Generic models and optimization algorithms for sustainable supply chain network design

Majid Eskandarpour

Thèse de Doctorat

Majid ESKANDARPOUR

Mémoire présenté en vue de l'obtention du
grade de Docteur de l'École nationale supérieure des mines de Nantes
sous le label de l'Université de Nantes Angers Le Mans

École doctorale : Sciences et technologies de l'information, et mathématiques

Discipline : Informatique et applications
Spécialité : Recherche opérationnelle
Unité de recherche : Institut de Recherche en Communications et Cybernétique de Nantes (IRCCyN)

Soutenue le 04 December 2014
Thèse n° : 2014EMNA0195

Generic models and optimization algorithms for sustainable supply chain network design

JURY

Président :	**M. Hamid ALLAOUI**, Professeur, Université d'Artois
Rapporteurs :	**M. Marc PAQUET**, Professeur, ÉTS Montréal
	M. Eric SANLAVILLE, Professeur, Université du Havre
Examinateur :	**M. Armand BABOLI**, Maître de Conférences, INSA de Lyon
Directeur de thèse :	**M. Pierre DEJAX**, Professeur, Ecole des Mines de Nantes
Co-encadrants :	**M. Joe MIEMCZYK**, Professeur Associé, Audencia Nantes
	M. Olivier PÉTON, Maître Assistant, Ecole des Mines de Nantes

Contents

List of Figures

Acknowledgements

I would like to gratefully acknowledge my supervisors, Prof. Pierre Dejax, Dr. Olivier Péton, and Dr. Joe Miemczyk, for their excellent guidance and encouragements. This thesis would not have been possible without the kind support, the enthusiasm, the probing questions, and the remarkable patience of them. I cannot thank them enough.

I would also like to thank my committee members, prof. Hamid Allaoui, prof. Marc Paquet, prof. Eric Sanlaville, and Dr. Armand Baboli for serving as my committee members even at hardship. I also want to thank you for letting my defense be an enjoyable moment, and for your brilliant comments and suggestions, thanks to you.

I would specially like to thank Agnès Le Roux, Tanguy Lapegue, Axel Grimault, Clement Fauvel, Xin Tang, Thomas Vincent Juliette Medina, and Mi Zhang for sharing memorable moments with me. Thanks are also due to Prof. Nathalie Bostel-Dejax for her support and encouragement.

I am forever indebted to my parents and my family for their understanding, endless patience and encouragement when it was most required.

Finally, this research has been partially supported by the Région Pays de la Loire through the research project OLASI which has been labeled by the competitiveness clusters EMC2 and Nov@log. This support is hereby gratefully acknowledged.

Résumé en français

0.1 Contexte

La problématique de la conception et de l'optimisation des réseaux logistiques est étudiée de longue date en recherche opérationnelle. La question de la localisation des sites constitue la plupart du temps le noeud de ces problèmes. Les états de l'art et travaux scientifiques récents montrent l'importance de développer de nouveaux modèles plus riches pour la conception et l'optimisation de réseaux logistiques complexes. Ces nouveaux modèles mathématiques sont fondés sur des réseaux multi-produits, multi-niveaux, permettant la production multi-sites de produits à nomenclature complexe. Ils intègrent la notion d'incertitude : incertitude de la demande des clients et des coûts, les risques de rupture dans la chaîne d'approvisionnement. Enfin le seul critère d'optimisation retenu dans les recherches passées est souvent le coût. La qualité de service ou les objectifs du développement durable, qui sont au coeur des préoccupations actuelles des entreprises, ont désormais une place à part entière dans les problèmes traités.

Les modèles mathématiques de conception de réseaux logistiques se caractérisent donc par leur très grande diversité. Lorsque le temps et les ressources de l'entreprise concernée le permettent, la résolution d'un problème de conception de réseaux logistiques fait appel à une méthode spécifique, qui nécessite un effort de recherche et de développement important. À l'autre bout de l'échelle, les modèles basiques sont trop incomplets pour répondre à des besoins réels.

L'objectif de cette thèse est de développer une méthode d'optimisation suffisamment flexible pour pouvoir résoudre plusieurs modèles riches de localisation et de planification stratégique dans les réseaux logistiques. Ce travail comporte trois contributions principales :

- un état de l'art sur les problème de conception de réseaux logistiques intégrant les principes du développement durable,
- le développement d'une méthode métaheuristique générique pour la résolution d'un problème mono-objectif visant à minimiser le critère économique,
- l'extension de la méthode précédente au cas bi-objectif, visant à minimiser les critères économique et environnemental.

0.2 État de l'art sur les problèmes de localisation intégrant les principes du développement durable

Plusieurs états de l'art sur les problèmes de localisation ou plus généralement sur la conception de chaînes logistique ont été publiés ces 15 dernières années dans la communauté recherche opérationnelle [Beamon, 1998, Owen and Daskin, 1998, Daskin et al., 2005, M. and G., 2005, Sahin and Süral, 2007, Melo et al., 2009]. Mais aucun ne parle de développement durable. Par ailleurs de multiples états de l'art sur la gestion de la chaîne logistique et le développement durable ont été publiés en sciences de gestion. Mais très peu d'entre eux mentionnent des modèles et méthodes de recherche opérationnelle.

Nous avons donc entrepris une revue de la littérature, qui a permis de recenser 74 articles, publiés dans 36 journaux différents. Un fait marquant est que 90% de ces articles ont été publiés depuis 2008. Sans surprise, la grande majorité des articles intègre une évaluation économique et environnementale des décisions de localisation. La dimension sociale, plus difficile à quantifier, mais également plus difficile à exprimer en critères communément admis, est moins souvent présente. Parmi les 70 articles intégrant la dimension environnementale, environ la moitié d'entre eux s'inscrit dans une démarche d'Analyse du Cycle de Vie (ACV). Nous avons donc répertorié les principales caractéristiques de ces ACV : champ de l'étude, méthode d'évaluation de l'impact. Pour les autres articles, nous avons analysé sur quels attributs des modèles étudiés est mesuré l'impact environnemental : sites à localiser, transport, produits. Nous passons ensuite en revue les modèles mathématiques et les méthodes de résolution, en distinguant modèles mono-objectif et modèles multi-objectifs largement majoritaires. Une première constatation est que la totalité des études entrant dans la catégorie ACV utilise des langages de modélisation et des solveurs mathématiques pour résoudre les modèles, tandis que les autres études utilisent une panoplie beaucoup plus large de méthodes.

Il semble donc exister une dichotomie entre deux familles de chercheurs. La communauté recherche opérationnelle résout de manière parfois très fine des modèles intégrant partiellement (voire grossièrement) les principes du développement durable. A contrario, les chercheurs issus des domaines d'application (chimie, énergie, industrie, agriculture) construisent des modèles très complets mais n'utilisent que des outils standard de résolution. Une collaboration entre ces deux communautés sera nécessaire pour résoudre des modèles étendus de localisation tels que par exemple les problèmes de localisation-routage.

0.3 Recherche à voisinage large pour un problème de localisation

L'algorithme LNS, qui a largement fait ses preuves pour résoudre de nombreuses variantes de problèmes de tournées de véhicules ou d'ordonnancement, n'a quasiment jamais été utilisé sur des problèmes de localisation dans les chaînes logistiques. Copado-Méndez et al. [2013] identifient pourtant un avantage lié à cette méthode : les opérateurs de destruction et de reconstruction, largement dépendants du modèles à résoudre, offrent une grande flexibilité. Ainsi, le LNS peut se présenter comme un cadre général dans lequel on définit une collection d'opérateurs qu'on mobilise ou non en fonction des attributs du modèle à résoudre.

En revanche, plusieurs difficultés nouvelles se font jour. Tout d'abord, il faut considérer séparément les variables binaires et les variables continues. Une approche hiérarchique est de fixer les variables binaires de localisation au moyen des opérateurs de l'algorithme LNS, et les variables continues de flux en résolvant un sous-problème à chaque itération. Ensuite, les caractéristiques de la solution optimale ne sont pas connues a priori. Dans les problèmes de tournées de véhicules, le nombre de clients à visiter est fixe, de même que le nombre de tâches dans les problèmes d'ordonnancement. En localisation, il est impossible de savoir à l'avance le nombre de sites actifs dans une solution optimale de problème (sauf bien sûr pour le problème p-médian). Dans un réseau multi-échelons, on appelle *configuration* le vecteur qui indique le nombre de sites actifs à chaque échelon. Plus le réseau comporte d'échelons et de sites candidats, plus le nombre de configurations possibles est élevé. Il est pourtant nécessaire d'assurer une bonne couverture de ces configurations pour trouver une solution optimale. Enfin, plusieurs attributs du problème, tels que le choix des modes de transport ou des technologies de production sont modélisés par des variables binaires qui viennent compliquer les modèles. Ces variables peuvent être traitées par les opérateurs de destruction, mais aussi par des heuristiques spécifiques intégrées dans l'algorithme LNS.

Notre recherche porte sur la définition et l'implémentation d'une méthode générique de type LNS pour résoudre des modèles riches de localisation. Les travaux concernent ici un modèle multi-niveaux multi-produits, mono-périodique, intégrant le choix entre plusieurs modes de transport.

L'algorithme développé incorpore plusieurs heuristiques gloutonnes pour déterminer les modes de transport et l'ensemble des variables continues. Comme c'est le cas des différents opérateurs dans l'ALNS, chaque *configuration* est évaluée par un score. À chaque itération, une *configuration cible* est sélectionnée aléatoirement en fonction des scores de toutes les configurations. Les opérateurs de destruction et de reconstruction ont alors la charge de passer de la configuration courante à la configuration cible.

Cet algorithme a été testé sur 60 instances générées aléatoirement et ses performances comparées avec celles de Cplex. En moyenne, l'écart relatif entre Cplex et le LNS est de 1.43% en faveur de Cplex. Mais sur les instances les plus grandes (60 sites candidats, 300 clients à servir), l'heuristique LNS trouve en 15 minutes des solutions meilleures que Cplex après 3h de calcul. Par ailleurs l'analyse des résultats des expérimentations en fonction des différentes instances et valeur des paramètres permettent de valider la pertinence du modèle et de l'approche utilisée.

0.4 Optimisation simultanée du coût et de l'impact environnemental

Nous nous sommes ensuite penchés sur la prise en compte de l'impact environnemental, et donc sur l'extension de notre modèle en y intégrant une évaluation environnementale. Nous présentons donc un modèle bi-objectif de conception de chaîne logistique durable.

Nous considérons les émissions de CO_2 comme l'unique impact environnemental. Cet élément est en effet fréquemment l'indicateur environnemental unique utilisé dans ce type de travaux et il peut être aisément mesuré et modélisé [Wang et al., 2011]. Les émissions du transport et des unités industrielles comptent pour 22% et 20% du total des émissions de CO_2 respectivement [OECD/IEA, 2012]. Ces statistiques justifient donc la considération de ces activités dans notre modèle en tant que source des émissions de CO_2. Nous considérons que les émissions CO_2 proviennent de deux sources principales:

- la production ou le traitement des produits, pour lesquels les émissions sont supposées proportionnelles aux quantités de produits traités. Elles dépendent également du type d'opérations effectuées (achats et approvisionnements, production et entreposage) et au type de technologie utilisée.
- le transport des produits, pour lequel les émissions sont basées sur la distance et le mode de transport utilisé.

Comme il apparaît dans notre revue de littérature, différents types de modèles de conception de chaînes logistiques intégrant les facteurs environnementaux ont déjà été développés et la plupart d'entre eux sont basés sur des applications pratiques. De ce fait il semble difficile de concevoir un modèle unique applicable à des situations différentes. Différents modèles portant sur des chaînes multi-niveaux ou considérant des choix technologies différents modes de transport ont été proposés. Cependant à notre connaissance, aucun modèle de conception de chaîne logistique durable intégrant simultanément ces différents facteurs n'a été proposé à ce jour.

Comme notre modèle mono-objectif, et de façon similaire à Abdallah et al. [2013], Bouzembrak et al. [2013], Ramudhin et al. [2010], et Sadrnia et al. [2013] le modèle que nous proposons comprend quatre niveaux: les fournisseurs, les unités de production et de distribution et les clients. De plus, nous considérons deux niveaux technologiques possibles au niveau des unités de production et des centres de distribution. Chaque niveau technologique correspond à un niveau de service associé à des coûts fixes et variables et à des émissions de CO_2. Nous supposons qu'un niveau technologique plus élevé peut conduire à des émissions réduites, mais exigera des investissements plus importants.

Le travail le plus proche du nôtre est celui de Devika et al. [2014]. Ces auteurs proposent un modèle générique de conception de réseau logistique en boucle fermée comprenant plusieurs niveaux technologiques. Cependant ils n'intègrent pas le choix de plusieurs modes de transport. Globalement nous considérons que notre modèle se distingue des autres par sa possibilité d'adaptation relativement aisée à différents types d'applications.

Le modèle de conception de chaîne logistique que nous proposons vise à la minimisation de l'ensemble des coûts fixes et variables et des émissions de CO_2 provenant des unités logistiques et du transport. Nous travaillons sur un réseau identique à celui du modèle mono-objectif, auquel il faut cependant ajouter la notion de choix de technologies. Nous aboutissons donc à un MILP bi-objectif dont l'objectif économique comprend l'ensemble des coûts fixes et variables relatifs aux unités logistiques et au transport, et dont l'objectif environnemental comprend trois termes : les émissions de CO_2 correspondant aux achats et approvisionnements des produits des fournisseurs aux unités de production, aux opérations de production et distribution suivant les différentes technologies et aux opérations de transport par les différents modes.

La résolution d'instances de grande taille peut se révéler inefficace ou impossible avec un solveur de MILP. Ceci est encore plus vrai pour la résolution d'un modèle bi-objectif. Le développement d'une méthode approchée est donc inévitable pour la détermination de solutions de compromis entre des objectifs contradictoires[Zanjirani Farahani et al., 2010].

Nous proposons une procédure associant la méta heuristique LNS avec la procédure de recherche locale multi-dimensionnelle (MDLS) proposée récemment par Tricoire [2012]. L'utilisation de l'algorithme MDLS permet en effet la conservation de la structure de notre LNS et de l'intégrer dans une procédure bi-objectif. La procédure MDLS a prouvé son efficacité pour la résolution de différentes classes de problèmes multi-objectifs, et son association avec une métaheuristique LNS de recherche à voisinage large est déjà citée par Tricoire [2012]. À notre connaissance cette technique n'a jamais été utilisée pour la résolution de modèles de conception de chaînes logistiques multi-objectif.

Nous appuyant sur la démarche de Caballero et al. [2007], nous proposons une méthode en trois étapes qui guide la recherche pour la détermination d'une approximation du front de Pareto utilisant la notion de *configuration*. Cette méthode permet de mieux contrôler l'espace de solution en terme des deux objectifs. En effet, le nombre plus ou moins grand d'unités logistiques ouvertes influence la valeur respective des objectifs de coût et environnemental.

Les trois phases de notre procédure, appelée *bi-objective large neighborhood search* (BOLNS) sont les suivantes :

- **Phase I**: recherche d'un front de Pareto approché initial. La phase initiale de la méthode LNS mono-objectif est exécutée séparément pour chaque objectif et chaque configuration. Il en résulte un ensemble de solutions mutuellement non dominées qui constitue l'approximation initiale du front de Pareto.
- **Phase II**: Intensification de le recherche autour de l'approximation du front de Pareto. L'approximation du front est améliorée par exploration du voisinage de toutes les solutions à l'aide de la recherche locale multi-directionnelle proposée par Tricoire [2012].
- **Phase III**: Optimisation finale des flux dans le réseau. Une fois stabilisées les décisions de localisation des unités logistiques et des choix de modes de transport prises lors de la phase II, nous déterminons la valeur des flux optimaux de produits à travers le réseau par programmation linéaire de la même façon que lors de la dernière étape de notre procédure LNS mono objectif, et ce pour l'ensemble des solutions du front de Pareto approximatif final.

À l'issue de cette procédure, nos vérifions que l'ensemble des solutions obtenues sont bien inclues dans l'approximation du front de Pareto, c'est à dire que nous ne retenons que les solutions effectivement non dominées. Le résultat final nous permet d'obtenir une approximation du front de Pareto.

Afin d'évaluer la pertinence de l'algorithme BOLNS, nous l'avons comparée aux résultats obtenus en résolvant, à l'aide de Cplex, le modèle MILP bi-objectif avec la méthode ε-constraint (EC). La résolution du modèle MILP/EC pour des instances de taille petite et moyenne taille permet d'obtenir une approximation du front de Pareto à comparer avec celle obtenue avec notre procédure BOLNS. Pour les instances de grande taille, le solveur MILP avec la procédure EC ne conduit pas toujours à l'obtention de solutions optimales. Mais dans tous les cas, nous obtenons une approximation du front de Pareto contenant un ensemble de solutions non dominées.

Nous comparons les algorithmes BOLNS et EC sur trois mesures de performance proposées dans la littérature : l'hypervolume introduit par Zitzler et al. [2003], l'indicateur unitaire proposé par Zitzler et al. [2003], et le ratio de l'approximation du front de Pareto introduit par Altiparmak et al. [2006]. Les nombreuses expérimentations que nous avons conduites sur l'ensemble de jeux de données tests prouvent la pertinence de notre modèle pour résoudre le problème de conception de chaînes logistique durables. Elle démontrent également l'efficacité de la procédure BIOLNS en terme de qualité des approximations des fronts de Pareto et de temps de calcul.

0.5 Perspectives de recherche

Cette recherche peut conduire à de nombreuses perspectives et il serait intéressant d'envisager son application sur un cas industriel réel. Sur la plan théorique, il est souhaitable d'étendre les problèmes étudiés au cas multi-périodique, de considérer les opérations de logistique inverse pour faire évoluer les modèles vers des modèles en boucle fermée, de considérer davantage de facteurs du développement durable et des objectifs et des contraintes riches et réalistes nécessaires à l'étude d'application réelles. Il serait également intéressant de considérer les incertitudes sur différents facteurs comme la demande ou les délais et de contrôler les risques de la chaîne logistique. Nous pensons que par leur flexibilité, les procédures proposées dans le cadre de cette thèse pourraient être adaptées pour prendre en compte ces extensions.

I

Problem presentation and state of the art

1

Introduction

Supply chain management has become a strategic issue for any company looking to meet targets in terms of economic competitiveness, time and quality of service especially in an economic environment characterized by the globalization of trade and the acceleration of industrial cycles. The trade press is replete with examples of logistics network configuration, re-configuration, re-organization, mergers, outsourcing, and so on. These developments have been influenced by successive trends in the economy and society resulting from computerization, increased complexity of trade flows, increased competition and certainly not least, sustainable development. Thus the strategic design and planning of logistics networks is a topic that is becoming more important for businesses and researchers alike. Supply chain network design is at the intersection of disciplines such as management, strategy, logistics, operations research and as such, there is a significant challenge to researchers to consolidate and synthesize the research in this field, which leads to the focus of this research.

Supply Chain Management (SCM) spans all movements and storage of raw materials, work-in-process inventory, and finished goods from the point-of-origin to the point-of-consumption [Simchi-Levi et al., 2004]. It encompasses three decision levels: strategic, tactical and operational. In particular, at the strategic level, Supply Chain Design comprises the decisions regarding the number and location of production and storage facilities, the amount of capacity at each facility, the conciliation of market demand, and decisions on supplier selection from a total cost perspective [Chopra and Meindl, 2004]. From an operations research point of view, Supply Chain Network Design (SCND) is the discipline used to determine the optimal location and size of facilities and the flow through the facilities [Autry et al., 2013]. As recalled by Zanjirani Farahani et al. [2014], "*there are many models in the SCND literature. Different decisions are made for SCND and perhaps the most critical one is locating the facilities in different tiers of the supply chain*".

The field of facility location has been very active since the description of the p-median problem by Hakimi [1964] fifty years ago, and the contemporaneous works by Kuehn and Hamburger (1963), Manne (1964), Balinsky (1965). In the field of supply chain management and logistics applications, the seminal facility location models have been progressively incorporated into larger models now constituting the family of Supply Chain Network Design (SCND) problems. The large amount of works in the area of facility location and SCND problems has been classified and synthesized in a number of review papers. See for example the following reviews published in the last ten years: Daskin et al. [2005], Klose and Drexl [2005], M. and G. [2005], ReVelle and Eiselt [2005], Sahin and Süral [2007], Melo et al. [2009]. In addition to facility location decisions, multiple variants of SNCD models encompass sizing decisions, allocation of products to facilities, supplier selection, choice of transportation modes, etc. The recent mathematical models generally include features such as multiple layers and types of facilities, multiple products and multiple periods. More advanced models integrate the bill of material for multi-product problems, multiple transportation modes, uncertainty, risk management, disruption, reverse logistics or sustainable development factors.

1.1 Toward sustainable supply chain network design problems

The SCND model considered in this study consists of a number of characteristics from both classical and advanced features. More precisely, we incorporate multiple layers and multiple products as classical features and transportation modes and sustainable development as advanced features into the mathematical models.

Sustainable development has been considered as a critical concern of societies, international organizations, and governments for the past decades. Environmental protection, resource conservation, along with economic and social progress are some of the necessary criteria for sustainable development [Pati et al., 2008]. Therefore, policy makers and industry practitioners are under increasing pressure to continuously reduce the negative environmental impact of their supply chains [Abdallah et al., 2012]. They urge actions to revisit many concepts in supply chain management (SCM) from the environmental and sustainability viewpoints [Chaabane et al., 2012a, Srivastava, 2007]. Consequently, concepts such as green supply chain management, sustainable supply chain management and reverse logistics have recently attracted many researchers and practitioners. Green supply chain management is defined as integrating environmental aspects into supply chain management. In general, the final goal is to consider environment in every decision making process along supply chain, especially the strategic level decisions [Linton et al., 2007, Srivastava, 2007].

