesting to generalize R_* and $LexiR_*$ criteria to a discrete set of scenarios with imprecise probabilities or to a continuous set of scenarios. Indeed, it could allow the use of the two criteria in cases where uncertain parameters cannot be expressed in the form of a discrete set of scenarios. Furthermore, the risk threshold e could be represented by a fuzzy number in order to better explore potential opportunities around the initial value chosen by the DM and thus allow more flexibility in the decision. Finally, other uninorms with different properties should be examined and compared to the one studied in our work. Indeed, numerous uninorms representing a large spectrum of ways to consider the DM behavior differently in areas of hazard or opportunity exist and the results returned by such operators in the context of RSC or CLSC design could provide an interesting analysis of the relation between different attitudes of DM for RSC or CLSC design decisions.

Another important research path is to generalize R_* and $LexiR_*$ criteria to the design model for sustainable CLSC. In addition, the social dimension could be completed by integrating other aspects besides job creation (e.g. regional development, health, customer satisfaction, etc). Furthermore, the objectives of minimizing the negative environmental impact and maximizing the positive social impact could be analyzed in the same model in parallel with environmental and social equity in order to evaluate the price of equity. Finally, a study of the distribution of the solutions found with the different MDM approaches on the Pareto front could be carried out. Such an investigation would allow to visualize which parts of the Pareto front are explored by the different criteria.

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Résumé — Afin de répondre aux enjeux environnementaux, économiques et sociaux actuels, de nombreux acteurs institutionnels encouragent la conception de Chaînes Logistiques Inverses (CLI). Celles-ci permettent notamment de minimiser les quantités de déchets produites et de réaliser des économies de matières premières. Deux difficultés principales apparaissent lors de la conception de tels systèmes. Le premier est la présence de nombreux facteurs d'incertitude lors de la prise de décision. Le deuxième concerne la prise en compte simultanée d'objectifs à la fois économiques, environnementaux et sociaux dans le but de permettre la durabilité de la CLI créée. Dans ce contexte, nous développons dans un premier temps des outils méthodologiques basés sur des nouveaux modèles de prise en compte de l'incertitude. Nous proposons en particulier deux critères (R_* et $LexiR_*$) qui permettent de différencier des zones de risque et d'opportunité où l'attitude du décideur ne sera pas considérée de la même manière. Nous comparons ces nouveaux critères avec des critères classiques de la littérature dans des expérimentations numériques approfondies et nous montrons qu'ils permettent d'explorer de nouvelles opportunités, tout en gardant le contrôle sur le niveau de risque pris. Dans un second temps, nous proposons de nouveaux modèles d'optimisation multi-objectifs prenant en compte les trois objectifs du développement durable simultanément. Nous mettons en évidence l'existence de nombreuses solutions de compromis, permettant au décideur de choisir la solution qui lui est le plus adapté en fonction de ses priorités. Enfin, nous réalisons une étude du concept d'équité sociale et environnementale lors du choix entre différents lieux d'implantation de la CLI.

Mots clés : Logistique Inverse, Optimisation sous incertitude, Optimisation multi-objectifs

Abstract — In order to respond to current environmental, economic and social challenges, many institutional actors promote the design of Reverse Supply Chains (RSC). These ones particularly allow to minimize waste and maximize savings in raw materials. Two main difficulties appear when designing such systems. The first one is the presence of many factors of uncertainty in the decision making process. The second one is the simultaneous consideration of economic, environmental and social objectives in order to enable the sustainability of the created RSC. In this context, firstly, we provide methodological tools based on new models for taking into account uncertainty. We particularly propose two criteria (R_* and $LexiR_*$) which make it possible to differentiate areas of risk and opportunity where the attitude of the decision-maker will not be considered in the same way. We compare these new criteria with classic criteria from the literature through extended numerical experiments and we show that they make it possible to explore new opportunities, while keeping control over the level of taken risk. Secondly, we propose new multi-objectives optimization models taking into account the three objectives of sustainable development simultaneously. We highlight the existence of many compromise solutions, allowing the decision-maker to choose the solution that is the most suitable for him/her according to his/her priorities. Finally, we propose a study of the concept of social and environmental equity between different locations where the RSC is implemented.

Keywords: Reverse Logistics, Optimization under uncertainty, Multi-objectives optimization

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