Industries such as steel, chemicals, computers, cell phones, appliances, aircraft, automobiles, and medical are examples that have proceeded toward these concepts [Du and Evans, 2008]. As an example, Figure 1.1 ([You and Wang, 2011]) displays the configurations of a biomass-to-liquid supply chain including three types of facilities called *integrated process*, *pre-conversion*, and *fuel upgrading*. Figure 1.1(a) shows the optimal biomass supply chain design for the minimum cost solution. Figure 1.1(b) shows the optimal biomass supply chain design for the minimum emissions solution. It can be seen that a number and location of facilities in those cases are different. You and Wang [2011] noted that all the facilities are located in counties with relatively large populations to minimize cost. Such location decisions lead to lower average transportation distances of liquid transportation facilities. On the contrary, the minimum emissions solution leads to a reduction of GHG emissions.

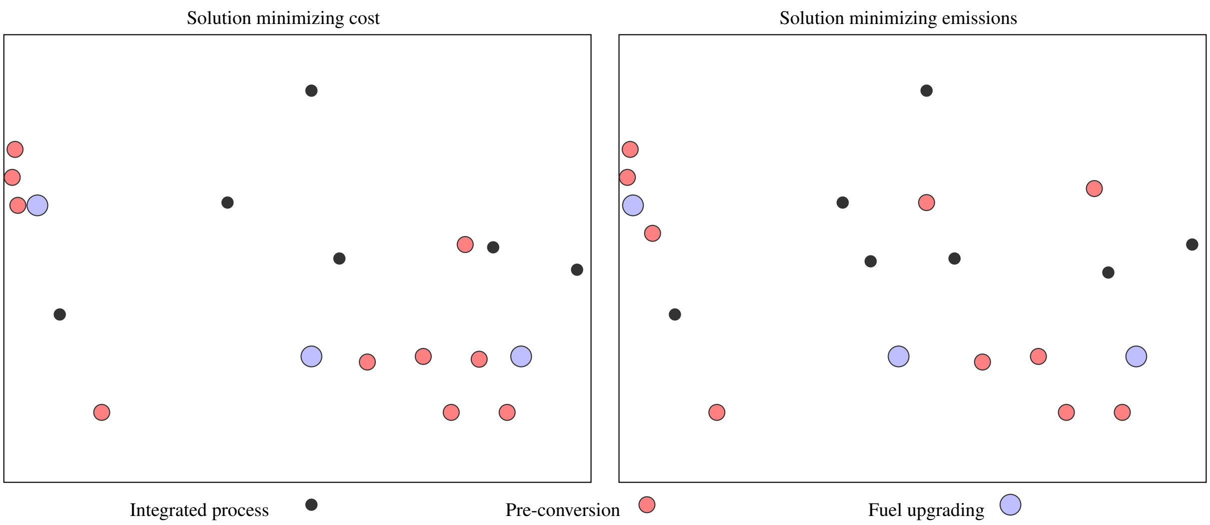

Figure 1.1: Considering GHG emissions changes the logistics network.

The benefit of environmental issue generally depends on long term investment in modern technologies, supplier selection, product design and so on. It also depends on tactical decisions such as the choice of transportation modes. Therefore, facility location and capacity allocation decisions should be integrated with the decision on environmental investment [Wang et al., 2011].

In spite of the fact that typically no location decisions are made on the tactical or operational level, a series of subjects are strongly related to them such as inventory control policies, the choice of transportation modes and capacities, warehouse layout and management, and vehicle routing [Melo et al., 2009]. In particular, the choice of transportation modes; by air, by sea or by land, leads to a trade-off between time and cost in a supply chain [Olivares-Benitez et al., 2013, Cardona-Valdés et al., 2014]. However, only few works consider the choice of transportation modes as a decision to be made [Melo et al., 2009, Cardona-Valdés et al., 2014]. Hence, we include this feature into our SCND model.

1.2 Solution method

A large variety of exact or approximate solution techniques have been proposed for solving SCND problems. Most papers on SCND aim at finding out the best configuration of the network regarding a single objective function representing an economic goal. The great majority of such problems is classified as NP-hard [Gupta and Könemann, 2011]. General solvers are often able to solve small- or medium-sized SCND instances to optimality. However, rich models or large enough instances of classic models cannot be solved to optimality even by state-of-the-art solvers. Hence, using heuristic or metaheuristic approaches is inevitable to tackle hard SNCD problems. As an example, we can cite simulated annealing [e.g. Yaghini et al., 2012, Subramanian et al., 2013], tabu search [e.g. Der-Horng and Meng, 2008, Melo et al., 2012], VNS [e.g. Eskandarpour et al., 2014, 2013], genetic algorithms [e.g. Altiparmak et al., 2009, Wang and Hsu, 2010], memetic algorithms [e.g. Pishvaee et al., 2010a, Jamshidi et al., 2012], scatter search [e.g. Du and Evans, 2008]. Although many heuristic methods have been used to solve SCND problems, there is still space to develop more efficient solution methods [Barbosa-Póvoa, 2014a].

Further research aims at extending the model and solution technique to encompass other advanced supply chain design features.

Since a supply chain network design problems may include multiple variants, efficient approaches must be flexible enough to be able to adopt to various variants of models. Surprisingly enough, the Large Neighborhood Search (LNS) heuristic has almost never been used. The LNS has been introduced by Shaw [1998] in a constraint programming framework. The underlying principle is to iteratively destroy and repair the current solution in order to progressively improve it. Destroying the current solution consists in removing a subset of decision variables from the solution. Repairing the solution consists in restoring feasibility. This principle is similar to the *ruin and recreate* introduced by Schrimpf et al. [2000]. The authors identify a benefit of the LNS: removal and repair operators, largely dependent on the models to be solved, provide high flexibility. Thus, the LNS can be presented as a general framework in which we define a collection of operators that are mobilized or not based on the attributes of the model to solve.

1.3 Thesis objectives

The research work presented in this thesis aims at proposing relevant models for sustainable SCND problems and developing efficient and flexible methods based on the LNS framework for solving them. The goal is to describe and evaluate an LNS approach to solve a sustainable SCND. As stated before, the LNS approach has almost never been proposed for solving such problems, although it has proven its efficiency and flexibility in solving other complex combinatorial optimization problems. With the idea that a good metaheuristic for the single objective will likely produce good solutions for the multi-objective problems [Tricoire, 2012], we first develop an LNS for single objective SCND. Therefore, we consider a generic single period multi-product multi-layer supply chain network. The goal is to evaluate performance of the proposed method for solving single objective problems. The considered supply chain includes both strategic and tactical decision levels including locating plants and distribution centers, assigning product flows to the facilities, as well as selecting transportation modes.

We extend the considered supply chain network to a bi-objective model by incorporating a general objective function measuring the environmental impact of emissions. Knowing that transport and industrial facilities account for 22% and 20% of global CO_2 emissions respectively [OECD/IEA, 2012], we integrate CO_2 emissions due to transport and facilities into the considered supply chain as a second objective. The bi-objective model is made more realistic by the possibility of having several potential technology levels. Eventually, we evaluate performance of the method in terms of cost and CO_2 emissions objectives. The results of the thesis contribute to solve large sized problems in reasonable computational time.

1.4 Thesis plan

This thesis contains three parts: part I includes a comprehensive state of the art about sustainable supply chain network design (chapter 2). Part II includes chapters (3 – 6) related to single objective supply chain network design. Finally, chapters (7 – 9) about bi-objective supply chain network design are presented in part III.

Chapter 2 presents a comprehensive review of sustainable supply chain network design models and methods. We consider the models which explicitly integrate sustainable development aspects into mathematical models. We investigate the literature from different points of view: mathematical models, solution methods, environmental and social aspects, and applications. Finally, we provide a conclusion with future research directions.

Chapter 3 presents a generic mathematical model for a supply chain network design problem regarding cost objective. First, the comprehensive problem is defined. Then the notations and variables are explained. Finally, a mathematical formulation is provided.

Chapter 4 presents the solution method proposed for solving the mono objective supply chain network design problem. We detail each component of the LNS framework and the way to explore the solution space regarding each type of variables are explained in detailed.

Chapter 5 describes the way to generate the data used to evaluate the performance of the LNS algorithm. We try to respect the literature and practice cases in generating the required parameters.

Chapter 6 presents the computational results obtained with our LNS. We compare them with the results obtained by CPLEX on a set of instances of different sizes.

Chapter 7 describes the mathematical model for the bi-objective supply chain network design minimizing cost and environmental impact.

Chapter 8 presents our bi-objective LNS method for solving the sustainable SCND problem. The goal is to provide a good approximation of the Pareto front.

Chapter 9 shows comprehensive computational experiments. We investigate the performance of each phase of our method. We compare the LNS algorithm described in chapter 8 against the well known $\varepsilon-$constraint method. In order to provide a fair evaluation of the performance of the proposed method, several performance measures are presented in this chapter.

Chapter 10 gives an overview of the contribution presented in this thesis and concludes with future research directions.

2

Literature review of Sustainable SCND

Among the major trends in SCM, the principles of sustainable development have spread across the scientific literature. Current research mainly consists of assessing SCM policies according to a triple bottom line including economic aspects, environmental performance and social responsibility. Sustainable SCM has been the subject of numerous survey papers in both qualitative and quantitative disciplines. A number of review papers have been published in recent years, which relate to major trends in supply chain management and investigate and suggest research opportunities. Importantly, quantitative research in sustainable SCND has hardly been reviewed at all. The goal of this research is to bridge this gap. More precisely, our objective is to review SCND problems that include a clear assessment of at least two of the three pillars of sustainable development: economic aspects, environmental performance and social responsibility. We review papers containing mathematical models (linear and nonlinear programs with integer or mixed-integer variables) with binary decision variables modeling the selection of candidate facilities.

Our research questions can be briefly stated as follows: (i) which environmental and social criteria are considered in sustainable SCND research? (ii) how are they integrated into mathematical models? (iii) which optimization methods and tools are used? (iv) which real-life applications of sustainable SCND are described in the scientific literature?

Section 2.1 describes the methodology adopted for the collection of research papers and compares our work with existing reviews on related topics. SCND problems with environmental and social aspects are investigated in sections 2.2 and 2.3, respectively. In section 2.2, we give a special focus on LCA-based methods and review the scope of the environmental assessment, the environmental criteria used and the metrics chosen to evaluate these criteria. The section 2.4 reviews the mathematical models. We used 3 main classification dimensions: single objective versus multi-objective models, linear versus non linear, deterministic versus stochastic. The solution methods are described in section 2.5, which lists the use of solvers, other exact methods and heuristic or metaheuristic approaches. Section 2.6 is devoted to the description of case studies and real-life applications of sustainable SCND. The references are classified according to the type of economic activity and the nature of the data. Finally, in section 2.7 we conclude and suggest a number of future research directions.

2.1 Review methodology

2.1.1 Delimitations and search for literature

A comprehensive search of related research from 1990 to 2014 was applied to produce a synthesis of peer-reviewed literature. The start of the time period was chosen such that the Brundtland Report of the World Commission on Environment and Development [Burton, 1987] served as a starting point, in a similar way to Seuring and Müller [2008] and Chen et al. [2014].

We searched papers published in international peer-reviewed journals from the main electronic bibliographical sources (Scopus, Web of Science) using keywords such as *sustainable development*, *green*, *environmental* or *social* along with classic keywords such as *supply chain*, *network design* or *facility location* in the titles or the topics covered. We use back-tracking to find earlier relevant sources, and forward-tracking in Web of Science to find literature that are referring to the central sources. We also looked for recent surveys in related domains in order to find additional sources including a few conference papers.

From the collected material, we filtered the papers according to the following rules: (i) the papers must be written in English language, (ii) they include decision variables modeling the location or selection of candidate facilities, (iii) the measure of environmental or social impact is explicit either in the objective function or in the constraints of the model.

From the second rule, we excluded a large number of articles dealing with the routing of product flows in an already defined network. This is the case, for example, in the paper by Ramos et al. [2014], in which the authors present depot selection as an extension of their work. The third rule enabled us to filter many papers in the field of reverse logistics and management of undesirable facilities. Reverse logistics and closed-loop supply chain have become a major area of supply chain management. Several surveys have been published in the last fifteen years (see for example the surveys by Fleischmann et al. [1997], Dekker et al. [2004], Bostel et al. [2005], Pokharel and Mutha [2009] or the special issues [Guide and Van Wassenhove, 2006a,b]). Clearly, the goal of reverse or closed-loop supply chain is closely related to that of sustainable supply chain management. However, as explained in Srivastava [2008] (Figure 4), the main optimization often relies on a single economic objective. Environmental and social dimensions are generally not explicitly assessed, but the resolution of these problems evidently contributes to designing sustainable supply chain networks.

Undesirable facilities are those facilities that have adverse effects on people or the environment. They generate some form of pollution, nuisance, potential health hazard, or danger to nearby residents; they also may harm nearby ecosystems [Melachrinoudis, 2011]. Thus, the modeling of SCND problems that include undesirable facilities often implicitly include environmental or social aspects.

On that basis, 87 papers were identified. In the following, they are denoted as *reference papers* and listed in a separate category in the reference list in the end of this review.

2.1.2 Position in the literature

As many review papers have been written in neighboring domains, we needed to check whether the scope of the present paper was not already covered by the existing literature. Table 2.1 summarizes the reviews published in related areas. The symbol ● in columns 2 means that the corresponding paper considers facility location as a main topic. The symbols ○ and ✕ mean that facility location is one topic among others or is not studied in the paper. The symbols have the same meaning in further tables.

We can classify the review papers in two categories. The first category gathers papers dealing with Supply Chain Management in general. In these papers, facility location is either not studied or is only one feature among many others. For example, Brandenburg et al. [2014] mention network design as one out of 13 application areas. They mention 13 papers in this area, all except one being published between 2010 and 2013. Seuring [2013] indicates that more than 300 articles have been published in the last 15 years on the topic of green or sustainable (forward) supply chains, only 36 articles of which apply quantitative models.

Table 2.1: Existing reviews in related areas. RL = Reverse Logistics, CL = Closed-Loop

Article	Facility location	Sustainability	Scope or special focus
Supply Chain Management			
Srivastava [2007]	○	●	Green SCM, RL, CL
Awudu and Zhang [2012]	○	●	Biofuel SCM, uncertainty
Dekker et al. [2012]	○	●	Green logistics
Soysal et al. [2012]	○	●	Quantitative models, food logistics
Nikolopoulou and Ierapetritou [2012]	○	●	Chemistry
Boukherroub et al. [2012]	○	●	Multi-criteria models
Brandenburg et al. [2014]	○	●	OR models and methods
Masoumik et al. [2014]	○	●	RL,CL
Barbosa-Póvoa [2014b]	○	○	Chemical process
Yue et al. [2014b]	○	○	Biomass-for-bioenergy
Arioglu Salmona et al. [2010]	×	●	
Sarkis et al. [2011]	×	●	Green SCM
Ashby et al. [2012]	×	●	
Miemczyk et al. [2012]	×	●	Purchasing
Seman et al. [2012]	×	●	Green SCM
Zailani et al. [2012]	×	●	Malaysia
Beske et al. [2013]	×	●	Dynamic capabilities, food industry
Seuring [2013]	×	●	Forward supply chain
Yusuf et al. [2013]	×	●	UK oil and gas supply chains
Ashby et al. [2012]	×	●	
Seuring and Müller [2008]	×	●	
Gupta and Palsule-Desai [2011]	×	●	
Johnsen et al. [2012]	×	●	
Supply Chain Network Design			
Terouhid et al. [2012]	●	●	Socially responsible location
Chen et al. [2014]	●	●	Manufacturing
Devika et al. [2014]	●	○	Forward, RL,CL
Zanjirani Farahani et al. [2014]	●	○	Competitive SCND
Beamon [1998]	●	×	
Owen and Daskin [1998]	●	×	
Daskin et al. [2005]	●	×	
M. and G. [2005]	●	×	
Sahin and Süral [2007]	●	×	
Akçali et al. [2009]	●	×	RL,CL
Melo et al. [2009]	●	×	
Aras et al. [2010]	●	×	RL,CL
Pati et al. [2013]	●	×	RL,CL, single objective
Hassini et al. [2012]	○	●	Metrics
De Meyer et al. [2014]	○	●	Biomass-to-bioenergy

Note that the review by Barbosa Póvoa [Barbosa-Póvoa, 2014b] concerns supply chain management, but with a strong emphasis on supply chain network design. The second category regroups review papers on SCND. Only 5 of them deal with sustainability.

Table 2.2 details the content of the reviews which could potentially cover the sections 3, 5 and 6 of our work: LCA based approaches (column 4), optimization models (column 5) and optimization methods (column 6). The last column reports the number of references also mentioned in the present review.

Table 2.2: Existing reviews in related areas

Article	Facility location	Sustainability	LCA	Optimization models	Optimization methods	# of shared references
Nikolopoulou and Ierapetritou [2012]	○	●	●	○	○	12
Boukherroub et al. [2012]	○	●	●	●	●	12
Dekker et al. [2012]	○	●	×	○	×	7
De Meyer et al. [2014]	○	●	×	●	●	5
Barbosa-Póvoa [2014b]	○	○	×	○	○	7
Yue et al. [2014b]	○	○	○	○	○	12
Terouhid et al. [2012]	●	●	×	×	×	1
Chen et al. [2014]	●	●	×	×	×	1
Devika et al. [2014]	●	○	×	●	●	10
Zanjirani Farahani et al. [2014]	●	○	×	×	×	9

Several reviews are dedicated to one activity: chemical and process industries [Barbosa-Póvoa, 2014b, Nikolopoulou and Ierapetritou, 2012], biomass-to-energy [De Meyer et al., 2014, Yue et al., 2014b].

Boukherroub et al. [2012] focus on multi-criteria decision making models for supply chain design. They point 42 papers with environmental or social concern, and 43 papers with facility location decisions, 12 of them having both characteristics. The broad review by Dekker et al. [2012] contains one section on facility location (7 shared papers).

Terouhid et al. [2012] and Chen et al. [2014] propose a framework for classifying the sustainability characteristics. They study the factors affecting location decisions, but these reviews do not review the quantitative models and methods. Devika et al. [2014] is a research paper including a section with a review of the literature.

We conclude that none of these reviews addresses the subject of OR models and methods for sustainable supply chain network design.

2.1.3 Distribution across the time period and main journals

Figure 2.1.3 displays the yearly distribution of the reference papers. A remarkable fact is that almost 90% of these papers have been published since 2008, making it clear that sustainable SCND has been receiving growing attention.

The reference papers can be found in 41 distinct journals, only 17 of them having published more than 1 paper. Figure 2.1.3 shows the distribution of the reference papers in these 17 journals, which represent 72% of the reference papers. The high number of papers in *Computers and Chemical Engineering* and *Industrial & Engineering Chemistry Research* underlines the importance of sustainability in chemical and process industry. Many papers are published in journals which focus on sustainability or on one field of application. For example, *Resources, Conservation and Recycling* and *Waste Management* fall into this category. On the other hand, the papers published in Industrial Engineering and Operational Research journals are spread out in a large variety of journals.

2.1.4 The 3 pillars of sustainable development

The reference papers do not all address the 3 dimensions of sustainable development: economic aspects, environmental performance and social responsibility. Figure 2.1.4 shows their distribution with respect to

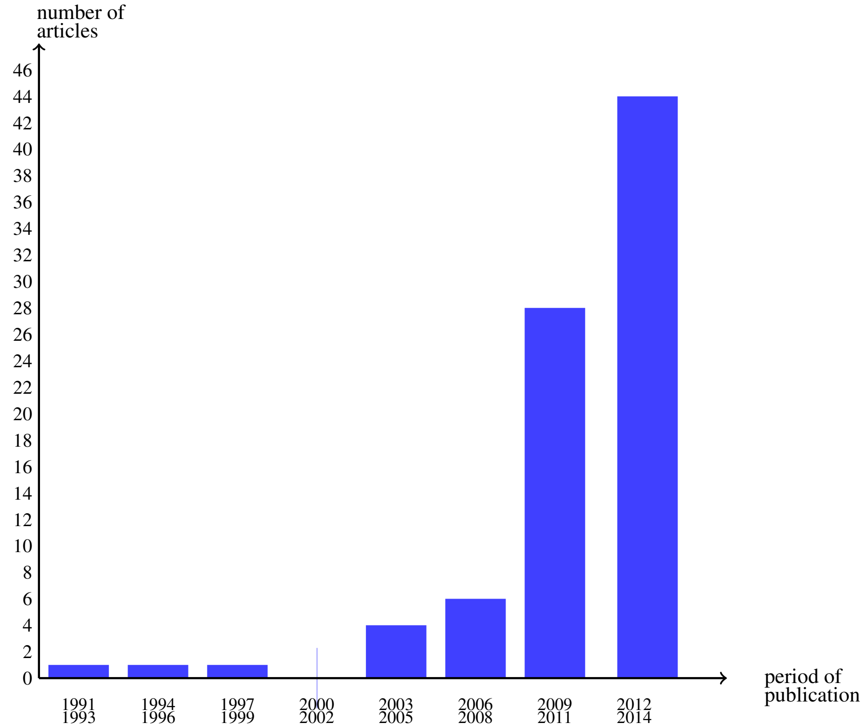

Figure 2.1: Time distribution of reference papers

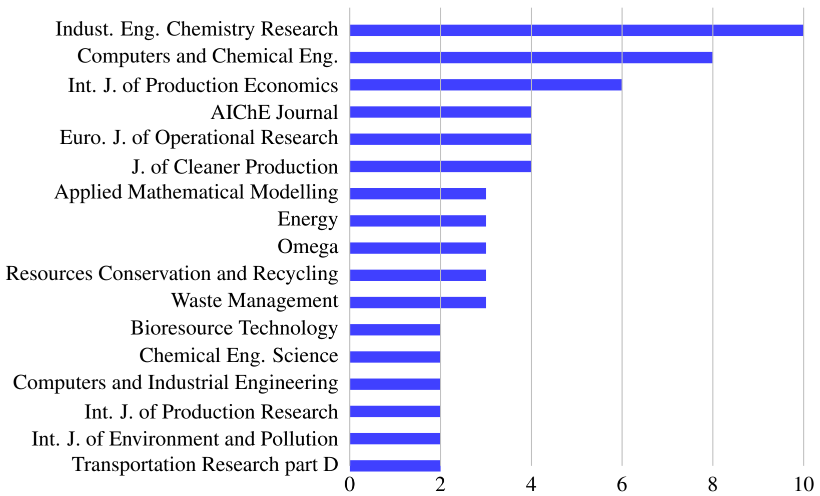

Figure 2.2: Distribution of reference papers by journal

these dimensions. This distribution is consistent with that already observed in other reviews, such as Chen et al. [2014]. The paucity of papers including social aspects has been already observed by many preceding reviews, and this is even more striking in quantitative models.

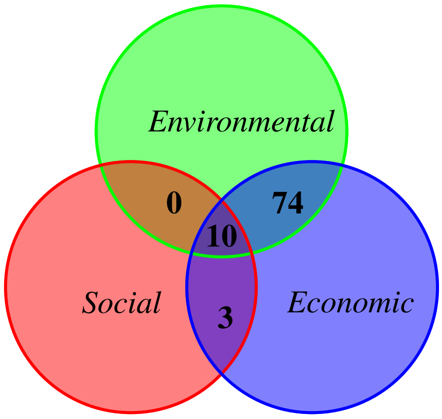

Figure 2.3: Distribution of reference papers with respect to the 3 sustainability dimensions

2.2 Environmental Supply Chain Network Design

Network design mathematical models traditionally aimed at minimizing cost or maximizing profit, with very little consideration of environmental objectives and constraints. The increasing importance of environmental issues has prompted decision-makers to incorporate environmental factors fully into the decision process [Ilgin and Gupta, 2010], giving birth to Environmental Supply Chain Network Design (ESCND). In other words, ESCND generalizes SCND by incorporating environmental factors, which may concern facilities, transportation modes, processes, product design, technological choices, etc. As shown for example in the case study in You and Wang [2011], the optimal solutions of pure economic, environmental or intermediate models differ a lot.

This raises several questions that should be clarified when designing supply chains. Which environmental factors should be considered? How can they be quantified? How can they be integrated into mathematical models and optimization methods?

Table 4 in Brandenburg et al. [2014] or Table 1 in Seuring [2013] show that many possible way to model environmental decision making: Life Cycle Assessment (LCA), reasoning maps, Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Data Envelopment Analysis (DEA), equilibrium models, simulation, etc. However, LCA is the most commonly used technique and it is particularly convenient to integrate its output in optimization models. Moreover, this technique is a general framework for a holistic assessment of a supply chain from extraction of raw material to disposal of end products. Thus, in subsection 2.2.1, we focus on papers which assess supply chain environmental impact through an LCA approach. Some reference papers adopt a full LCA approach and others only calculate one or a few LCA indicators which are further integrated into optimization models. These two approaches will be discussed in sections 2.2.1. Subsection 2.2.2 concerns papers that do not adopt an LCA approach. They rather propose partial assessment of environmental factors, focused on one or several dominating aspects of the application considered, for example emissions caused by transportation or facilities.

2.2.1 LCA based models

LCA assesses environmental impacts associated with all stages of a product life-cycle from raw material extraction to final disposal or recycling [ISO, 2006]. It compiles and evaluates inputs, outputs and potential environmental impacts of a product system throughout its manufacturing process (see the reviews by Azapagic [1999] and Pieragostini et al. [2012]), its life-cycle and all related supply chain decisions.

The Figure 2.4 represents the four main steps of LCA as defined by the ISO 14040 and 14044 standards [ISO, 2006].

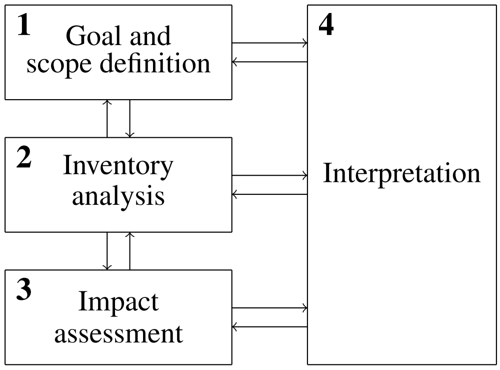

Figure 2.4: Conceptual framework of LCA [ISO, 2006]

1. *Goal and scope definition* sets out main objectives of the study, defines functional units considered and boundaries of the system.
2. *Inventory analysis* is inventory of all flows from and to nature for a product system. All emissions (in air, water and soil), extractions and land use are listed and quantified.
3. *Impact assessment* measures environmental impact of all emissions listed in the preceding step.
4. *Results interpretation* consists in analyzing and interpreting results of each of the three preceding steps. The outcome of the interpretation phase is a set of conclusions and recommendations for the study.

We found 39 papers that integrate principles of LCA into their supply chain network design models. Among the four LCA steps, we review the *goal and scope definition* and the *impact assessment* steps. The *inventory analysis* is an important intermediate step but it is directly related to supply chain decisions. The mathematical models resulting from the preceding steps are considered by several authors as a part of the *interpretation* step.

Scope definition

To determine boundaries of the supply chain is the first critical decision in LCA.

The *cradle-to-grave* scope assumes a comprehensive assessment of environmental impact through the whole supply chain from raw material to materials processing, manufacture, distribution, use, repair and maintenance, disposal and recycling. This category regroups 12 papers. In the context of fuel supply chains, cradle-to-grave is called well-to-wheel (WTW). For example, Elia et al. [2011] provide an analysis for hybrid coal, biomass, and natural gas to liquid (CBGTL) plants. The supply chain described includes both cultivation of biomass and coal and natural gas mining, followed by industrial and logistics operations. In the context of biomass supply chains, cradle-to-grave is called field-to-wheel (FTW). This is applied to cellulosic ethanol [You et al., 2012], sugar cane to ethanol [Mele et al., 2009] or to a general "biomass-to-liquid" supply chain [You and Wang, 2011].

The *cradle-to-gate* scope concerns all steps from extraction to the factory gate (23 papers). This scope is frequent for B2B companies having multiple customers. In fuel supply chains, this LCA scope is called *well-to-tank* in order to distinguish the GHG emitted during fuel production from those emitted by the vehicle operations. It is called *field-to-tank* in biomass supply chains.

Gate-to-gate (3 papers) generally concerns companies in intermediate echelons of a supply chain, which manufacture or transform and deliver goods to their customers without extracting raw materials or playing any role in disposal of end-of-life products. This scope is also used in transformation of end-of-life products

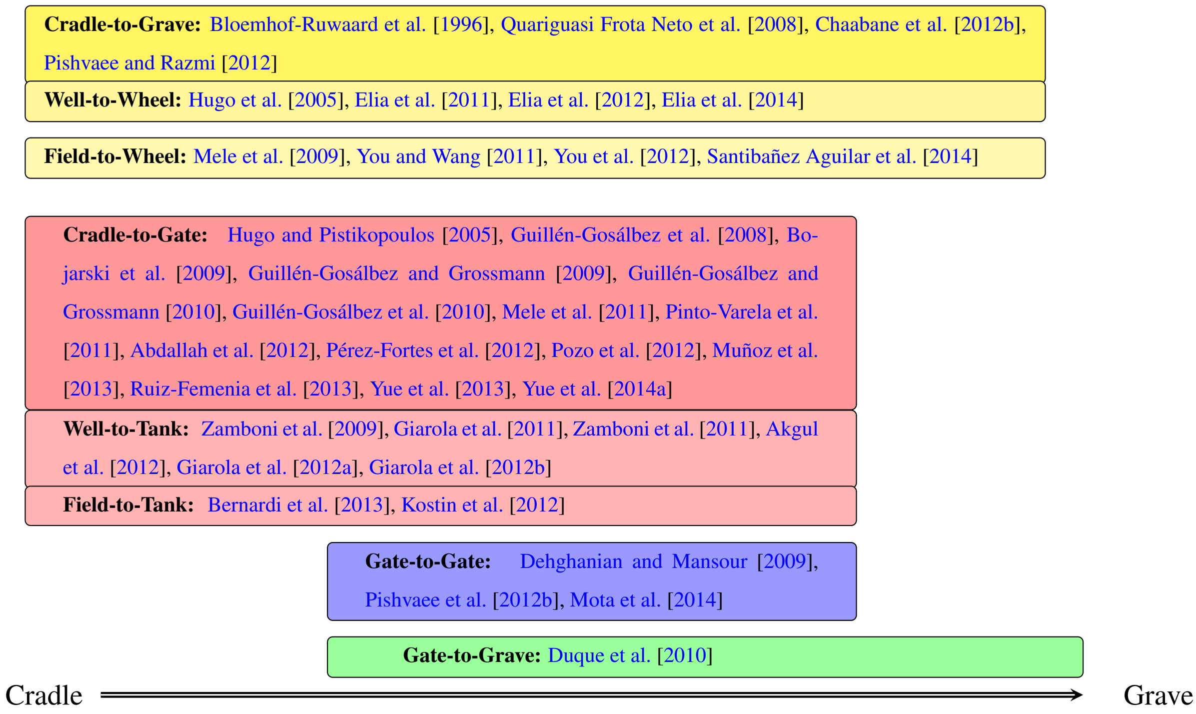

Figure 2.5: LCA scopes

which are re-used in the same or another supply chain. For example, Dehghanian and Mansour [2009] study a recovery network for scrap tires which can be used as a substitute for fuel in cement plants.

Gate-to-Grave (1 paper) focuses on the last steps of a supply chain, from factory gate to product disposal. This scope is convenient in the study of waste supply chains or reverse logistics activities.

Life-Cycle Impact Assessment

The goal of life-cycle impact assessment (LCIA) is to express the complex output of inventory analysis into a few environmental areas of interest. Mid-point oriented LCIA methods cover various impact categories such as greenhouse effect (or climate change), natural resource depletion, stratospheric ozone depletion, acidification, eutrophication, human toxicity, aquatic toxicity, etc. Damage-oriented methods (or endpoint methods) aggregate mid-point categories into fewer categories of damage: damage to human health, ecosystem health or damage to resources. There exist several LCIA methodologies, which include different midpoint and endpoint categories.

In the mathematical models described in the reference papers, the environmental assessment can be based either on midpoint or endpoint categories. Models can include exhaustive LCA or only a small subset of pertinent impact categories. We call the latter approach an *LCA-based approach*.

LCIA methods

The Table 2.3 lists papers based on endpoint methodologies. Three methods are described in reference papers: Eco-Indicator 99 (EI-99), Impact 2002+ and ReCiPe.

Eco-indicator 99 [Goedkoop and Spriensma, 2000] gathers 11 impact categories into three damage categories (human health, ecosystem quality and resources). The overall environmental impact is finally measured as a single metric. EI-99 is chosen in 15 papers, mainly with a cradle-to-gate scope.

Depending of the industrial activity, some impact categories can be omitted. For example, in the context of chemical supply chain, Hugo and Pistikopoulos [2005] use the 10 most relevant impact indicators.

IMPACT 2002+ [Jolliet et al., 2003] has 14 midpoint indicators and 4 categories of damage: human health, quality of ecosystems, climate change and resource depletion. It is used in 3 papers with a cradle-

Table 2.3: LCIA methods

Method	Articles
Eco-Indicator 99 (EI-99)	Pishvaee and Razmi [2012], Hugo and Pistikopoulos [2005], Guillén-Gosálbez et al. [2008], Guillén-Gosálbez and Grossmann [2009], Duque et al. [2010], Guillén-Gosálbez and Grossmann [2010], Mele et al. [2011], Abdallah et al. [2012], Pozo et al. [2012], Dehghanian and Mansour [2009], Chaabane et al. [2012b], Kostin et al. [2012],Santibañez Aguilar et al. [2014],Yue et al. [2013]
IMPACT 2002+	Bojarski et al. [2009], Pérez-Fortes et al. [2012], Muñoz et al. [2013]
CML92	Bloemhof-Ruwaard et al. [1996]
ReCiPe	Mota et al. [2014]

to-gate scope. In these papers, an overall environmental objective is the sum of all endpoint damages for each facility in the supply chain.

CML92 is used in Bloemhof-Ruwaard et al. [1996] with seven impact categories. **ReCiPe** [Goedkoop et al., 2009] has 18 midpoint categories combined into 3 endpoint damage categories (human health, ecosystems, resource surplus cost). This method also results in one single score.

Impact categories

The score provided by Eco-Indicator 99 or ReCipe can be easily incorporated into optimization models as an environmental objective function. However, although they use this approach, Pishvaee and Razmi [2012] claim that LCA process is costly, time consuming and needs expertise in environmental management. Several authors do not lead an exhaustive LCIA approach and only borrow one or a few impact categories which are directly integrated into their mathematical models. The papers that adopt this approach are listed in Table 2.4.

Table 2.4: Impact categories and indicators

Impact	Articles
Climate Change	Hugo et al. [2005], Quariguasi Frota Neto et al. [2008], Zamboni et al. [2009], Elia et al. [2011], Giarola et al. [2011], Mele et al. [2011], You and Wang [2011], Zamboni et al. [2011], Akgul et al. [2012], Chaabane et al. [2012b], Elia et al. [2012], Elia et al. [2012], Giarola et al. [2012a], Giarola et al. [2012b], Kostin et al. [2012], Pishvaee et al. [2012b],You et al. [2012], Bernardi et al. [2013], Ruiz-Femenia et al. [2013], Elia et al. [2014], Yue et al. [2014a]
Biochemical Oxygen Demand (BOD_{20})	Mele et al. [2009]
Damage to human health	Guillén-Gosálbez et al. [2010], Pinto-Varela et al. [2011], Kostin et al. [2012],
Water footprint	Bernardi et al. [2013]

Climate change is often quantified by the **Global Warming Potential (GWP)** indicator [IPCC, 2007]. It is captured by inventorying CO_2, CH_4, N_2O emissions and regrouping them in a single indicator expressed as CO_2-equivalent emissions during a predefined period, typically 100 years. GWP is mainly used with cradle-to-grave, well-to-wheel, field-to-wheel and well-to-tank scopes.

It is often used as a single indicator of environmental impact or is completed with some application dependent indicators: Bernardi et al. [2013] consider GWP and water footprint, which indicates the amount of freshwater consumed or polluted during the whole production process of a commodity.

Mele et al. [2009] measure environmental performance with biochemical oxygen demand (BOD_{20}), because of its importance as an indicator of pollution of watercourses.

There can be two reasons for resorting to partial LCIA approach instead of exhaustive LCIA: simplifying calculation or focusing on impacts which are most relevant for the application considered. Guillén-Gosálbez et al. [2010] explore the environmental benefits of adopting a hydrogen economy, in terms of overall contribution to climate change. For this reason, instead of calculating the EI-99 itself, they focus on only one of its impact categories: damage to human health caused by climate change. Pinto-Varela et al. [2011] calculate a partial EI-99 by only considering damage to human health caused by electricity and diesel consumption. Other authors choose to consider individual impact indicator to complement one LCIA score. Kostin et al. [2012] consider three impact categories from the EI-99 (damage to human health, damage to eco-system quality, damage to resource), the EI-99 itself, and the GWP. Mele et al. [2011] consider the EI-99 and the GWP.

2.2.2 Partial assessment of environmental factors

For various reasons, implementing a methodology such as LCA is not always possible. Awareness of environmental concerns in companies is generally gradual, so that assessing only a subset of environmental factors can be viewed as an intermediate step towards full integration. Partial assessment of environmental factors also makes sense when obtaining environmental data and modeling the whole supply chain is too difficult. This section has a structure similar to that of the preceding section. We first review the *scope* chosen for integrating environmental concerns, i.e. which activity in the supply chain is concerned. Then, we list the performance measures used in each paper.

Scope

The easiest way to partially assess environmental factors has been to enrich traditional SCND models with one or a number of environmental objectives, constraints or parameters. This keeps the focus on logistics operations in the supply chain, while integrating new concerns into the decision process. For example, knowing that transport and industrial facilities account for 22% and 20% of global CO_2 emissions respectively [OECD/IEA, 2012], several SCND models integrate CO_2 emissions due to transport or facilities.

Table 2.5 list three categories in which environmental criteria are most often incorporated: facilities, transport and product related criteria. Next paragraphs detail the content of this table.

- **Facilities**
  Since facility location is a central decision in SCND models, integrating environmental impact of facilities into mathematical models seems to be natural. This impact is considered in 28 of the papers in Table 2.5, but surprisingly enough only 6 of them measure the GHG emissions due to facilities. The most classic metric to assess the environmental impact of facilities is energy consumption, which can depend on sizing decisions and technological choices. The models by Amin and Zhang [2013], Caruso et al. [1993], Costi et al. [2004], Galante et al. [2010], Lam et al. [2013], Papapostolou et al. [2011], Pishvaee et al. [2012a] and Wang et al. [2011] include the choice between competing technologies as decision variables. Pishvaee et al. [2012a] integrate the average amount of waste generated with each technology in their environmental and social objective function. Other measures include the number of obnoxious facilities installed [Eskandarpour et al., 2013] (which is influenced by technological choices) or the risk placed on the nearby population [Alçada-Almeida et al., 2009].

Table 2.5: Scope used for partial assessment of environmental impact

Article	Facilities	Transport	Product
Caruso et al. [1993]	●		
Berger et al. [1999]	●		
Pati et al. [2008]	●		
Corsano et al. [2011]	●		
Erkut et al. [2008]	●		
Lira-Barragán et al. [2011]	●		
Pishvaee et al. [2012a]	●		
Eskandarpour et al. [2013]	●		
Costi et al. [2004]	●		
Minciardi et al. [2008]	●		
Alçada-Almeida et al. [2009]	●		
Saffar et al. [2015]	●		
Pourmohammadi et al. [2008]		●	
Galante et al. [2010]		●	
Elhedhli and Merrick [2012]		●	
Mallidis et al. [2012]		●	
Bouzembrak et al. [2013]		●	
Sadrnia et al. [2013]		●	
Xifeng et al. [2013]		●	
Zhang et al. [2013]		●	
Saffar et al. [2014]		●	
Harraz and Galal [2011]			●
Ramudhin et al. [2010]	●	●	
Chaabane et al. [2011]	●	●	
Harris et al. [2011]	●	●	
Liu et al. [2011]	●	●	
Tuzkaya et al. [2011]	●	●	
Wang et al. [2011]	●	●	
Jamshidi et al. [2012]	●	●	
Kannan et al. [2012]	●	●	
Kanzian et al. [2013]	●	●	
Lam et al. [2013]	●	●	
Govindan et al. [2013]	●	●	
Devika et al. [2014]	●	●	
Marufuzzaman et al. [2014]	●	●	
Mohammadi et al. [2014]	●	●	
Papapostolou et al. [2011]	●		●
Amin and Zhang [2013]	●		●
Krikke et al. [2003]	●	●	●
Krikke [2011]	●	●	●
Abdallah et al. [2013]	●	●	●
Diabat et al. [2013]	●	●	●
Baud-Lavigne et al. [2014]	●	●	●

- **Transport**
  One of the easiest ways to incorporate environmental criteria into pure economic models is to calculate emissions of GHG and particulates due to transport. Tools for calculating and converting emissions into a single CO_2 equivalent measurement can be provided by national or regional organizations, such as the Mobile6 software used by Elhedhli and Merrick [2012] for heavy duty diesel vehicles.
  Some models integrate selection of transportation modes into strategic network design decisions. In these models, transportation modes generally compete on cost, environmental impact and capacity. The choice between transportation modes can also be determined by loading/unloading conditions, frequency, minimum lot-size etc.
  Since SCND models generally consider aggregated data, operational characteristics such as vehicle speed and daily variations are mostly ignored. We did not find any reference considering more global assessment of transportation, such as impact of vehicles on road network.
- **Process and product design**
  Decisions concerning product flows and design can also be fully integrated into environmental SCND. Krikke et al. [2003] propose a Mixed-Integer Linear Program (MILP) whose decision variables concern both network design and product design. They analyze interactions between both types of variables and conclude that logistics network structure has most impact on costs, whereas product design has most impact on energy and waste. Abdallah et al. [2013] observe that price of raw material increases as the product becomes greener. Thus, supplier selection has contradictory impact on cost and environmental dimension [Kumar et al., 2014]. Amin and Zhang [2013] assess impact of choosing environmentally-friendly materials in the production process.

Performance measures

According to Krikke et al. [2003] or Harraz and Galal [2011], given LCA complexity, it becomes regular practice to use more pragmatic indicators such as residual waste and energy used.

Ahi and Searcy [2015] identified 2555 unique metrics to measure performance in green and sustainable supply chains. Due to lack of a generic assessment methodology, a wide range of *ad hoc* performance measures have been developed to assess environmental performance of a supply chain, so that identifying the most appropriate performance measures is still a challenging issue [Nikolopoulou and Ierapetritou, 2012].

Table 2.6 details the metrics found in the reference papers for assessing the environmental impact. Columns 2–6 report various families of performance measures: GHG emissions (column 2), amount of waste generated (column 3), energy consumption (column 4), amount of material recycled (column 5) and others measures (column 6).

- **Carbon footprint**
  The most popular metric for measuring environmental impact is the carbon footprint, which is the total amount of GHG emitted by a company or a supply chain (25 papers). All GHG emissions may be considered, but for practical reasons, baseline indicators with only CO_2, CH_4 and N_2O are also used [Wright et al., 2011]. For example, Jamshidi et al. [2012] consider two objective functions: one minimizes the total costs within the supply chain and the other one minimizes dangerous gases produced, such as NO_2, CO and Volatile Organic Compounds.
  GHG emissions are not always calculated explicitly. In Pourmohammadi et al. [2008] the amount of GHG emitted is considered through an input-output approach to estimate the cost of air pollution. In Harris et al. [2011], the quantity of energy used is a mean to estimate GHG emissions.
- **Waste generated, energy use, material recovery and other measures**
  Environmental performance can be measured by many possible criteria which generally arise from the economic sector concerned. The quantity of waste generated is mentioned in 16 papers, the use of energy is included in 8 models and the material recovery in 7 models. For example, Pati et al. [2008]

Table 2.6: Metrics used for partial assessment of environmental impact

Article	GHG emissions	Waste	Energy use	Material recovery	Others
Ramudhin et al. [2010]	●				
Chaabane et al. [2011]	●				
Krikke [2011]	●				
Wang et al. [2011]	●				
Elhedhli and Merrick [2012]	●				
Jamshidi et al. [2012]	●				
Kannan et al. [2012]	●				
Mallidis et al. [2012]	●				
Abdallah et al. [2013]	●				
Diabat et al. [2013]	●				
Govindan et al. [2013]	●				
Kanzian et al. [2013]	●				
Sadrnia et al. [2013]	●				
Xifeng et al. [2013]	●				
Zhang et al. [2013]	●				
Baud-Lavigne et al. [2014]	●				
Marufuzzaman et al. [2014]	●				
Saffar et al. [2014]	●				
Saffar et al. [2015]	●				
Caruso et al. [1993]		●			
Berger et al. [1999]		●			
Lira-Barragán et al. [2011]		●			
Pishvaee et al. [2012a]		●			
Eskandarpour et al. [2013]		●			
Galante et al. [2010]			●		
Pati et al. [2008]				●	
Lira-BarragÃąn et al. [2013]					●
Verma et al. [2013]					●
Alçada-Almeida et al. [2009]	●	●			
Liu et al. [2011]	●	●			
Lam et al. [2013]	●	●			
Devika et al. [2014]	●	●			
Harris et al. [2011]	●		●		
Tuzkaya et al. [2011]	●				●
Krikke et al. [2003]		●	●		
Harraz and Galal [2011]		●		●	
Amin and Zhang [2013]			●	●	
Corsano et al. [2011]			●	●	
Papapostolou et al. [2011]			●		●
Costi et al. [2004]	●	●		●	
Erkut et al. [2008]	●	●		●	
Minciardi et al. [2008]	●	●		●	
Bouzembrak et al. [2013]	●	●			●
Mohammadi et al. [2014]	●		●		●
Pourmohammadi et al. [2008]		●	●	●	●

measure the value of wastepaper recovered by a paper recycling system. Amin and Zhang [2013] measure the use of renewable and recycled energy, such as solar power. Finally, 7 papers use criteria that cannot be classified in the preceding categories. Other metrics include use of water [Caruso et al., 1993, Lira-BarragÃąn et al., 2013, Papapostolou et al., 2011], noise pollution [Bouzembrak et al., 2013, Mohammadi et al., 2014] or an overall estimation of long-term impact and cleanup cost of oil-spill caused by vessels [Verma et al., 2013]. Pourmohammadi et al. [2008] measure a *virgin material opportunity costs* which is the extra expense that a firm is willing to pay when it refuses to substitute the virgin material market by an acceptable recycled material. Other metrics are sometimes not detailed, such as the land specific technical requirement in Tuzkaya et al. [2011].

2.2.3 Conclusion

The integration of environmental criteria in SCND is a natural idea for activities with a high impact. The 83 papers dealing with environmental SCND share almost equally between LCA (39) and non-LCA (44) approaches. The most popular LCIA methods are Eco-Indicator 99 and Impact 2002+. To our knowledge, ReCipe has been used only in Mota et al. [2014]. Since it is a more recent method and it provides a single score, more authors are likely to use it in forthcoming years. As far as impact indicators are concerned, GWP is particularly designed for very long-horizon activities such as process industries or fuel/energy supply chains. Other indicators are used when they are relevant for their respective domain of application. Non-LCA approaches measure environmental performance on tangible domains (facilities, transport, product design) and measures (GHG emission, waste produced, energy used etc.). This goes along with a collection of various ad hoc measures depending on the application considered.

Finally, let us point out 2 papers about sustainable extensions to special facility location problems: the hub location problem [Mohammadi et al., 2014] and the location routing problem [Govindan et al., 2013]. Incorporating environmental criteria into these problems seems to be a novel research issue.

2.3 Social Supply Chain Network Design

Social sustainability has been examined to a far lesser degree than environmental or green supply chain management [Seuring and Müller, 2008]. Furthermore the definition of social sustainability itself is still under development [BenoÃőt-Norris, 2014]. Social sustainability in supply chains addresses issues of social justice and human rights with studies focusing on practices such as supplier human rights actions, labor conditions, codes of practices and social auditing, supplier compliance with child labor laws, and the delivery of social equity through sourcing from diverse suppliers in terms of gender, size, ethnicity and avoidance of conflicts of interest. Including social aspects in network design decisions allows to better evaluate the impact of a supply chain on its stakeholders: employees, customers and local communities. This also helps obtaining consistency between qualitative and quantitative decisions. We analyze 13 references papers having an assessment of social impact with the framework proposed in Chardine-Baumann and Botta-Genoulaz [2014]. The Table 2.7 presents this classification. Columns 2 to 4 correspond to 3 of the 5 fields proposed in Chardine-Baumann and Botta-Genoulaz [2014]. It is worth noting than no paper addresses the two last fields: human rights (child and forced labor, freedom of association, discrimination) and business practice (fight against corruption, fair-trading, promotion of corporate social responsibility in the sphere of influence). Reference papers followed by a * do not include the environmental dimension.

In the field *work conditions*, employment is the main social indicator used in literature. The number of jobs created is considered by most authors, with slight variations. Mota et al. [2014] define a *social benefit indicator* which prefers job creation in the less developed regions. Devika et al. [2014] distinguish the fixed jobs opportunities (which are independent of the level of activity) from the variables jobs (which increase with the level of activity). Dehghanian and Mansour [2009] aim at creating jobs in the widest range of communities. They maximize the number of facilities installed, which corresponds to the idea of fixed jobs

Table 2.7: Models with the social dimension

Article	Work conditions	Societal commitment	Customer issues
Harraz and Galal [2011]	●		
Pérez-Fortes et al. [2012]	●		
Pishvaee et al. [2012a]	●		
You et al. [2012]	●		
Devika et al. [2014]	●		
Mota et al. [2014]	●		
Santibañez Aguilar et al. [2014]	●		
Yue et al. [2014a]	●		
Caruso et al. [1993]		●	
Datta [2012]*		●	
Bouzembrak et al. [2013]		●	
Beheshtifar and Alimoahmmadi [2014]*		●	
Malczewski and Ogryczak [1990]*			●
Tuzkaya et al. [2011]	●	●	
Dehghanian and Mansour [2009]	●	●	●

in Devika et al. [2014]. The damage to workers and security measures, such as the exposure to chemical elements is considered in Dehghanian and Mansour [2009] and Pishvaee et al. [2012a].

The *Societal commitment* field regroups all decisions contributing to improve a population's health, education, culture [Datta, 2012]. It includes local development policies [Dehghanian and Mansour, 2009], equity in access to healthcare [Beheshtifar and Alimoahmmadi, 2014], the impact of the supply chain on real estate [Bouzembrak et al., 2013], but also the political opposition [Caruso et al., 1993, Tuzkaya et al., 2011].

The field *customer issues* regroup all impacts individually affecting each customers. Malczewski and Ogryczak [1990] consider the environmental pollution at hospital sites as a social criterion since its impact relates directly to patients and users. In Dehghanian and Mansour [2009], the customer issue concerns the risk of using recycled material.

As pointed by several previous reviews, including social concerns into sustainable SCND models raises many modeling and assessment difficulties. First of all, social responsibility is a fully multi-disciplinary and multi-stakeholder issue [Pishvaee et al., 2012a]. As a consequence, social performance is generally hard to model with pertinent quantitative indicators. For example, Chaabane et al. [2012b] state that tangible indicators such as noise and pollution can play the role of indicators of both environmental and social performance. However, they do not integrate them in their MILP since they do not identify good measures of social sustainability. Moreover, social and environmental impacts sometimes strongly interact. Pishvaee et al. [2012a] aggregate three social impacts and one environmental impact (amount of waste generated) into a single indicator. Since the social impact is often qualitative by nature, it is difficult to build a single metric to measure it. Multi-Criteria Decision Making (MCDM) can be a suitable tool to overcome this problem. Dehghanian and Mansour [2009] aggregate their four social criteria into a single indicator with an Analytical Hierarchy Process (AHP) [Saaty, 1990]. AHP is also used in Datta [2012]. Hence, selecting the most appropriate criteria and incorporating them into mathematical models are still challenging issues.

2.4 Modeling Approaches

In this section, we review the main characteristics of mathematical models for sustainable supply chain design problems. Such problems have resulted in a large variety of models. This can be explained not only by the variety of industrial contexts (single or multiple period, single or multiple products, structure of the logistics network), but also by modeling issues: single or multiple objectives, deterministic or uncertain data.

The main decision variables in SCND models are binary variables concerning the location of facilities, sizing decisions, the selection of suitable technology levels and the selection of transportation modes between facilities. Since product flows along the supply chain are generally modeled by continuous constraint, the SCND models are often mixed-integer formulations, which can be linear or nonlinear. Some stochastic models are also found that enable the consideration of uncertainties such as the demand level.

The section is organized into two parts. In section 2.4.1, we review the models with a single objective function. This objective can be either economic or environmental, but is never social only. Multi-objective models are then described in section 2.4.2. Both sections are divided into two subsections, describing deterministic and stochastic models, respectively.

2.4.1 Models with a single objective

The easiest way to incorporate environmental issues into classic SCND models is to express the objective function as a weighted average of all objective functions. This requires applying conversion factors to convert non-homogeneous measures into a single one.

For example, when the whole environmental impact can be expressed through a quantity of GHG emissions, it is possible to convert the environmental impact into its monetary equivalent by using conversion factors. Then the monetized environmental damage can be aggregated with the economic objective into a single objective.

The main characteristics of single objective deterministic and stochastic models are summarized in Table 2.8.

Deterministic models

As mentioned above, some authors consider the economic objective as the main one and represent the environmental dimension by constraints in their models. These constraints may express a maximal authorized level of GHG emissions. For example, the objective function in Elia et al. [2011] is to minimize the cost of facility investment, feedstock purchase and transportation. The authors introduce an environmental constraint by imposing an overall GHG emission target level for each hybrid coal, biomass and natural liquid gas plant. Papapostolou et al. [2011] consider a pure economic objective function. Environmental constraints limiting the land use and water consumption are included in their linear model.

Other authors mix economic and environmental criteria into the objective function. In Elhedhli and Merrick [2012], the objective function includes two terms related to pollution cost and three terms related to the cost of logistics operations. In Abdallah et al. [2012] and Kannan et al. [2012] the objective function is the sum of various logistics costs and an additional term associated with CO_2 emissions above the amount allocated by the government.

Lira-Barragán et al. [2011] minimize the total annual cost of a new industrial plant which impacts the water quality throughout a surrounding watershed. The objective function includes the wastewater treatment costs whereas the water quality appears as a constraint. Mallidis et al. [2012] propose a model with several objective functions related to cost, and the emission of CO_2 or particulate matters (fine dust). The model is solved with each objective being considered one by one.

Note that Krikke [2011] proposes a *linear variant of mixed integer programming*: binary facility location variables are pre-fixed, resulting in one linear program for each scenario.

In some of the reference papers, the technical context leads to the formulation of nonlinear models. Costi et al. [2004] propose an MINLP model for the location of treatment facilities for solid waste management. The objective function concerns the economic cost and environmental issues are modeled as constraints. The binary decision variables concern the existence of facilities. Continuous variables model the material flows between facilities. Non-linearity comes from multiplications between continuous variables. Corsano et al. [2011] consider ethanol plant design and ethanol supply chain design simultaneously. Non-linearity arises from some non-convex constraints in the ethanol plant design model.

Table 2.8: Models with single objective

Article	Dimensions	Multi-product	Multi-period	Multi-mode
Linear models				
Krikke [2011]	Eco - Env			
Datta [2012]	Eco - Soc			
Elhedhli and Merrick [2012]	Eco - Env			
Kannan et al. [2012]	Eco - Env			
Bloemhof-Ruwaard et al. [1996]	Eco - Env	●		
Liu et al. [2011]	Eco - Env	●		
Papapostolou et al. [2011]	Eco - Env	●		
Abdallah et al. [2012]	Eco - Env	●		
Abdallah et al. [2013]	Eco - Env	●		
Amin and Zhang [2013]	Eco - Env	●		
Diabat et al. [2013]	Eco - Env	●		
Mallidis et al. [2012]	Eco - Env			●
Bouzembrak et al. [2013]	Eco - Env - Soc			●
Elia et al. [2011]	Eco - Env	●		●
Elia et al. [2012]	Eco - Env	●		●
Elia et al. [2014]	Eco - Env	●		●
Stochastic linear models				
Verma et al. [2013]	Eco - Env			
Giarola et al. [2012a]	Eco - Env	●	●	
Non-linear models				
Lira-BarragÃąn et al. [2013]	Eco - Env			
Verma et al. [2013]	Eco - Env			
Costi et al. [2004]	Eco - Env	●		
Corsano et al. [2011]	Eco - Env	●		
Lira-Barragán et al. [2011]	Eco - Env	●		

Stochastic models

By definition, sustainable SCND models aim at impacting the structure of the logistics network of a company in the long term. It is therefore realistic to expect to face uncertainties in the analysis of the problem. This is particularly true for the consideration of the uncertainties on the level of customer demands within a strategic planning horizon. Other factors such as transportation costs or the amount of waste or emissions generated or returned products may also be considered as uncertain parameters. Moreover, the data available at the moment strategic decisions are made are generally aggregated and lose accuracy as the time horizon recedes. A survey on the inclusion of stochastic components in facility location models is proposed by Snyder [2004].

However we found only two references of single objective stochastic models for sustainable SCND problems. Giarola et al. [2012a] propose a MILP for the design of a bio-ethanol supply chain, in which the costs of carbon and biomass are considered as uncertain parameters. To overcome this uncertainty, a two-stage stochastic programming approach is used. Verma et al. [2013] present a two-stage stochastic programming approach which tackles both the location and stockpile of equipment at emergency response facilities that deal with potential oil-spill emergencies on the south cost of Newfoundland in Canada. Their model includes two variants corresponding to linear and non-linear formulation of equipment acquisition cost.

2.4.2 Multi-objective models

Deterministic models

The deterministic multi-objective models for sustainable SCND are summarized in Table 2.9 (linear models) and Table 2.10 (non-linear models)

In practice, most sustainable SCND models are bi-objective linear models. Many authors see the economic objective as the traditional objective function, whereas the environmental or social objectives are considered as extensions of the traditional single objective models. A frequent modeling approach is to consider one economic objective and one environmental objective such as minimizing GHG emissions.

Amin and Zhang [2013] extend their mono-objective model by considering an additional environmental objective. In the area of domestic waste treatment, Berger et al. [1999] propose a comprehensive multi-periodic MILP model for the strategic design and tactical planning of an integrated regional solid waste management planning. The model considers several types of treatment technologies and sites for treatment and land-fill as well as the possibility of recycling waste on the markets. Several environmental parameters and indicators may be used.

Chaabane et al. [2012b] propose a bi-objective model for the design of an aluminum supply chain. A carbon credit component is included in the economic objective, whereas the second objective is to minimize the GHG emissions. The model also considers tactical issues such as inventory control decisions. Akgul et al. [2012] propose a multi-period, multi-product MILP model for the optimization of a biofuel supply chain regarding cost and environmental issues. All stages of the biofuel life-cycle, such as cultivation, transportation and production, are integrated into the proposed model. Quariguasi Frota Neto et al. [2008] propose a bi-objective model to assess the flow of materials, the amount of production at each plant and to select the most suitable end-of-use alternatives, such as refurbishing and recycling. Guillén-Gosálbez et al. [2010] develop a bi-objective MILP model for a hydrogen supply chain design. The influence of the hydrogen network operation on climate change is investigated as an environmental issue. In chance-constrained programming, the models embed the probability of satisfying constraints subject to uncertain data. The model considers capacity expansion (see also Hugo et al. [2005]).

A two-echelon multiple-vehicle locationâĂŞrouting problem with time windows for optimization of sustainable supply chain network of perishable food is studied by Govindan et al. [2013]. They propose a deterministic model involving an economic goal for the minimization of all fixed and variable costs and an environmental goal for the global minimization of environmental impacts of opening manufacturing and

Table 2.9: Deterministic multi-objective linear models

Article	Dimensions	multi-product	multi-period	multi-mode
Malczewski and Ogryczak [1990]	Eco-Soc			
Caruso et al. [1993]	Eco-Env-Soc			
Erkut et al. [2008]	Eco-Env			
Minciardi et al. [2008]	Eco-Env			
Alçada-Almeida et al. [2009]	Eco-Env			
Dehghanian and Mansour [2009]	Eco-Env-Soc			
Galante et al. [2010]	Eco-Env			
Tuzkaya et al. [2011]	Eco-Env-Soc			
Pozo et al. [2012]	Eco-Env			
Xifeng et al. [2013]	Eco-Env			
Govindan et al. [2013]	Eco-Env			
Devika et al. [2014]	Eco-Env-Soc			
Krikke et al. [2003]	Eco-Env	●		
Pati et al. [2008]	Eco-Env	●		
Quariguasi Frota Neto et al. [2008]	Eco-Env	●		
Harraz and Galal [2011]	Eco-Env-Soc	●		
Amin and Zhang [2013]	Eco-Env	●		
Lam et al. [2013]	Eco-Env	●		
Baud-Lavigne et al. [2014]	Eco-Env	●		
Hugo et al. [2005]	Eco-Env		●	
Jamshidi et al. [2012]	Eco-Env			●
Kanzian et al. [2013]	Eco-Env			●
Sadrnia et al. [2013]	Eco-Env			●
Hugo and Pistikopoulos [2005]	Eco-Env	●	●	
Pourmohammadi et al. [2008]	Eco-Env	●	●	
Mele et al. [2009]	Eco-Env	●	●	
Bojarski et al. [2009]	Eco-Env	●	●	
Pinto-Varela et al. [2011]	Eco-Env	●	●	
Zamboni et al. [2011]	Eco-Env	●	●	
Giarola et al. [2012b]	Eco-Env	●	●	
Pérez-Fortes et al. [2012]	Eco-Env-Soc	●	●	
Zamboni et al. [2009]	Eco-Env	●		●
Ramudhin et al. [2010]	Eco-Env	●		●
Chaabane et al. [2011]	Eco-Env	●		●
Mota et al. [2014]	Eco-Env-Soc	●		●
Marufuzzaman et al. [2014]	Eco-Env		●	●
Berger et al. [1999]	Eco-Env	●	●	●
Duque et al. [2010]	Eco-Env	●	●	●
Guillén-Gosálbez et al. [2010]	Eco-Env	●	●	●
Giarola et al. [2011]	Eco-Env	●	●	●
Mele et al. [2011]	Eco-Env	●	●	●
You and Wang [2011]	Eco-Env	●	●	●
Akgul et al. [2012]	Eco-Env	●	●	●
Chaabane et al. [2012b]	Eco-Env	●	●	●
Kostin et al. [2012]	Eco-Env	●	●	●
You et al. [2012]	Eco-Env-Soc	●	●	●
Bernardi et al. [2013]	Eco-Env	●	●	●
Santibañez Aguilar et al. [2014]	Eco-Env-Soc	●	●	●

distribution facilities and for the emissions due to shipments between facilities.

Very few models have more than three objective functions. Erkut et al. [2008] develop a multi-criteria facility location model for the municipal solid wastes management at the regional level in North Greece. Their MILP model includes 5 objective functions : 1 relative to minimum total cost of facilities implementation and flows, and 4 related to the environmental impacts (GHC effects, landfilling, energy and materials recovery. A solution to the model consists of locations and technologies for transfer stations, material recovery facilities, incinerators and sanitary landfills, as well as the waste flow between these locations.

Table 2.10: Deterministic multi-objective non-linear models

Article	Dimensions	multi-product	multi-period	multi-mode
Beheshtifar and Alimoahmmadi [2014]	Eco-Soc			
Guillén-Gosálbez et al. [2008]	Eco-Env	●		
Muñoz et al. [2013]	Eco-Env	●	●	
Zhang et al. [2013]	Eco-Env	●		●
Eskandarpour et al. [2013]	Eco-Env	●		
Wang et al. [2011]	Eco-Env	●		
Yue et al. [2014a]	Eco-Env-Soc		●	
Liu et al. [2011]	Eco-Env	●	●	
Yue et al. [2013]	Eco-Env	●		●

Only a few bi-objective models are non-linear. In Beheshtifar and Alimoahmmadi [2014], one of the objective is to minimize the standard deviation of distances from the place of demand points to the open facilities. Due to economies of scale, Zhang et al. [2013] includes non-linear CO_2 emissions due to transportation. In the last five references in the Table, the models can be linearized. Yue et al. [2014a] and Yue et al. [2013] linearize their model with the Charnes-Cooper transformation and Glover's linearization. The authors compare the performance of the linear and non-linear formulations of their models.

Stochastic models

Like many supply chain management problems, SCND problems are subject to uncertainty. Uncertainty can have many different sources, like the level of demand or the proportion of returned products in closed-loop supply chains. Uncertainty can also affect the outputs and depend on the performance of the process. Such an example is the level of GHG emissions. As pointed out by Guillén-Gosálbez and Grossmann [2009], many uncertainties exist in the life-cycle inventory but many LCA methods assume nominal values for the input data. These authors mention however that the Eco-indicator 99 methodology is affected by three main sources of uncertainty: the operational or data uncertainty, but also the fundamental or model uncertainties, and the uncertainty on the completeness on the model. If well taken into account, uncertainty will impact the design of a supply chain. The number and size of production and transport facilities clearly depends on the mean values of input data, but also of their possible variation. Uncertainty will also affect the evaluation of a supply chain in terms of costs, GHG emissions, etc.

The stochastic multi-objective models encountered in our review are summarized in Table 2.11.

In Pishvaee et al. [2012a], a first objective function minimizes a sum of logistics costs and a second objective function aggregates the four social and environmental impacts already presented in section 2.3. Amin and Zhang [2013] extend their deterministic model by considering uncertain demand and amount of returned products. They use a scenario-based stochastic programming approach.

Ruiz-Femenia et al. [2013] study the effect of demand uncertainty on the economic and environmental performance of supply chains. Their model seeks to maximize the expected profit and minimize the probability for environmental factors to exceeding a given limit.

Table 2.11: Stochastic multi-objective models

Article	Dimensions	Multi-product	Multi-period	Multi-mode
Linear models				
Pishvaee et al. [2012a]	Eco - Env - Soc			
Ruiz-Femenia et al. [2013]	Eco - Env	●	●	
Saffar et al. [2014]	Eco - Env	●	●	
Saffar et al. [2015]	Eco - Env	●	●	
Pishvaee and Razmi [2012]	Eco - Env			
Pishvaee et al. [2012b]	Eco - Env			●
Amin and Zhang [2013]	Eco - Env	●		
Non-linear models				
Guillén-Gosálbez and Grossmann [2009]	Eco - Env	●	●	
Guillén-Gosálbez and Grossmann [2010]	Eco - Env	●	●	
Mohammadi et al. [2014]	Eco - Env			

Guillén-Gosálbez and Grossmann [2009] provide a MINLP model to maximize the net present value and minimize the environmental impact for chemical supply chains, with uncertainty about the amount of emissions released and the feedstock requirement. In Guillén-Gosálbez and Grossmann [2010], the value of damage factors is considered an uncertain parameter so a chance-constraint model is applied to handle them.

Mohammadi et al. [2014] propose a novel variant of the hub location model called the sustainable hub location problem (SHLP) in which two new environmental-based cost functions accounting for air and noise pollution of vehicles are incorporated and related to fuel consumption. The cost of emission at the hubs is also considered. To cope with uncertain data incorporated in the model, a mixed possibilisticâĂŞstochastic programming approach is proposed to construct the crisp counterpart, resulting in a mixed integer nonlinear programming (MINLP) optimization model according to the nonlinear form of the objective functions.

Fuzzy set theory [Zadeh, 1978] provides an efficient tool to capture the imprecision of data. It is employed when there are not enough historical data to estimate probability distribution functions of uncertain parameters. This approach is chosen in Pishvaee and Razmi [2012], Pishvaee et al. [2012a] and Pishvaee et al. [2012b].

Pinto-Varela et al. [2011] model two case studies in a Portuguese industry with multiple products and periods. Their approach includes a fuzzy-like modeling to indicate the trade-off between the economic and environmental objectives considered. Like in Guillén-Gosálbez and Grossmann [2009], the stochastic model is converted into a deterministic one to facilitate its solution.

2.4.3 Conclusions on modeling

In summary, a large variety of modeling techniques have been used in order to address sustainable SCND problems among which most used techniques are MIP for linear or non linear problems. Non linearity often arises from the modeling of non-linear industrial processes.

Some models consider a single objective aggregating the economic and environmental or sometimes social factors. However most of the models explicitly consider two or three different objectives functions (or sometimes more) , which is natural to cope with the different dimensions of sustainable development. Since the social impact can be difficult to quantify, it is sometimes not addressed explicitly into a mathematical model, but rather in a preliminary step of scenario definition or in a post-optimization evaluation of the solutions

2.5 Solution Methods

The goal of this section is to review the solution methods and the tools employed for solving sustainable SCND models. SCND problems are NP-hard [Pishvaee et al., 2010a], since they generalize facility location problems. However, instances of average size are still tractable by mathematical solvers. Thus a large variety of solution methods are used. This section is divided into three subsections. Subsection 2.5.1 reviews the methods used for solving single-objective models. This includes multi-objective models for which the objective function is a weighted sum of the objectives. Subsection 2.5.2 is devoted to methods for multi-objective models: ε-constraint, metaheuristics, multi-criteria decision analysis (MCDA), and other methods. Finally, subsection 2.5.3 describes the use of modeling tools and solvers in all reference papers.

2.5.1 Solution methods for models with a single objective

Heuristics and metaheuristics are widely applied in the SCND literature, but still rarely employed in sustainable SCND. Elhedhli and Merrick [2012] use Lagrangean relaxation to decompose their three-echelon model into a capacitated facility location problem with single sourcing and a concave knapsack problem that can be solved easily. The Lagrangean relaxation is completed with a Lagrangean heuristic which finds a near-optimal solution for a set of instances with up to 10 suppliers, 20 plants and 150 customers. Tuzkaya et al. [2011] use the weighted sum to integrate the two objective functions of their bi-objective model. Then they resort to a genetic algorithm to solve single objective models.

2.5.2 Solution methods for multi-objective models

The multi-objective methods for solving sustainable SCND models are summarized in Table 2.12.

Weighted sum of objectives

An intuitive approach to handle multi-objective models is to weight each criterion and to minimize the weighted sum of all criteria. The main advantage of this approach is to model and solve multi-objective problems with single-objective approaches. Unfortunately, this modeling may not represent the decision-maker's interest and may modify the Pareto structure of the problem [Pozo et al., 2012]. It can be used only when the Pareto set is convex. Such an approach is chosen in Bernardi et al. [2013] where the three conflicting objectives are the economic one, the impact on global warming, and the impact on water resources.

Pinto-Varela et al. [2011] use a symmetric fuzzy linear programming (SFLP) for a bi-objective model. The model maximizes a single variable $0 \leq \lambda \leq 1$ representing the degree to which each objective must be satisfied.

Epsilon-constraint

The ε-constraint method consists in prioritizing a primary objective while expressing other objectives as constraints. Fixing various values of constraint enables the Pareto front to be approximated. 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.

The model in Pérez-Fortes et al. [2012] includes economic, social and environmental criteria. Since the social metric is discrete, only the environmental criterion is represented in the ε-constraint and the authors represent one Pareto front for each possible value of the social metric.

Guillén-Gosálbez and Grossmann [2009] and Guillén-Gosálbez and Grossmann [2010] propose bi-criteria MINLPs. In Guillén-Gosálbez and Grossmann [2009], the environmental criterion is transferred to the ε-constraint. The MINLP model is decomposed into two levels: a master convex MINLP is solved to provide a vector of integer variables. In the second level, a continuous nonlinear problem is solved to

Table 2.12: Solution methods for multi-objective models

Type of method	Articles
Weighted sum of objectives	Caruso et al. [1993], Krikke et al. [2003], Bojarski et al. [2009], Galante et al. [2010], Amin and Zhang [2013], Bernardi et al. [2013], Kanzian et al. [2013], Marufuzzaman et al. [2014]
ε-constraint	Guillén-Gosálbez et al. [2008], Guillén-Gosálbez and Grossmann [2009], Mele et al. [2009], Duque et al. [2010], Guillén-Gosálbez and Grossmann [2010], Guillén-Gosálbez et al. [2010], Chaabane et al. [2011], Mele et al. [2011], You and Wang [2011], Akgul et al. [2012], Kostin et al. [2012], Pérez-Fortes et al. [2012], You et al. [2012], Pishvaee and Razmi [2012], Pishvaee et al. [2012a], Pozo et al. [2012], Amin and Zhang [2013], Ruiz-Femenia et al. [2013], Xifeng et al. [2013], Yue et al. [2013], Baud-Lavigne et al. [2014], Marufuzzaman et al. [2014], Mota et al. [2014], Santibañez Aguilar et al. [2014], Yue et al. [2014a]
Goal Programming	Alçada-Almeida et al. [2009], Galante et al. [2010], Pati et al. [2008], Ramudhin et al. [2010], Chaabane et al. [2011], Harraz and Galal [2011]
Interactive fuzzy approach	Malczewski and Ogryczak [1990], Pinto-Varela et al. [2011], Pishvaee et al. [2012b]
Metaheuristics	**GA:** Dehghanian and Mansour [2009], Tuzkaya et al. [2011], Zhang et al. [2013], **MA:** Jamshidi et al. [2012], **VNS:** Eskandarpour et al. [2013], Devika et al. [2014], **PSO:** Govindan et al. [2013], **SA+ICA:** Mohammadi et al. [2014] **NSGA II+TOPSIS:** Beheshtifar and Alimoahmmadi [2014] **NSGA II+Fuzzy:** Saffar et al. [2014] **NSGA II+ε-constraint:** Saffar et al. [2015]
Others	Hugo and Pistikopoulos [2005], Erkut et al. [2008], Minciardi et al. [2008], Quariguasi Frota Neto et al. [2008], Zamboni et al. [2009], Galante et al. [2010], Wang et al. [2011], Datta [2012], Sadrnia et al. [2013]

obtain a lower bound. The approach in Guillén-Gosálbez et al. [2010] is similar: an upper level problem and a lower level problem are solved repeatedly. Integer and logic cuts are added until the bounds converge. The model in Guillén-Gosálbez and Grossmann [2010] is non-convex with a specific structure. The net present value is transferred to the ε-constraint. The resulting single-objective model is solved with a spatial branch-and-bound that exploits the specific structure of the model.

Pozo et al. [2012] solve their multi-objective optimization problem with an ε-constraint approach. They then use Principal Component Analysis (PCA) to reduce the dimensionality of the model with the objective of preserving its Pareto structure. Finally, the ε-constraint approach is used again on the reduced model. In Kostin et al. [2012], the ε-constraint is followed by the rigorous MILP dimensionality reduction approach based on the δ-error definition [Guillén-Gosálbez, 2011b].

In their multi-objective uncapacitated facility location problem, Xifeng et al. [2013] consider the minimization of CO_2 emissions as the main objective. The economic and the service objectives are reformulated as constraints. The single-objective problem is solved with a *greedy-drop* heuristic.

Metaheuristics for multi-objective models

Dehghanian and Mansour [2009], Tuzkaya et al. [2011], and Zhang et al. [2013] propose Genetic Algorithms (GA) to solve their models. Tuzkaya et al. [2011] propose a two-stage methodology for the strategic design of a reverse logistics network. The weights of each criterion are calculated with an Analytic Network Process (ANP) procedure, and then the candidate locations are evaluated with a fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution). In a second stage, the facility location problem is solved by means of a genetic algorithm. In Zhang et al. [2013], the upper level searches for the optimal terminal network configurations by using a genetic algorithm, while the lower level performs multi-commodity flow assignment over a multimodal network. Jamshidi et al. [2012] develop a Memetic Algorithm (MA) to solve a multi-objective supply chain problem with cost and environmental issues. The Taguchi method is used to reduce the computational time in the crossover step.

Eskandarpour et al. [2013] use a parallel Variable Neighborhood Search (VNS) to solve a multi-objective reverse supply chain design problem for a post-sales service. The effectiveness of parallelization is proved by a comparison with the results of a generic VNS.

The closed-loop MILP model proposed by Devika et al. [2014] is solved through an hybrid approach combining three novel hybrid metaheuristics based on adapted imperialist competitive algorithms and variable neighborhood search. Imperialist competitive algorithm as a state-of-the-art evolutionary algorithm simulates the social-political process of imperialism and imperialism competition. Similar to the other evolutionary algorithms, this algorithm starts with an initial population. The 2-echelon location routing model proposed by Govindan et al. [2013] is solved using a hybrid metaheuristic algorithm combining the adapted multi-objective particle swarm optimization (MOPSO) and the adapted multi-objective variable neighborhood search algorithm (AMOVNS).

In order to solve their sustainable hub location problem, Mohammadi et al. [2014] model their MINLP with GAMS and solve it with the BARON software. However computing times are huge for the instances with 15 nodes. Due to this limitation, they developed a simulated annealing and an Imperialist Competitive Algorithm (ICA) to find good solutions.

Multi-Criteria Decision Analysis and interactive methods

Multi-Criteria Decision Analysis is able to handle a larger number of environmental and social criteria. Interactive methods are generally preferred when the number of objective functions increases and when the decision makers wish to be involved in the construction of a solution.

The hospital location problem described by Malczewski and Ogryczak [1990] is solved as an illustration of an interactive approach proposed by the authors : DINA (Dynamic Interactive Network Analysis System). This method is specialized for the solution of facility location or transport problem and facilities user-system interactions for the determination of Pareto optimal solutions.

As an alternative to Analytic Hierarchy Process [Saaty, 1990], Datta [2012] develop a multi-criteria decision making process based on Reasoning Maps [Montibeller et al., 2008] to solve a rural development problem.

Pishvaee et al. [2012b] propose an interactive fuzzy solution approach based upon a credibility measure. At each iteration, a crisp bi-objective MILP is converted into a single objective model according to a dedicated aggregation function. The model is then solved by LINGO 8.0. The decision maker can then alter the main parameters of the model if the proposed solution is not satisfactory.

Alçada-Almeida et al. [2009] describe an Interactive Decision Support System (IDSS) based on goal programming and integrating techniques from the fields of atmospheric dispersion modeling, facility location and geographical information systems. The goals are the ideal solution value for each of the five objectives.

Other methods and Hybrid Approaches

Galante et al. [2010] analyze the solution space by means of goal programming, weighted sum and fuzzy multi-objective programming techniques. First, the valu of the objectives are determined via goal programming. Next, a Pareto-optimal solution between these solutions is obtained by means of weighted sum and fuzzy multi-objective programming methods. Goal programming is also used in Alçada-Almeida et al. [2009], Pati et al. [2008] and Ramudhin et al. [2010]. Quariguasi Frota Neto et al. [2008] evaluate Pareto efficiency using Data Envelopment Analysis (DEA). The model aims to minimize the necessary reduction in cost and environmental impact to eliminate efficiency. Hugo and Pistikopoulos [2005] and Zamboni et al. [2009] reformulate their multi-objective model as a multi-parametric MILP which is solved by the algorithm described in Dua and Pistikopoulos [2000]. Wang et al. [2011] use the normalized normal constraint method [Messac et al., 2013] and the subproblems are solved with IBM Ilog Cplex 9.0.

2.5.3 Modeling tools and solvers

Faced with high complexity of the supply chains, modeling the chain network design problems is often an issue it itself. Modeling languages are often used in combination with an MIP solver. The Table 2.13 details the use of modeling tools and solvers in the reference papers. We distinguish the LCA-based models (column 2) for the non-LCA-based models (column 3) in order to exhibit the differences between the two branches.

The table shows that almost all LCA-based approaches use a modeling tools combined with a solver (GAMS/Cplex or Lingo/Lindo are the most popular combinations). This suggests the main difficulty in these problems is the modeling of the processes and their environmental burden. In contrast, usual optimization methods can solve the model to optimality, although sometimes with a very long calculation time. On the contrary, non-LCA models are generally more simple to express and do not always require using modeling tools.

The solvers can be used to solve either single-objective or multi-objective models with the weighted sum or ε-constraint techniques. However, they are not always used to solve the whole optimization model. Dehghanian and Mansour [2009] use Lindo to solve single objective models considering each objective separately in order to find the ideal point. Mallidis et al. [2012] minimize the economic objective, or the GHG emissions, or the particulate matter. Pourmohammadi et al. [2008] use Cplex to solve an LP subproblem once the facilities have been set by a genetic algorithm.

The *other* solvers are generally non-linear programming solvers, which include DICOPT [Guillén-Gosálbez et al., 2008, Guillén-Gosálbez and Grossmann, 2009, Yue et al., 2013, Corsano et al., 2011, Lira-Barragán et al., 2011, Lira-BarragÃąn et al., 2013], SBB [Yue et al., 2013, Muñoz et al., 2013], BARON Yue et al. [2013, 2014a], Mohammadi et al. [2014] CONOPT [Guillén-Gosálbez et al., 2008, Guillén-Gosálbez and Grossmann, 2010] and SNOPT [Guillén-Gosálbez and Grossmann, 2009].

Modeling /solver tool	**Reference papers** **LCA-based models**	**Other models**
GAMS/CPLEX	Guillén-Gosálbez et al. [2008], Bojarski et al. [2009], Guillén-Gosálbez and Grossmann [2009], Mele et al. [2009], Zamboni et al. [2009], Duque et al. [2010], Guillén-Gosálbez et al. [2010], Giarola et al. [2011], Mele et al. [2011], Pinto-Varela et al. [2011], You and Wang [2011], Zamboni et al. [2011], Abdallah et al. [2012], Akgul et al. [2012], Giarola et al. [2012a], Giarola et al. [2012b], Kostin et al. [2012], Pérez-Fortes et al. [2012], Pozo et al. [2012], You et al. [2012], Bernardi et al. [2013], Ruiz-Femenia et al. [2013], Yue et al. [2013], Mota et al. [2014], Santibañez Aguilar et al. [2014], Yue et al. [2014a]	Galante et al. [2010], Liu et al. [2011], Marufuzzaman et al. [2014]
GAMS/others	Guillén-Gosálbez et al. [2008], Guillén-Gosálbez and Grossmann [2009], Guillén-Gosálbez and Grossmann [2010], Muñoz et al. [2013], Yue et al. [2013], Yue et al. [2014a]	Papapostolou et al. [2011], Corsano et al. [2011], Lira-Barragán et al. [2011], Lira-BarragÃąn et al. [2013], Mohammadi et al. [2014]
Lingo/Lindo	Dehghanian and Mansour [2009], Chaabane et al. [2012b], Pishvaee and Razmi [2012], Pishvaee et al. [2012a], Pishvaee et al. [2012b]	Costi et al. [2004], Minciardi et al. [2008], Pati et al. [2008], Harraz and Galal [2011], Kannan et al. [2012], Mallidis et al. [2012], Lam et al. [2013]
AMPL/Cplex		Berger et al. [1999]
None/Cplex	Elia et al. [2011]	Krikke et al. [2003], Erkut et al. [2008], Pourmohammadi et al. [2008], Ramudhin et al. [2010], Chaabane et al. [2011], Wang et al. [2011], Elhedhli and Merrick [2012], Elia et al. [2012], Amin and Zhang [2013], Bouzembrak et al. [2013], Diabat et al. [2013], Verma et al. [2013], Baud-Lavigne et al. [2014], Elia et al. [2014]
None/Excel		Krikke [2011]

Table 2.13: Use of modeling tools and solvers

2.5.4 Conclusion

In conclusion to this section, many generic or specific solution techniques have been used to solve the complex and usually large size SCND models analyzed in this review. Many problems are solved using modeling tools such as GAMS, Lingo or AMPL and linear or non-linear programming solvers. Single objective models are often modeled as MIPs and solved with standard solvers. To the opposite, a large variety of techniques have been proposed for solving multi-objective models, including MIP techniques again, but also metaheuristic approaches and hybrid exact/metaheuristic methods. Interactive and scenario analysis methods involving the decision maker's expertise are often called for. In the future, we can still expect further use of standard solvers to handle real-life problems, but solvers will probably not be able to solve all rich problems such as sustainable location routing problems. Moreover, we observe a contradictory situation: most papers report huge calculation effort in seeking optimal solutions to problems that contain much uncertainty or aggregated data. Obtaining good quality robust solutions within limited computation time would probably enable better interaction with the decision makers. There is a real need for developing efficient solution technique methods for large complex problems involving uncertainty, as well as the development of robust multi-criteria heuristic methods.

2.6 Applications

Most published papers on sustainable SCND are based upon specific applications or an industrial context. Indeed, the study of sustainable development problems emerged from real-life concerns and the modeling of environmental or social factors generally requires the description of a specific context and depends of a particular case. Few papers propose generic models not based upon a specific application or sector, but that can apply to different contexts and address fundamental questions for the supply chain design. In classical approaches of SCND or reverse logistics, we indeed observe a much larger proportion of generic models compared to sector specific rich models. Analyzing, modeling and solving supply chain design problems integrating environmental or social factors is much more complex and makes it difficult to design generic models without a specific case in mind.

The goals of this section are to classify and discuss the published works according to their application area or economic sector, types of problems and type of experiments. In doing so, we want to identify what are the leading sectors of application on which research on sustainable SCND has been focused, what are the reasons for that and to investigate possible differences between sectors and the reasons for that. We wish to address these questions in view of the analysis conducted in the previous sections, and investigate if sectorial approaches differ in environmental and social factors considered and their assessment methods, analyze the types of models and solution techniques used and what is the influence of including environmental and social aspects in the network design in these sectors.

It is also of interest to discuss the kind of experiments that have been conducted order to validate or apply the models and solution techniques developed for a given problem. Likewise for other supply chain design or optimization problems in general, we found two different experimental approaches in the reviewed papers : papers based upon *empirical data*, that are based on real data arising from one or several companies, and papers pertaining to an *industrial context*, that are inspired from a realistic context. To some extent, this latter category may address problems in a more generic way than the former one.

In addition to generic papers, the papers which we have reviewed belong to six main application sectors. Figure 2.6 indicates the classification of these papers according to these sectors and the type of experiments conducted (either from empirical data or from an industrial context).

As can be seen, most papers in Figure 2.6 use empirical data and are based on real applications. Also one can observe that a few economic sectors related to the process industries (biomass-to-bioenergy, chemical processes) or waste management concentrate about half of the research. This is probably due to the great impact of these activities in environmental factors, both regarding energy consumption and pollution generation. These industries are probably those with the greatest maturity on these topics, while sectors

	EMPIRICAL DATA	INDUSTRIAL CONTEXT
Biomass to bioenergy	Mele et al. [2009], Giarola et al. [2011], You and Wang [2011], Akgul et al. [2012], Elia et al. [2011], Papapostolou et al. [2011], Elia et al. [2012], Giarola et al. [2012a,b], Kostin et al. [2012], Pérez-Fortes et al. [2012], You et al. [2012], Zamboni et al. [2011, 2009], Mele et al. [2011], Bernardi et al. [2013], Lam et al. [2013], Yue et al. [2013], Elia et al. [2014], Marufuzzaman et al. [2014], Santibañez Aguilar et al. [2014], Yue et al. [2014a]	Guillén-Gosálbez et al. [2010], Corsano et al. [2011]
Chemical processes	Hugo et al. [2005], Guillén-Gosálbez et al. [2008], Bojarski et al. [2009], Guillén-Gosálbez and Grossmann [2009, 2010], Pozo et al. [2012], Ruiz-Femenia et al. [2013]	Hugo and Pistikopoulos [2005], Guillén-Gosálbez and Grossmann [2010], Liu et al. [2011]
Waste management	Caruso et al. [1993], Bloemhof-Ruwaard et al. [1996], Berger et al. [1999], Costi et al. [2004], Erkut et al. [2008], Minciardi et al. [2008], Alçada-Almeida et al. [2009], Duque et al. [2010], Galante et al. [2010], Bouzembrak et al. [2013], Lam et al. [2013]	
Industrial Goods	Dehghanian and Mansour [2009], Ramudhin et al. [2010], Chaabane et al. [2011], Kannan et al. [2012], Kanzian et al. [2013], Zhang et al. [2013], Mota et al. [2014]	Pati et al. [2008], Pourmohammadi et al. [2008], Quariguasi Frota Neto et al. [2008], Pinto-Varela et al. [2011], Chaabane et al. [2012b]
Consumer goods	Krikke et al. [2003], Harraz and Galal [2011], Krikke [2011], Tuzkaya et al. [2011], Abdallah et al. [2012], Mallidis et al. [2012], Pishvaee and Razmi [2012], Pishvaee et al. [2012a,b], Sadrnia et al. [2013], Devika et al. [2014]	Diabat et al. [2013], Eskandarpour et al. [2013], Govindan et al. [2013]
Public sector	Beheshtifar and Alimoahmmadi [2014], Datta [2012], Malczewski and Ogryczak [1990], Verma et al. [2013]	

Figure 2.6: Review of industrial applications

related to the production and distribution of industrial and consumer goods are still mainly focused on the economic factors. The following sections present the application-oriented papers by economic sector.

2.6.1 Biofuels – bioenergy

Due to increasing concerns about climate change, energy safety, and the decreasing availability of fossil fuels, renewable energies such as biofuels have received growing attention in the past decade [Giarola et al., 2012b, You et al., 2012, Corsano et al., 2011]. Biomass-to-biofuel supply chains include two parts: biomass and the energies or fuels. The former concerns sourcing/biomass cultivation, biomass pretreatment and raw matter transportation, while the latter concerns fuel generation and distribution. Biofuel supply chains differ from classic ones since they generally use multiple biomass sources from different origins that are geographically distributed. Moreover, pretreatment is required to homogenize the material in mass and energy terms [Pérez-Fortes et al., 2012]. Thus, the mathematical models include many specific parameters such as bulk density, deterioration of biomass over time, moisture content, supply seasonality, and geographical availability. Similarly, for the production of biofuel, the diverse conversion pathways and the transportation infrastructures should be taken into account [You et al., 2012]. In practice, all stages of a biofuel supply chain from biomass supply to biofuel generation are considered in the corresponding published research:

- **Biomass cultivation:** criteria such as the size and capacity of the land for growing biomass [Giarola et al., 2012b] and availability of biomass [You et al., 2012, Giarola et al., 2012a, Akgul et al., 2012] have been investigated to select the most suitable feedstock. Biomass energy can be obtained from several sources: wood [You et al., 2012, Elia et al., 2011], plants such as sugar cane [Corsano et al., 2011], wheat [Akgul et al., 2012], corn [Giarola et al., 2012a,b, You et al., 2012], and stover [Giarola et al., 2012a,b, You et al., 2012], waste energy such as municipal solid waste and manufacturing waste [Pérez-Fortes et al., 2012, Zamboni et al., 2011] and energy crops [You et al., 2012].
- **Biomass pretreatment:** covers the drying and storage operations after biomass harvesting and collection [Giarola et al., 2012a]. Pre-treatment activities can result in weight or volume reduction, which can benefit subsequent operations such as transportation and fuel production [Pérez-Fortes et al., 2012].
- **Distribution system:** the selection of suitable transportation modes is included in several papers. This can be based on cost, distance, speed, availability and transport capacity [Guillén-Gosálbez et al., 2010]. For example, in Giarola et al. [2011], the distribution infrastructure includes trucks, rail, barges and ships. Rail, road and ships are considered in Akgul et al. [2012]. Truck, rail and pipeline are considered in Elia et al. [2011]. For an application in the state of Illinois, You et al. [2012] consider train, large trucks or small trucks. In some special cases, such as hydrogen generation there is a need for special infrastructures such as liquid hydrogen (LH2) tanker trucks, liquid hydrogen railway tank cars, or compressed-gaseous hydrogen (CGH_2) tube trailers, compressed gaseous hydrogen railway tube cars [Guillén-Gosálbez et al., 2010].
- **Production of finished product:** the type of technology to implement in a treatment facility has to be determined with regard to the feedstock supply system and type of final products. Among biofuels, ethanol and hydrogen production has been investigated more frequently. For converting biomass to ethanol, the main candidate transformation technologies are (i) the dry grind process, which is the standard corn-based ethanol process [Giarola et al., 2012a,b, 2011] (ii) the dilute acid process, where cellulosic feedstock is hydrolyzed with dilute sulfuric acid [Giarola et al., 2012a] (iii) the steam explosion process, where the cellulosic biomass is pretreated with high pressure steam before being converted into ethanol [Giarola et al., 2012a] (iv) the gasification biosynthesis process, where biomass-based syngas is fermented to ethanol [Giarola et al., 2012a] (v) the ligno-cellulosic ethanol process, where only stover is converted into ethanol [Giarola et al., 2011, 2012b]. To produce hydrogen, technologies such as steam methane reforming, coal gasification, and biomass gasification are considered in Guillén-Gosálbez et al. [2010] and Hugo et al. [2005]. Another issue is the capability

of selecting either first generation technologies, including biofuels made from sugar, starch, or vegetable oils, or second generation technologies, including feedstock such as ligno-cellulosic products, for converting biomass to biofuel. This is considered in Giarola et al. [2011], Akgul et al. [2012].

2.6.2 Chemical Processes

Chemical products such as polymers and plastics are used as raw materials to produce a wide range of final products. Owing to the increased awareness of the impact of chemical production systems on the environment, the design of sustainable chemical supply chains has received attention in recent years [Hugo and Pistikopoulos, 2005]. To ensure sustainability within a chemical supply chain, an efficient global network should be designed from raw material suppliers to end-users. The most common topology of a chemical supply chain consists of a set of suppliers, plants, warehouses, and end markets devoted to the conversion of raw materials to final products through chemical processes. Nikolopoulou and Ierapetritou [2012] review sustainable chemical processes and supply chain design considering three major factors: the role of waste management in sustainable supply chains, the impact of chemical supply chains on the environment, and sustainable water management. The main factors to take into account in the design of chemical processes, such as product design, uncertainty, and methodologies are discussed in this paper.

Selecting suitable raw materials is one of the issues that have been investigated comprehensively for sustainable chemical SCND. It can be concluded from the case studies analyzed by Bojarski et al. [2009], Guillén-Gosálbez and Grossmann [2009] and Guillén-Gosálbez and Grossmann [2010] that raw material production has the most significant environmental impact compared with other issues such as transportation modes and process determination. Moreover, the type of raw material can influence the selection of a suitable technology. Bojarski et al. [2009] investigate the role of benzene and butane in selecting the most suitable process for maleic anhydride production. Benzene and butane processes have their own attributes in terms of electricity consumption and CO_2 emissions. Using other raw materials, such as ethylene, propylene, and ammonia, is considered to produce the desired final products in Guillén-Gosálbez and Grossmann [2009, 2010].

Shipping raw materials and products through a chemical supply chain is another interesting issue, because some are liquid and others can be gaseous in standard conditions. Therefore, the strategy for shipping material should be determined *a priori*. Bojarski et al. [2009] use two types of truck to transport liquid materials. To this end, the butane is liquefied during the production process.

2.6.3 Regional Planning, Waste Management, Public Services

Solid waste management takes into consideration activities such as the collection of waste materials and treatment strategies including recycling, landfill, and incineration. In their review, Pires et al. [2011] list many assessment tools and engineering techniques to solve solid waste management problems, such as optimization, simulation and forecasting. They point out that solid waste management models are often multi-objective, interactive, dynamic, and involve uncertain features. This complicates the application of modeling and assessment techniques.

However, the main decision variables in quantitative models generally concern the location of landfill and incineration centers. According to the type of waste material, various treatment facilities may need to be located: separators, sorting centers, sanitary landfill and recycling. There are more restrictions in the selection of candidate locations for waste management activities in comparison with common locations such as plants and warehouses. These facilities can be harmful to the nearby population, because of health and environmental considerations. To this end, the imposed risk and the pollution emissions concerning the nearby population should be taken into account when locating facilities [Costi et al., 2004]. For example, Alçada-Almeida et al. [2009] evaluate potential locations by means of criteria such as the wind direction to locate two incineration plants of hazardous industrial waste in Portugal. Other characteristics include social responsibility, global economics, material technology and environmental impact [Galante et al., 2010].

Minciardi et al. [2008] extend the single objective model proposed by Costi et al. [2004] by explicitly considering the environmental issue as an objective function. However, the set of facilities is fixed *a priori*, so that all decision variables are continuous.

Berger et al. [1999] propose a comprehensive multi-criteria optimization model for integrated regional solid waste management planning. They apply this model in design studies for the collection, treatment, elimination and valorization of waste in Quebec.

The multiobjective MILP model of Erkut et al. [2008] has been designed to study the regional planning network and location facilities and allocation decisions for the treatment of municipal solid wastes over a region in North Greece.

Giannikos [1998] study the location of hazardous waste treatment facilities over a network. They demonstrate their MILP goal programming model with a small hypothetical problem with 13 population centers, three of which generate hazardous wastes, and five candidate locations for treatment facilities.

2.6.4 Industrial goods

As mentioned above, sustainable SCND has been applied in various industrial sectors: tires, steel and aluminum, plastics, etc. The most challenging issues are briefly described below:

- **Tires:** due to the increasing number of scrap tires and, proportionally, their emitted waste, sustainable SCND for tires is considered in [Dehghanian and Mansour, 2009]. The main activities included are the collection of scrap tires, separation, end-of-life treatment processes such as mechanical pulverization and cryogenic pulverization, incineration in cement kilns and transportation of tires throughout the network.
- **Steel and aluminum:** recycling aluminum is more efficient than extracting it from bauxite ore. Therefore, aluminum recycling has attracted attention from both economic and environmental points of view [Pourmohammadi et al., 2008]. Sustainable SCND for aluminum is considered in Ramudhin et al. [2010], Pourmohammadi et al. [2008] and Chaabane et al. [2012b].
- **Paper:** Raw materials such as forests are one of the essential pillars of the paper industry [Pinto-Varela et al., 2011]. The location of raw material sources plays a crucial role in the whole logistics network. In the multi-echelon convergent supply chain described by Pati et al. [2008] for the recovery of recycled paper, the efficiency of the activity depends on three objectives: minimizing the logistics cost, minimizing the quantity of non-relevant paper collected and maximizing the wastepaper recovery target.
- **Glass Industry:** Devika et al. [2014] address a comprehensive, 4 echelon closed loop supply chain network design problem involving manufacturing, distribution, and product recovery through manufacturing and recycling. They test the hybrid solution techniques on 24 randomly generated test problems and on a real case study of a glass manufacturer in Iran.
- **Containers:** Zhang et al. [2013] optimize the configuration of the Dutch container terminal network. Their study show that the network configuration may be changed if the CO_2 pricing varies.

2.6.5 Consumer goods

- **Medical items:** single-use medical needles and syringes have a significant environmental impact, particularly in their end-of-life phase. There are three alternatives for dealing with used medical needles and syringes: incineration methods, such as cement or rotary kiln incinerators; non-incineration methods such as steam autoclaving with sanitary landfill and microwave disinfection; and recycling. Incineration is the easiest method but has a negative environmental impact so other options are more beneficial from an environmental point of view. As a result, selecting the appropriate method for disposing of medical needles is investigated in Pishvaee and Razmi [2012], Pishvaee et al. [2012a] and Pishvaee et al. [2012b].

– **White goods:** one of the characteristics of white goods supply chain design is the location of treatment and separation activities. The model in Krikke et al. [2003] is applied to a closed-loop supply chain design problem for refrigerators using real-life data from a Japanese consumer electronics company concerning its European operations. Due to there being a number of options to handle returned products, such as reuse and proper disposal, selecting the right treatment activities and the location of these facilities are among the main decisions to be made [Krikke et al., 2003, Tuzkaya et al., 2011, Mallidis et al., 2012].

2.6.6 Public sector

The model and multiobjective decision making methodology (DINA) proposed by Malczewski and Ogryczżak [1990] has been applied for solving the problem of locating pediatric hospitals in Warsaw. The decision making process involved three interest groups (public authorities, health authorities, professionals, and the client population. The methodology, decision making process and final compromise solution, are illustrated in the paper. [Datta, 2012] describes the original problem of locating public service facilities for serving villages in a rural area in Rajasthan. 16 different facilities are located in 5 groups for serving 45 villages over a 10 years implementation plan.

2.6.7 Intersectorial analysis

We can see than generic models rarely resort to LCA-based assessment but mostly for partial assessment based on the GHG emissions. W e explain this because using LCA requires a very detailed analysis of product and activity which is difficult for a generic approach. Besides, evaluating GHG emissions is a fairly straightforward method and results in formulae that can be easily incorporated into a mathematical model. Indeed we observe that LCA is used for a majority of papers in the bio-energy and chemical processes sectors, but also for consumer and industrial goods sectors. This is understandable because the concerned works are very specific, which allows using LCA.

Regarding the explicit inclusion of the social dimension into the models, we did not identify reasons explaining that the social factors are considered or not for a given sector of application and actually the public sector paper considers the economic and social factors only, but concerns a very specific study.

Consistently with the analysis of Section 2.4, we could not find any correlation between the type of models used and the sector of application. We believe that the use of a linear or non-linear formulation with a deterministic or stochastic context is more linked to the technical specificity of the problem studied than to the economic sector. Indeed advanced modeling calls for the inclusion of a multi-objective and a stochastic approach rather than a deterministic one, whatever the considered sector. Moreover, we did not find any correlation between these approaches and the fact that the models are generic or applied to a given sector. The choice of approach depends more on the complexity of the problem and size of experimental data.

2.6.8 Conclusion on applications

In summary to this section, we have observed that the research on quantitative optimization models for sustainable SCND problems covers a wide variety of areas and specific applications, while only a few works only are devoted to the study of generic sustainable SCND problems. Process industry sectors such as energy and chemical processes as well as waste management concentrate more than half of the works, while the rest is concentrated on the analysis of consumer and industrial goods problem, the public sector and generic problems. The specificity of supply chains in different areas, especially for the assessment of environmental factors makes it very difficult to develop generic models that would remain realistic enough. But this should be a goal for the future.

Sustainable SCND problems for biomass-to-bioenergy, chemical processes or waste management are already well studied due to the importance of environmental factors (mainly energy consumption and pollution), but should be further investigated. To the contrary, industrial and consumer goods sectors are well studied in some areas such as tires, steel and aluminum, paper, glass and containers, as well as medical items, and white goods. But surprisingly enough, areas like manufacturing in general, aeronautics and the automotive industry, transportation services, retail and food distribution have hardly been studied, although they are well present in the research on SCND in general. Extending research on SCND by explicitly incorporating the environmental and social dimensions, should be a fruitful area of research. Finally, applications regarding the public sector have been limited so far and provide a great potential for the consideration of both the environmental and social dimensions of sustainable development.

2.7 Discussion

2.7.1 Summary of findings

The broad field of supply chain management has become an essential domain with the globalization and the constant search for competitiveness. Simultaneously, the growing consideration for sustainable development has led private and public actors to integrate the three pillars of sustainability within their management. At the strategic level, the design or re-engineering of supply chain networks is a key issue, centered around questions of locating and sizing facilities and defining material flows trough the network. Optimization techniques have always been a key tool for addressing these problems. The consideration of sustainable development factors within the network design problem has indeed been the subject of many works since the publication of the Bruntland Report. These were our motivations for proposing this review of the literature focused on optimization models and techniques on supply chain network design problems integrating sustainable development factors, for which no previous review had been published. The overall justification of research in this area can be summarized by the observation that the consideration of sustainable development factors may have a significant impact on the design and configuration of the supply chain, as illustrated by the case study in You and Wang [2011].

Amidst the many works on closely related areas to sustainable SCND problems, we decided to limited our analysis to works relying on mathematical optimization models, and integrating explicitly at least two of the three dimensions of sustainable development in the objective function(s) or the constraints. We therefore excluded papers focused on only one of the dimensions or on closely related areas such as reverse logistics or undesirable facility location when they only addressed sustainable development implicitly. Besides, fields like reverse logistics or facility locations have been the subject of many previous reviews.

Within our literature survey, we have addressed the four questions stated in the Introduction, (i) which environmental and social criteria are considered in sustainable SCND research? (ii) how are they integrated into mathematical models? (iii) which optimization methods and tools are used? (iv) which real-life applications of sustainable SCND are described in the scientific literature?

We summarize our findings below and point out a number of research directions for the future in the following sub section. The global contribution of our work has been to identify, to our best knowledge, classify and analyze all the published literature within the scope of survey and determine key factors of these works as well as identify future directions. We have indeed identified 87 papers published in 41 international peer-reviewed journals, among which 10 addressed simultaneously the three dimensions of sustainable development, 74 the economic and environmental factors and only 3 were focused on both the economic and social dimensions, while no work integrates the environmental and social factors only. We have identified that a majority of the works were focused on specific areas of applications, while only some of the published papers addressed generic sustainable SCND models. The major contribution of our work has been to analyze and compare the research works and determine their key characteristics: methodologies used for environmental assessment, factors retained for integrating social dimension, mathematical modeling approaches and solution methods developed, as well as the applications developed in different sectors and types of experiment conducted with these models.

As mentioned above, we identified that a large majority of the works focus on the economic and environmental factors. In contrast, social aspects of sustainable development are rarely considered in quantitative studies in comparison with environmental issues and even less research addresses all three dimensions together. Furthermore, there are a limited number of sub-factors of the three main dimensions considered in published studies. The consideration of environmental factors is often limited to GHG emissions or energy consumption, or the consideration of social factors is often limited to evaluation of jobs created or respect of working legislation. The many possible factors proposed by specialized works such as Chardine-Baumann and Botta-Genoulaz [2014] are far from being considered. Regarding environmental factors, several performance measures have been considered to tackle environmental impacts, especially for proposing analytic measures for GHG emissions or their global cost impact. These are the principal factors used in quantitative models. Simultaneously, we observed that LCA is the dominant approach to incorporate environmental issues in SCND, but all impact categories are not considered in general.

In contrast, the lack of published research addressing social factors together with other dimensions appears to be due to the difficulty of modeling such factors. Social factors are sometimes considered indirectly within the evaluation of economic and environmental factors. Hence, research that is able to find a balance between supply chain costs and the broad spectrum of impact categories remains largely an uncharted territory to date. Still the models reviewed are from integrating the characteristics of the ISO 26000 norm.

Regarding modeling techniques, research concentrates on the development of deterministic MILP models solved with standard modeling tools and solvers. This is due to the ability of these modeling techniques to integrate environmental or social aspects in complex industrial process for each particular sector. Performance of state-of-the-art solvers allows solving real-life instances even though very long computing time are sometimes reported. Developing advanced heuristic solution techniques for solving large-sized problems efficiently seems yet to be difficult because of the complexity of these types of problems. Indeed few works use heuristic or metaheuristic approaches.

Although uncertainty is often an intrinsic characteristic of the studied problems, most authors still use deterministic models. One main reason is that large stochastic models would be intractable whereas deterministic models can be solved by state-of-the-art solvers. Because of the characteristics of the addressed problems, some of the works consider non-linear models and call for specific solution techniques or nonlinear solvers.

Sustainable SCND problems are multi-objective by nature and the models that we have studied consider at least two dimensions in the objective function or constraints and sometimes several sub-factors. However about one third of the proposed models are limited to a single aggregated objective, while two thirds explicitly consider several objective functions. In terms of solution techniques, however, a large majority of papers are limited to the use of a weighted sum of objectives or the ε-constraint approach with minimization of an economic criterion and an environmental criterion expressed as a constraint. However a significant number of works call for available multi-objective solution techniques such as goal programming or metaheuristics. We identified a significant lack of studies on truly multi-objective approaches with adequate consideration of uncertainties and risks (see Heckmann et al. [2015] for a review on supply chain risk).

In terms of applications, besides the proposition of generic models, a strong emphasis is made on process industries (biofuel, chemical processes) and on waste management problems. Such works account to about half of the published works devoted to specific applications. We can argue that the upstream part of a supply chain is often where greatest environmental impact arises and so this focus makes sense. However these applications reflect highly integrated, often automated processes, whereas supply chains in the industrial or consumer goods areas are often decentralized and involve more uncertainty due to human factors. It is noteworthy to remark that many sectors (automotive industry, distribution of consumer products and transport) have not yet or little been considered.

2.7.2 Suggestions for future works

These findings lead us to suggest some directions for future theoretical and applied research works to fill the gaps found in the literature of sustainable SCND. Some of the possible future directions are however direct consequences of the analysis of the preceding paragraphs and will not be repeated here.

Social aspects should be given more attention in future research to achieve a sustainable SCND. However, developing methodologies for quantifying the social aspects is a challenging task. Their consideration at the stage of scenarios definition before optimization may remain an effective alternative within a decision making process. A real challenge is probably to define the scope for the social impact to consider. Contrary to environmental studies (and more especially LCA based approaches), this question is never discussed in the papers we found addressing the social dimension. This results in very disparate metrics, with a relative dominance of metrics concerning employment and health impacts. The generalization of LCA to the social dimension is known as social LCA (or S-LCA). Its goal is to deliver decision-making support related to the social impacts of products or systems (see the reviews by Jorgensen [2013] and Jorgensen et al. [2008]). S-LCA was not used in our reference papers. This is a serious track to better integrate social dimension into quantitative models. Recent developments have led the definition of the ISO 26000 norm on social responsibility. However, due to its recent publication, there is still no research on the impact of this standard on supply-chain practices [Castka and Balzarova, 2008, Hahn, 2013]. This seems another fruitful research avenue.

Regarding the environmental dimension, it is worthy to consider GHG emissions relative to nodes (facilities) and arcs (transport links) of the supply chain network together with other performance measures such as waste generation or energy consumption. In other words, optimizing only one criteria does not allow the minimization of overall environmental impact. Classical process-based LCA is the most frequently used method to assess the environmental impacts. But employing this approach is sometimes difficult for practical reasons. Besides, LCA pays a greater attention to the early stages of the life-cycle of a new product development which is often before the supply chain network has been designed. Therefore, developing novel approaches combining Input-Output LCA (such as material flow analysis) and process-based approaches may better consider environmental damage throughout the entire product life-cycle. Carbon credit exchange schemes (despite their current limitations) could be also be more widely considered at the strategic decision level together with efforts to reduce the GHG emissions within the supply chain.

As already mentioned, sustainable development problems are clearly multi-objective problems. They cannot be expressed with a single dimension unless all factors are reduced to their cost equivalent. Alternatively, a model focused on economic optimization has to consider explicit environmental or social factors as constraints. Still very few published models handle the economic, environmental and social dimensions simultaneously. This calls for the development of efficient multi-objective models and dimensionality reduction techniques that adequately address the different dimensions of sustainable development. Uncertainty and risk should also be better considered in sustainable SCND. In real problems, uncertainty is present in many estimated factors: demand level, impact assessment, costs, social impacts, etc. The consideration of realistic management features such as supplier selection and risk management have been frequently considered in supply chain and procurement research, but quantitative sustainable SCND models incorporating these features are still scarce.

Government legislation and customers' awareness are among main reasons that prompt companies or organizations to pay an increased attention to environmental and social impacts of their activities. Many major companies concentrate on their core business and outsource a large of their production or distribution activities to subcontractors, distributors, third party logistics providers. Thus, sustainable development goals can indeed be truly achieved only by considering the supply chain as a complex system with collaborating stakeholders (government, consumers and multiple companies) which address the life-cycle perspectives together.

2.8 Concluding remarks and research proposed

Up to now, the literature concentrates on specific rich models focused on a particular real-life application. For general industrial companies, there is a need to develop generic models for sustainable SCND, such as in classical works on SCND. Generic models should include features such as multiple commodities, bill of materials, multi-layer supply chains and multiple periods. Assumptions such as capacity expansion and technology levels also deserve future research. Environmental impact should be measured at all steps in the supply chain. For example GHG emissions should be considered at nodes (production or storage facilities) and on the arcs (transport activities and the modes used). Studies that consider social dimension use a large variety of assessment metrics and are all based on empirical case studies. This shows that we are not close to having generic models including the three dimensions of sustainable development.

As mentioned earlier, there are two major approaches to integrate environmental issues: LCA approach and partial assessment. Usually, environmental management experts use the LCA method to assess environmental impact of activities and processes. However, the LCA is a complicated, time consuming and costly process which needs to be weighted and interpreted [Pishvaee et al., 2012b]. As a result, we follow the partial assessment approach described in section 2.2 to integrate environmental issues. Since social aspect depends on the context of operation of the supply chain, the government policies, and cultural norms [Chaabane et al., 2012b], we do not include it in the proposed sustainable SCND models.

When it comes to solution techniques, standard (but powerful) solvers have been the most widely used tools to solve the resulting models in sustainable SCND. However, the size and particularly the number of binary variables in practical SCND problems raises difficulties for solving them in a reasonable amount of time. This issue is even more crucial for adequately solving non-linear, stochastic or multi-objective models. The capability of solvers practically restricts the scope of most studies. Therefore, developing efficient exact or heuristic solution methods is a real need for the future, especially for solving extension of SCND problems (e.g. location-routing problems).

There is no dominant metaheuristic method for solving multi-objective sustainable SCND models (see Table 2.12) therefore, several choices are open. The LNS has proven its efficiency and flexibility in solving several complex optimization problems and it has almost never been proposed for solving SCND problems. Moreover, its flexibility in terms of defining operators makes this method adaptable to different variants of SCND problems. Therefore, we feel this could be an appropriate method for our purpose and we chose the LNS framework for solving our proposed models.

II

Single objective SCND model

3

SCND mathematical model

In this chapter, we introduce the SCND model to be solved by the LNS method. The model includes classic decisions such as the number of facilities and their locations, capacities, the quantity of product flows between facilities. It also integrate advanced decision variables such as the transportation modes between each pair of facilities. The challenge is to choose a mode between two connected facilities with respect to the criteria such as fixed cost, shipping cost, and minimum load of the mode.

A few papers have incorporated selection of an appropriate transportation mode into SCND models. Carlsson and Rönnqvist [2005] describe a case study in the distribution of pulp from Sweden to several European countries. The international customers are supplied by three possible modes of transportation: vessel, train and lorry. Eskigun et al. [2005] describe the outbound supply chain network of an automotive company. It is assumed that all vehicle types from the same plant are delivered to a destination using the same transportation mode to take advantage of economies of scale and to simplify the delivery process (e.g., loading, unloading, tracking, etc.) of the vehicles. The model is solved with a Lagrangean heuristic. Wilhelm et al. [2005] study the strategic design of an assembly system in the international business environment created by NAFTA. It therefore includes facility location and many associated decisions, such as the choice of technologies, capacities, suppliers and transportation modes. Cordeau et al. [2006] develop a comprehensive multi-stage network design model: at the strategic level, they investigate facility location and capacity expansion decisions. At the tactical level, they also integrate the selection of transportation modes regarding fixed and variable costs and the capacity usage. Their model is solved by two methods: a simplex-based branch-and-bound and a Benders decomposition approach.

Other recent works proposing models closely related to ours and including transportation mode determination are the following. Tiwari et al. [2010] develop a 5-layer supply chain concerning strategic and tactical decisions. The solution space is explored through a hybrid Taguchi-Immune System metaheuristic approach. Wu et al. [2011] study a spare parts logistics network encompassing three types of decision: facility location, item vendor selection and transportation mode. They compare two approaches consisting of determining all decisions simultaneously or determining the location decisions first. Sadjady and Davoudpour [2012] propose a single-period two-echelon multi-commodity model regarding strategic and tactical decisions as well as the selection of transportation modes. The problem is solved with a Lagrangean relaxation heuristic. In the paper by Rahmaniani and Ghaderi [2013], each arc between two facilities is associated with fixed and variable cost as well as a capacity. Olivares-Benitez et al. [2013] propose a three-stage supply chain including plants, distribution centers and customers to minimize cost and temporal considerations. In order to reduce the shipping time from plants to customers, several transportation modes between two nodes are considered in terms of their own cost and travel time. Cardona-Valdés et al. [2014] propose a two-echelon distribution network regarding economical and service level objectives. They incorporate demand uncertainty and transportation mode allocation decisions.

This chapter is organized as follows. Problem definition and the corresponding assumptions are explained in section 3.1. Section 3.2 introduces required notations for data, sets, parameter and decision variables. A verbal description and mathematical formulation of the model are presented in section 3.3.

3.1 Problem definition and modeling

We consider a multi-product supply chain network consisting of four layers: suppliers, production plants, distribution centers (DCs) and customers (retail stores or final customers), as depicted in Figure 3.1.

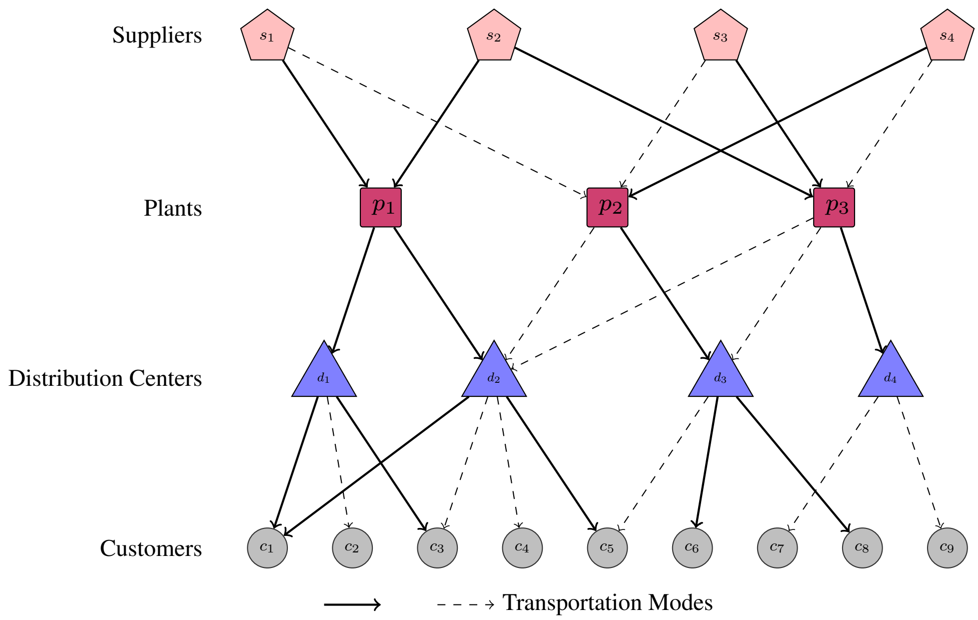

Figure 3.1: The supply chain considered

The location of suppliers and customers are known, whereas those of plants and DCs have to be determined from a list of candidate locations. At the first layer, suppliers provide the raw materials or components to the plants. These products are then converted to finished goods through value-added operations performed in plants. As mentioned above, finished goods are shipped from plants to DCs and from DCs to customers. Customer demand is assumed deterministic. We do not consider single sourcing constraints, *i.e.* a facility can be delivered by several facilities from the preceding layer.

The model treats facilities as black boxes: the detail of all internal activities such as storage, production operations and internal logistics, is not considered. Thus, the capacity of a facility can be expressed as a single value limiting the output flow for each product at this facility. Without loss of generality, the mathematical model assumes that each product can be processed by every facility. If a facility cannot process one given product, this can be modeled by setting the corresponding capacity at 0.

The facility location decisions at plants and DCs are guided by two types of costs. Fixed costs for opening facilities are paid only if the corresponding facility is selected. Processing costs are variable costs assumed proportional to the level of activity (i.e. the outgoing flow) of the corresponding facility.

Several transportation modes are available, such as road, rail, inland navigation or air transport, to ship products between the nodes of the network. However we assume that a restricted list of suitable transportation modes has been identified *a priori* for each pair of nodes, with respect to criteria such as availability and safety, shipping costs, CO_2 emissions, shipment capacities, speed and frequency. At the strategic level, the cost of most transportation modes is assumed linear with respect to the quantity carried. However, some transportation modes incur a fixed charge. For example, a company with an internal fleet of trucks will pay a fixed cost (amortization, maintenance, insurance, etc.) even if the vehicles are not used. All transportation modes have a known maximal load. Some modes also require a minimal quantity of goods to be shipped. We assume that only one transportation mode is selected between any pair of nodes and that all products are compatible enough to be loaded onto the same transportation mode.

With respect to the above-mentioned description, the main decisions are to select a subset of plants and DCs, to choose a transportation mode between suppliers, selected facilities and customers, and to determine the product flows in the logistics network. The objective function of this problem is to minimize the overall cost over one single period, including the fixed cost of opening facilities, processing costs and transportation costs.

3.2 Data, sets and parameters and variables

We consider a set I of suppliers, a set J of plants, a set K of DCs, a set L of customers, a set P of products and a set M of potential transportation modes. The subsets of open plants and DCs are denoted as J^o and K^o. The SCND problem is defined on a directed graph $\psi = (V, A)$ with $V = I \cup J \cup K \cup L$ and the set A of arcs defines all possible links between facilities. This potentially includes all links between two successive layers represented in Figure 1. In practice, there may not be an arc between two vertices when the capacity is set at 0, or a transportation mode is unavailable or has an arbitrarily large value.

We introduce the following notations:

- d_l^p: demand of customer $l \in L$ for product $p \in P$;
- cap_i: capacity of facility $i \in I \cup J \cup K$;
- v_{ij}^{mp}: variable transportation cost of a unit of product $p \in P$ on arc $(i, j) \in A$ by mode $m \in M$;
- a_i^p: unit processing cost of product $p \in P$ at $i \in I \cup J \cup K$;
- g_{ij}^m: fixed cost of transportation mode $m \in M$ along arc $(i, j) \in A$.
- $\underline{V}_{ij}^m$: minimum threshold volume for using transportation mode $m \in M$ along arc $(i, j) \in A$.
- $\overline{V}_{ij}^m$: capacity of transportation mode $m \in M$ along arc $(i, j) \in A$.
- c_j: fixed cost of opening facility $j \in J \cup K$.

Binary variable y_j is set at 1 if a facility $j \in J \cup K$ is open and 0 otherwise. In order to select the transportation modes throughout the network, we consider binary variables t_{ij}^m set at 1 if the transportation mode $m \in M$ is selected for arc $(i, j) \in A$ and 0 otherwise. Continuous variables x_{ij}^{mp} represent the flow of product $p \in P$ on arc $(i, j) \in A$ using transportation mode $m \in M$.

3.3 Mathematical formulation

In order to represent and solve the above described problem, we propose the following Mixed Integer Linear Programming (MILP) model minimizing the economic objective (3.1):

$$min\ z = \sum_{j \in J \cup K} c_j y_j + \sum_{(i,j) \in A} \sum_{m \in M} \sum_{p \in P} a_i^p x_{ij}^{mp} + \sum_{(i,j) \in A} \sum_{m \in M} g_{ij}^m t_{ij}^m + \sum_{(i,j) \in A} \sum_{m \in M} \sum_{p \in P} v_{ij}^{mp} x_{ij}^{mp} \tag{3.1}$$

This objective function contains four terms, representing the sum of opening fixed costs, processing costs, and fixed and variable parts of transportation costs respectively.

Constraints (3.2) are the flow conservation constraints throughout the network.

$$\sum_{i \in V} \sum_{m \in M} x_{ij}^{mp} = \sum_{k \in V} \sum_{m \in M} x_{jk}^{mp} \qquad \forall j \in J \cup K, p \in P \tag{3.2}$$

Constraints (3.3) ensure the satisfaction of customer demands.

$$\sum_{k \in K} \sum_{m \in M} x_{kl}^{mp} \geq d_l^p \qquad \forall l \in L, p \in P \tag{3.3}$$

Constraints (3.4)–(3.6) force the model to respect capacity constraint at suppliers, plants and DCs, respectively. In addition, (3.5) and (3.6) state that the products can be shipped only to open facilities.

$$\sum_{j\in J}\sum_{m\in M}\sum_{p\in P} x_{ij}^{mp} \leq cap_i \qquad \forall i \in I \tag{3.4}$$

$$\sum_{k\in K}\sum_{m\in M}\sum_{p\in P} x_{jk}^{mp} \leq cap_j\ y_j \qquad \forall j \in J \tag{3.5}$$

$$\sum_{l\in L}\sum_{m\in M}\sum_{p\in P} x_{kl}^{mp} \leq cap_k\ y_k \qquad \forall k \in K. \tag{3.6}$$

Constraints (3.7) ensure that one transportation mode at most is selected between two nodes. Constraints (3.8) – (3.9) guarantee that the volume limitation of each given mode is respected.

$$\sum_{m\in M} t_{ij}^{m} \leq 1 \qquad \forall (i,j) \in A \tag{3.7}$$

$$\sum_{p\in P} x_{ij}^{mp} \leq \bar{V}_{ij}^{m}\ t_{ij}^{m} \qquad \forall (i,j) \in A, m \in M \tag{3.8}$$

$$\sum_{p\in P} x_{ij}^{mp} \geq \underline{V}_{ij}^{m}\ t_{ij}^{m} \qquad \forall (i,j) \in A, m \in M \tag{3.9}$$

We also consider restrictions on the number of open facilities. Constraints (3.10)–(3.11) bound the number of open plants and DCs, respectively. These constraints can be discarded by setting minimal values at 0 and maximal values at $+\infty$.

$$J_{min} \leq \sum_{j\in J} y_j \leq J_{max} \tag{3.10}$$

$$K_{min} \leq \sum_{j\in K} y_j \leq K_{max} \tag{3.11}$$

Constraints (3.12) – (3.14) state non-negativity and binary restrictions on decision variables.

$$y_j \in \{0,1\} \qquad \forall j \in J \cup K \tag{3.12}$$

$$t_{ij}^{m} = \{0,1\} \qquad \forall (i,j) \in A, m \in M \tag{3.13}$$

$$x_{ij}^{mp} \geq 0 \qquad \forall (i,j) \in A, p \in P, m \in M \tag{3.14}$$

3.4 Conclusion

We propose an MILP model for designing a generic supply chain network. Our model is able to handle multi-commodity through supply chain from upstream to downstream. We also integrate transportation modes selection into designing supply chain network.

Number of constraints and decision variables highly impress by the number of transportation modes. Let's suppose that there is only one mode available between each pair of nodes through network. The model has $(J + K)$ binary variables and $((IJ + JK + KL)P)$ continues variables. Besides, the number of constraints is $((J+K+L)P+(I+J+K)+2)$. First term refers to the flows conservation constraints. Second term refers to the capacity constraints. And last term mentions the two constraints for bounding the number of open plants and DCs. While by assuming 2 modes between each pair of nodes, total number of binary and continues variables would be double. Even the number of constraints would be increased more than double.

More precisely, It would be $((J + K + L)P + (I + J + K) + 2 + (IJ + JK + KL) + 4(IJ + JK + KL))$. Thus, transportation modes plays an important role in increasing the complexity of the model.

The model can apply either for designing supply chain from scratch or expanding an existing supply chain network. To expand the supply chain, If a given plant/DC was supposed to be opened, then the corresponding y_j/y_k variable can explicitly be set to 1 in the model. This is useful in the case of existing facilities which should remain active or former decisions that can not be changed. The same reasoning also applies to transportation mode variables t_{ij}^m.

4

A Large Neighborhood Search for the SCND problem

The proposed SCND model reduces to a Capacitated Facility Location Problem (CFLP) by considering only flows conservations and capacity constraints between DCs and customers. Since the CFLP is NP-complete [Davis and Ray, 1969], the proposed model is an NP-hard problem. Because of the computational complexity of the problem and its large number of variables and constraints, using commercial software and exact optimization methods may no longer be tractable. Thus the development of a meta-heuristic/heuristic method is suitable to find a near optimal solution for particularly large instances [Olivares-Benitez et al., 2013, Der-Horng and Meng, 2008].

We propose an LNS heuristic able to deal with the three main types of decision variables: facility location, selection of transportation mode and calculation of optimal product flows. The location and transportation modes are modeled by binary variables while the product flows are modeled by continuous variables.

A key issue is to determine the number and location of plants and DCs. We call the *network configuration* the number of plants and DCs open in the current solution, represented by the pair $\left(\sum_{j\in J} y_j, \sum_{k\in K} y_k\right)$.

This network configuration has great influence on the whole solution. One of the main issues is that there are $(J_{max} - J_{min}) \times (K_{max} - K_{min})$ possible network configurations. Good heuristic methods should explore all promising network configurations. The main challenges of the LNS algorithm are thus to handle both binary and continuous variables, to determine the strategy to visit and evaluate promising network configurations and lastly to select transportation modes.

The rest of this chapter is organized as follows. Section 4.1 gives an overview of the general LNS approach. Section 4.2 gives an overview of our LNS approach. Sections 4.2.1, 4.2.2, and 4.2.3 describe the proposed removal and repair operators, and combinations of both. The management of network configurations is detailed in section 4.3. The greedy heuristics to determine transportation modes and product flows are presented in section 4.3.1.

4.1 A Large Neighborhood Search heuristic

Large Neighborhood Search (LNS) has been introduced by Shaw [1998] in a constraint programming framework. LNS is similar to the *ruin and recreate* method introduced by Schrimpf et al. [2000]. Ropke and Pisinger [2010] present an extensive survey of the method and its application to combinatorial optimization problems, and more particularly vehicle routing problems. As depicted in Algorithm 1, the underlying principle of the LNS is to partially destroy and repair iteratively a solution in order to improve it.

Algorithm 1 Main scheme of the Large neighborhood Search (LNS)

Require: An initial solution $\mathcal{S}^0$
1: $BestSolution \leftarrow \mathcal{S}^0$
2: $CurrentSolution \leftarrow \mathcal{S}^0$
3: **while** the termination criterion is not satisfied **do**
4: Selection of $Destroy$ and $Repair$ heuristics
5: $\mathcal{S} \leftarrow CurrentSolution$
6: $\mathcal{S} \leftarrow Destroy(\mathcal{S})$
7: $\mathcal{S} \leftarrow Repair(\mathcal{S})$
8: **if** $\mathcal{S} < BestSolution$ **then**
9: $BestSolution \leftarrow \mathcal{S}$
10: $CurrentSolution \leftarrow \mathcal{S}$
11: **else**
12: **if** $NewSolutionAccepted(\mathcal{S})$ **then**
13: $CurrentSolution \leftarrow \mathcal{S}$
14: **end if**
15: **end if**
16: **end while**
17: **return** $BestSolution$

LNS relies on repetitive use of problem dependent heuristics for destroying and repairing the current solution (lines 4–7). The resulting solution is saved when it dominates the preceding ones (lines 8–10) and it may be accepted even if it deteriorates the objective function during the search (line 11–13). In this case, the most common acceptance criteria come either from Simulated Annealing [Kirkpatrick et al., 1983] or from the Record-to-Record Travel algorithm [Dueck, 1993].

Recent heuristic in the literature based on Large neighborhood Search achieves a remarkable success in the fields of vehicle routing problems and scheduling. Generally, the key idea of the LNS algorithm in those problems is to remove a number of customers or tasks with a destroy operator and then re-insert them with a repair operator.

To our knowledge, the use of LNS for solving SCND problems is still very scarce. Copado-Méndez et al. [2013] model two cases studies in chemical engineering and solve them with an hybrid LNS algorithm. They combine LNS with standard branch-and-cut techniques. They randomly choose a set of variables to remove and invoke a commercial MIP solver to improve the solution changing the value of the variables removed. They consider several stopping criteria such as maximum number of iterations and maximum execution time of the algorithm.

4.2 An LNS heuristic for supply chain network design

The schematic view of the LNS heuristic is presented in Figure 4.1. The LNS heuristic is composed of three main steps: generating initial solution and score of each network configuration, LNS procedure, and post optimization. The detailed of the proposed method is depicted in Algorithm 2.

The LNS heuristic is initialized with a simple greedy heuristic that iteratively opens facilities with the least fixed cost. Each network configuration is given an initial score.

A keypoint of the heuristic is that only one layer is modified in the current iteration. In line 4, this layer is randomly chosen between plants or DCs. A target network configuration for the next instance (line 5) is chosen *a priori*, before removal and repair operators are applied. This helps the operators decide how

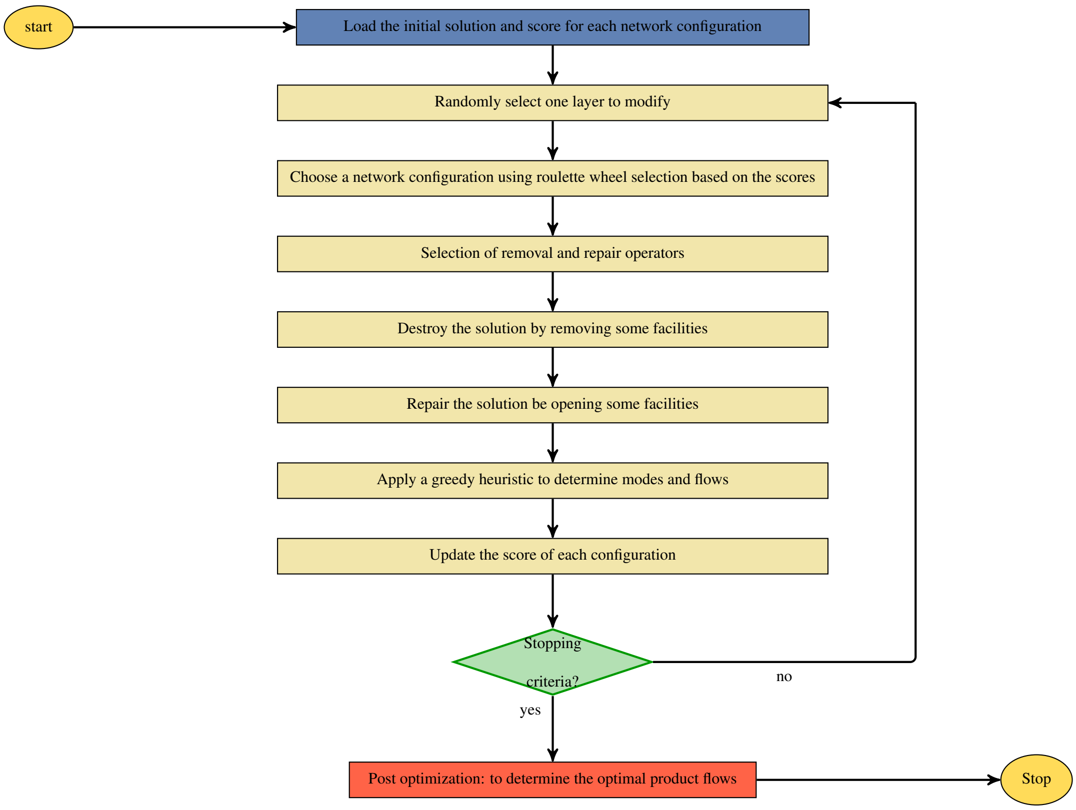

Figure 4.1: schematic view of the LNS heuristic for the SCND problem

Algorithm 2 LNS heuristic for the SCND problem

Require: Initial solution $\mathcal{S}^0$ and score for each network configuration.
$BestSolution \leftarrow \mathcal{S}^0$
$CurrentSolution \leftarrow \mathcal{S}^0$
while the termination criterion is not satisfied **do**
  randomly select one layer to modify between J and K
  choose a network configuration using roulette wheel selection based on the scores
  Selection of $Removal$ and $Repair$ operators to be applied
  $\mathcal{S} \leftarrow Removal(CurrentSolution)$
  $\mathcal{S} \leftarrow Repair(\mathcal{S})$
  Apply a greedy heuristic to obtain transportation modes and product flows variables
  if $\mathcal{S} < BestSolution$ **then**
    $BestSolution \leftarrow \mathcal{S}$
    $CurrentSolution \leftarrow \mathcal{S}$
  else
    if $AcceptanceCriterion(\mathcal{S})$ **then**
      $CurrentSolution \leftarrow \mathcal{S}$
    end if
  end if
  Update the score of each network configuration
end while
Post optimization: determine the optimal product flows with the simplex algorithm.
return $BestSolution$

many facilities can be removed and rebuilt, which drastically simplifies the definition of removal and repair operators.

A pair of removal and repair operators is randomly selected from a pool of operators (line 6)

The transportation modes and product flows are determined only when all facilities have been settled (line 9). Determining the optimal flow is a linear program, which can be optimally solved in polynomial time. Nevertheless, this step has to be performed in each iteration and can represent a large computation effort, especially for large-size instances. Thus, we resort to a greedy fast heuristic consisting of assigning product flows to the closest facility via the cheapest transportation mode.

When the new solution improves the current solution, it is automatically accepted and saved (lines 11 and 12). Otherwise, an *acceptance criterion* similar to that of simulated annealing, is used to determine whether the new solution should replace the current solution (line 14). See [Pisinger and Ropke, 2007] for the complete description of the acceptance criterion.

In line 18, the score of the current network configuration is updated based on the value of the objective function. At the last iteration, we slightly improve the solutions provided by the LNS method with a post-optimization step (line 20): instead of the greedy heuristic, we optimize the product flows with the simplex algorithm. The computation time is about 10 seconds for the largest instances.

4.2.1 Removal operators

The aim of the destruction operators is to remove some open facilities from one layer of the current solution. For the sake of simplicity, we describe the remove and repair operators and give mathematical notations only for the layer corresponding to plants. All formulas can be easily transposed to the case of DCs.

Let us assume that a number n_d of plants must be removed from the current solution. All removal (resp. repair) operators except the *random* one work as follows. For each candidate plant, we calculate a score representing the benefit of closing (resp. opening) this plant. This score can be based on distance, cost, demand or other logistic criteria. All candidate plants are ranked in order of scores. The n_d plants are selected with a biased roulette wheel giving much higher probability to the plants with the best scores (see Ropke and Pisinger [2006] for more detail).

Obviously, other decision variables related to the selected facilities have to be modified accordingly. If a facility is removed from the current solution, all associated variables (e.g. ingoing and outgoing flows) are set at 0.

1. **Random removal:** this operator randomly chooses n_d open facilities to be closed. Its aim is to diversify the search in the solution space.

2. **Total cost-based removal:** this operator closes facilities with the highest estimated cost. To this end, we sum two normalized indicators for each facility, representing fixed and variable costs.

   The normalized fixed cost FC_j of facility $j \in J$ is defined as the ratio $FC_j = \dfrac{c_j}{\max\limits_{j' \in J^o} c_{j'}}$ between its fixed cost c_j and the maximal one among open plants $j' \in J^o$.

   The normalized variable cost of plant $j \in J$ is a similar ratio in which each term includes the processing costs as well as the ingoing and outgoing transportation costs related to j. It is expressed by the following formula:

$$VC_j = \frac{\sum\limits_{p \in P}(a_j^p + \sum\limits_{i \in I}\sum\limits_{m \in M} v_{ij}^{mp} + \sum\limits_{k \in K^o}\sum\limits_{m \in M} v_{jk}^{mp})}{\max\limits_{j' \in J^o}(\sum\limits_{p \in P}(a_{j'}^p + \sum\limits_{i \in I}\sum\limits_{m \in M} v_{ij'}^{mp} + \sum\limits_{k \in K^o}\sum\limits_{m \in M} v_{j'k}^{mp}))}.$$

   Note that, in the above formula, only one m index in each sum has a non-zero value. The normalized cost indicator for plant j is $FC_j + VC_j$. Our numerical experiments show that this value balances fixed and variable costs. We recall that we describe the operators only for the plant layer. The reasoning is the same for the DC layer.

3. **Capacity utilization:** this operator removes facilities with the least capacity utilization. The capacity utilization ratio RC of facility $j \in J \cup K$ is computed as follows:

$$RC_j = \frac{cap_j - \sum_{i \in V} \sum_{m \in M} \sum_{p \in P} x_{ji}^{mp}}{cap_j},$$

which indicates the percentage of remaining capacity in facility j.

4. **Unit cost removal:** this operator closes facilities with the least performance in terms of fixed costs and utilization of capacity. The performance of one facility $j \in J \cup K$ is measured by the ratio $S_j = \dfrac{RC_j}{FC_j}$.

5. **Horizontal cluster removal:** removes a number of facilities of the same layer located in the same region. To this end, for each cluster to be removed, a first location is randomly selected and considered as a *seed*. Then, the nearest open facilities are closed. To avoid removing too many clusters from the same region, the choice of the next cluster to be removed is based on a distance criterion from previously removed clusters.

6. **Vertical cluster removal:** the goal is to close a number of plants and DCs related to each other, i.e. clusters of plants and DCs. A first possibility is to close one plant randomly as a seed and then the nearest open DCs. A second possibility is to close one DC randomly as a seed and then the nearest open plants. We choose randomly between these two possibilities.

4.2.2 Repair operators

The goal of repair operators is to restore the feasibility of a partial solution after a removal operator has been used. This consists of rebuilding a number of missing facilities. The number of facilities to be opened at each layer depends on the network configuration selected in line 5 of Algorithm 2. Thereafter, we denote by n_r the number of facilities to be opened.

1. **Random repair :** n_r closed facilities are randomly selected. This operator acts as a diversification tool.

2. **Total cost repair:** this operator follows the same approach as the greedy repair heuristic (or best insertion) in vehicle routing problems. The principle is to select iteratively the facility whose insertion minimizes the cost of the future solution. Following Olivares-Benitez et al. [2013], the candidate locations $j \in J$ are ranked in ascending order of the values

$$S_j = \frac{c_j}{cap_j} + \frac{\sum_{i \in I \cup K^o} (\mu_{ij} \sum_{p \in P} a_j^p) + \sum_{i \in I} (\mu_{ij} \sum_{p \in P} \max_{m \in M} v_{ij}^{mp}) + \sum_{k \in K^o} (\mu_{jk} \sum_{p \in P} \max_{m \in M} v_{jk}^{mp})}{\sum_{i \in I \cup K^o} \mu_{ij}}$$

where $\mu_{ij} = \min(cap_i, cap_j)$ is the maximal admissible product flow between the candidate location and the adjacent layers. In the above formula, the first term represents the unit fixed cost. The second term takes into account the processing and variable transportation costs of all types of product between each candidate facility and open facilities in adjacent layers.

3. **Best substitution:** the idea of this operator is to substitute the facilities that have just been closed by the best set of substituting facilities. It can be applied only if $n_d = n_r$.

   The set $J \backslash J^o$ of closed plants can be partitioned into two subsets: the set J^c of plants that have just been closed by the removal operator at the current iteration and the set $J \backslash (J^o \cup J^c)$ of plants which were already closed at the beginning of the current iteration. The best set of substituting facilities can be determined by solving an assignment problem, in which each element of J^c is assigned by an alternative plant in $J \backslash (J^o \cup J^c)$. The criterion to be minimized is the sum of a normalized distance between plants and a normalized fixed cost.

4. **Unit cost ratio:** this operator favors facilities with high available capacity and lower fixed costs. For each closed facility, it is based on the capacity/cost ratio $\frac{cap_j}{c_j}$.
5. **Horizontal cluster:** this operator is symmetric to the *horizontal cluster* removal operator.
6. **Vertical cluster:** this operator is symmetric to the *vertical cluster* removal operator.
7. **Cluster Customers-DC:** the idea of this operator is to open DCs near clusters of customers. First, one cluster of customers is selected. Then a closed DC in the neighborhood of the cluster of customers is randomly selected and opened. The procedure repeats n_r times. This operator relies on the definition of clusters. More detail will be given in section 5.2.1.
8. **Top-down flow assignment:** in a partially destroyed solution, part of the demand may not be satisfied. This operator repairs the destroyed solution by adding material flow corresponding to the unsatisfied demand.

   We first add product flow from I to J and then from J to K, thus we call this operator *top-down flow assignment*. For each supplier, there is some unsatisfied demand for outgoing products. The corresponding quantities are sorted in descending order and placed in a priority list. We assign each element of this list to the nearest plant and update its capacity. If the nearest plant is among the non-operating plants, we open it.

   This reparation procedure continues until the target network configuration has not been reached. If the solution is still not feasible, the objective function is penalized by a quantity proportional to the amount of unsatisfied demand. If a feasible solution is found before the final network configuration is reached, we save the value of the objective function and the best solution found during the process is conserved. Hence, this operator may generate a solution with fewer open facilities than in the target network configuration.
9. **Bottom-up flow assignment:** this operator is symmetric to the *top-down assignment* described above. It assigns unsatisfied flows from customers to suppliers.

4.2.3 Removal and repair

These operators combine one *removal* and one *rebuild* operator sequentially.

1. **Swap operator:** if $n_d = n_r$, then we can use a swap operator, which sequentially removes and adds one facility. We first randomly choose one open facility and remove it from the current solution. Then, all closed facilities are ranked in increasing distance to the one that was just removed. One of them is selected according to the biased roulette wheel principle.
2. **History swap operator:** the goal of this operator is to diversify the search by strongly favoring facilities that were not frequently opened in previous iterations. A historical record of open and closed facilities in all iterations is collected. The history swap operator is one in which the facility to be closed (resp. opened) is selected with a biased roulette wheel based on the maximal (resp. minimal) use in past iterations.

4.3 Network configuration

In the network considered, the location decision variables are regrouped into two layers. The number of active plants in the solution varies from J_{min} to J_{max} and the number of active DCs varies from K_{min} to K_{max}. Thus the number of possible network configurations is $(J_{max} - J_{min}) \times (K_{max} - K_{min})$.

The LNS algorithm must have a good coverage of all network configurations, but their systematic exploration would be time consuming. We adopt an adaptive approach that gives a score to each network configuration. In each iteration, the next network configuration is randomly selected according to this score. This enables more computational effort to be dedicated to the most promising network configurations. The following subsections detail how we give a score to each network configuration, choose one at each iteration, and update its score during the LNS heuristic.

Initializing the score of all network configurations

To give an initial score to each network configuration, the problem is solved with each configuration for a predetermined number of iterations. Let us denote as N the set of all possible configurations, z_n the value of the objective function obtained with configuration $n \in N$, and $z_{n^*} = \min_{n \in N} z_n$ the overall best solution. The score w_n of configuration $n \in N$ is calculated as follows:

$$w_n = \frac{z_n - z_n^*}{\sum\limits_{n \in N} (z_n - z_n^*)}, n = 1, .., N \tag{4.1}$$

Choosing a network configuration

At each iteration, the *LNS* heuristic explores the solution space of location variables y_j according to the current network configuration. Having only one active configuration enables the search space, and thus the computation time to be reduced.

We recall that, in each iteration, only one layer among plants and DCs is modified. Without loss of generality, let us assume that the selected layer corresponds to the plants (a similar reasoning is used if it corresponds to the DCs). The number of open plants must be within the interval $[J_{min}, J_{max}]$. Assume that the number of open facilities in the current solution is $\bar{j}$. In order to avoid too large variations from one iteration to another, only slight variations in network configuration are authorized.

Then, the number of open facilities at the next iteration is chosen from the next three possibilities: $\max(J_{min}, \bar{j} - 0.2 \times J_{max})$, $\bar{j}$ and $\min(J_{max}, \bar{j} + 0.2 \times J_{max})$.

Following the idea of the adaptive large neighborhood search [Pisinger and Ropke, 2007], the probability of choosing each possibility depends on the network configuration score, which is calculated from the network configuration's performance in past iterations. The score is updated after each segment of 100 iterations, with an exponential smoothing formula (see [Pisinger and Ropke, 2007]). Hence, in the final iterations the LNS heuristic tends to focus on network configurations with the highest scores.

4.3.1 Determining transportation modes and product flows

In line 9 of Algorithm 2, we apply a greedy heuristic to select the product flows and the transportation modes between facilities. Hereafter, we call it allocation heuristic. We first determine the transportation modes and the product flows between all DCs and customers, which is described in Algorithm 3. Then, we adopt the same principle to determine transportation modes and product flows between plants and DCs and between suppliers and DCs.

Algorithm 3 is based on a priority order defined by the largest demands. All demands d_l^p are ranked in descending order (line 2) and we keep assigning products in descending order of this priority order (line 3) with a greedy criterion based on the transportation cost (line 5). Sometimes it is impossible to assign the whole customer demand d_l^p due to the capacity limitation cap_k (line 6). Then, the cheapest transportation mode is selected for arc $(k, l) \in A$ (line 9). Other available modes for this arc are discarded by increasing their cost to an arbitrary large value (line 10).

Algorithm 3 Assignment of transportation modes and product flows

Require: d_l^p : demand of customer $l \in L$ for product $p \in P$, cap_k : capacity of DC $k \in K$, v_{kl}^{mp} : variable transportation cost for product p on arc (k, l) with mode $m \in M$.

```
Initialization of transportation modes: t_ij^m = 0, ∀(i, j) ∈ A, m ∈ M.
Build a list ListD of demands with all demands d_l^p in decreasing order.
for all demands d_l^p ∈ ListD do
    while d_l^p > 0 do
        select the DC k* and the transportation mode m* with minimum cost v_{k*l}^{m*p}
        calculate the value of a maximal feasible shipment x_{k*l}^{m*p} = min(cap_k, d_l^p)
        update remaining capacity at DC: cap_k ← cap_k − x_{k*l}^{m*p}
        update customer demand: d_l^p ← d_l^p − x_{k*l}^{m*p}
        update transportation mode list: t_kl^{m*} = 1
        update ListD and values v_{k*l}^{mp} for m ≠ m*
    end while
end for
return values of x_kl^{mp} and t_ij^m
```

4.4 Conclusion

In this chapter, the LNS based framework presented to solve the considered supply chain. The LNS framework is mainly used to fix the location decisions. To this end, 3 different kinds of operators are defined: removal operators which are used to close a number of facilities, repair operators which are applied to open a number of facilities, and a combination operators which are responsible for closing and opening the facilities. Some of those operators guide the search to intensify the search and some others diversify the solution space like cluster operators. We also introduced a notion of *network configuration* to partition a solution space and guide the search in a more systematic and efficient way.

During the search a greedy heuristic is called to select the appropriate transportation modes and determine the product flows. Once the network configuration has been determined, a post-optimization step consists in using the simplex algorithm to optimally determine the product flows.

5

Generation of instances for the SCND model

To evaluate performance of the proposed model and solution approach, we provided computational experiments on a set of randomly generated test instances described in section 5.1. The procedure used to generate these instances is also explained in section 5.2.

5.1 Test Instances

We generated a total of 60 instances, with 15 distinct sizes and 4 types of supply chain network configurations. The number of products $|P| = 5$ for all instances. The size of these instances is determined by the number $|I|$ of suppliers, the number $|J|$ of candidate plants, the number $|K|$ of candidate DCs, the number $|L|$ of customers, and upper limits $|J_{max}|$ and $|K_{max}|$ on the number of plants and DCs that can be opened. Similarly to Cordeau et al. [2006], we set the number of potential suppliers and plants to $|I| = |J| = 0.1 \times |L|$. The number of potential DCs was set to $|K| = 0.2 \times |L|$. The values J_{max} and K_{max} were set to $0.5 \times |J|$ and $0.5 \times |K|$, respectively. Table 5.1 displays the value of all parameters for each size of instance. The goal of generating small test instances is to compare LNS solutions with known optimal solutions obtained with an MILP solver. The aim of large instances is to study how the LNS behaves when the solver is unable to solve the instances to optimality.

5.2 Data generation

5.2.1 Generating various patterns of supply chain

All locations were generated on a 200×200 grid. Since the physical layout of suppliers, facilities and customers may influence the network configuration, we generated four types of pattern corresponding to different realistic situations:

- **Pattern** 1**:** the coordinates of all vertices were randomly generated with a uniform distribution in the interval $[0, 200]$ along each axis.
- **Pattern** 2**:** we assumed that around 60% of all facilities are located in a few clusters representing large cities or areas with a large density. The remaining 40% are scattered randomly throughout the grid. To define the coordinates of each cluster, the 200×200 grid was divided into 25 sub-grids. We generated one cluster at most in each sub-grid and the facilities of each cluster were randomly generated within the corresponding sub-grid. As an example, Figure 5.1 represents the aforementioned assumptions in

Table 5.1: Characteristics of test instances

Problem size	$\lvert I\rvert$	$\lvert J\rvert$	$\lvert K\rvert$	$\lvert L\rvert$	$\lvert J_{max}\rvert$	$\lvert K_{max}\rvert$
s1	6	6	12	60	3	6
s2	7	7	14	70	4	7
s3	8	8	16	80	4	8
s4	9	9	18	90	5	9
s5	10	10	20	100	5	10
s6	12	12	24	120	6	12
s7	14	14	28	140	7	14
s8	16	16	32	160	8	16
s9	18	18	36	180	9	18
s10	20	20	40	200	10	20
s11	22	22	44	220	11	22
s12	24	24	48	240	12	24
s13	26	26	52	260	13	26
s14	28	28	56	280	14	28
s15	30	30	60	300	15	30

generating the coordinates of facilities. The facilities inside each clusters are connected together with dashed line.

– **Pattern** 3**:** we modeled industrial regions with clusters of suppliers and plants. The coordinates of a *seed* cluster of suppliers were first selected randomly with a uniform distribution in the 200×200 grid. Then, the coordinates of a cluster of plants were chosen randomly in the same sub-grid. The remaining vertices were randomly generated. As depicted in Figure 5.2 there are two clusters including a number of suppliers and plants close to each other. There are also four clusters of customers through the network.
– **Pattern** 4**:** we modeled areas with a high density of customers. 60% of all DCs and customers were regrouped into 4 to 5 clusters. A *seed* location was first selected randomly with a uniform distribution in the 200×200 grid. Then, a cluster of customers and a cluster of DCs were generated in the same sub-grid as the seed. The procedure was repeated until 60% of the customers and DCs had been generated. All remaining vertices were randomly generated. As it is shown in Figure 5.3, There are four cluster of customers which a number of DCs are located close to each of them.

Generation of transportation modes

We assumed three transportation modes in the network. Table 5.2 shows the main characteristics of these modes. Column 2 states whether the corresponding transportation mode is subject to fixed costs. Column 3 displays the relative variable cost of each mode compared with the others. Columns 4 and 5 detail the minimal load limitations and other restrictions on each transportation mode.

Table 5.2: Characteristics of transportation modes

Transportation mode	Fixed cost	Variable cost	Min limitation	Restrictions
mode 1	✓	Intermediate	×	×
mode 2	×	Highest	×	DCs to customers
mode 3	×	Lowest	✓	Long distance only (suppliers to plants, plants to DCs)

For example, mode 1 can be an internal fleet of trucks. Mode 2 can concern an outsourced fleet of trucks for the delivery of goods to the customers. Mode 3 can correspond to a vessel or a train, with a minimal

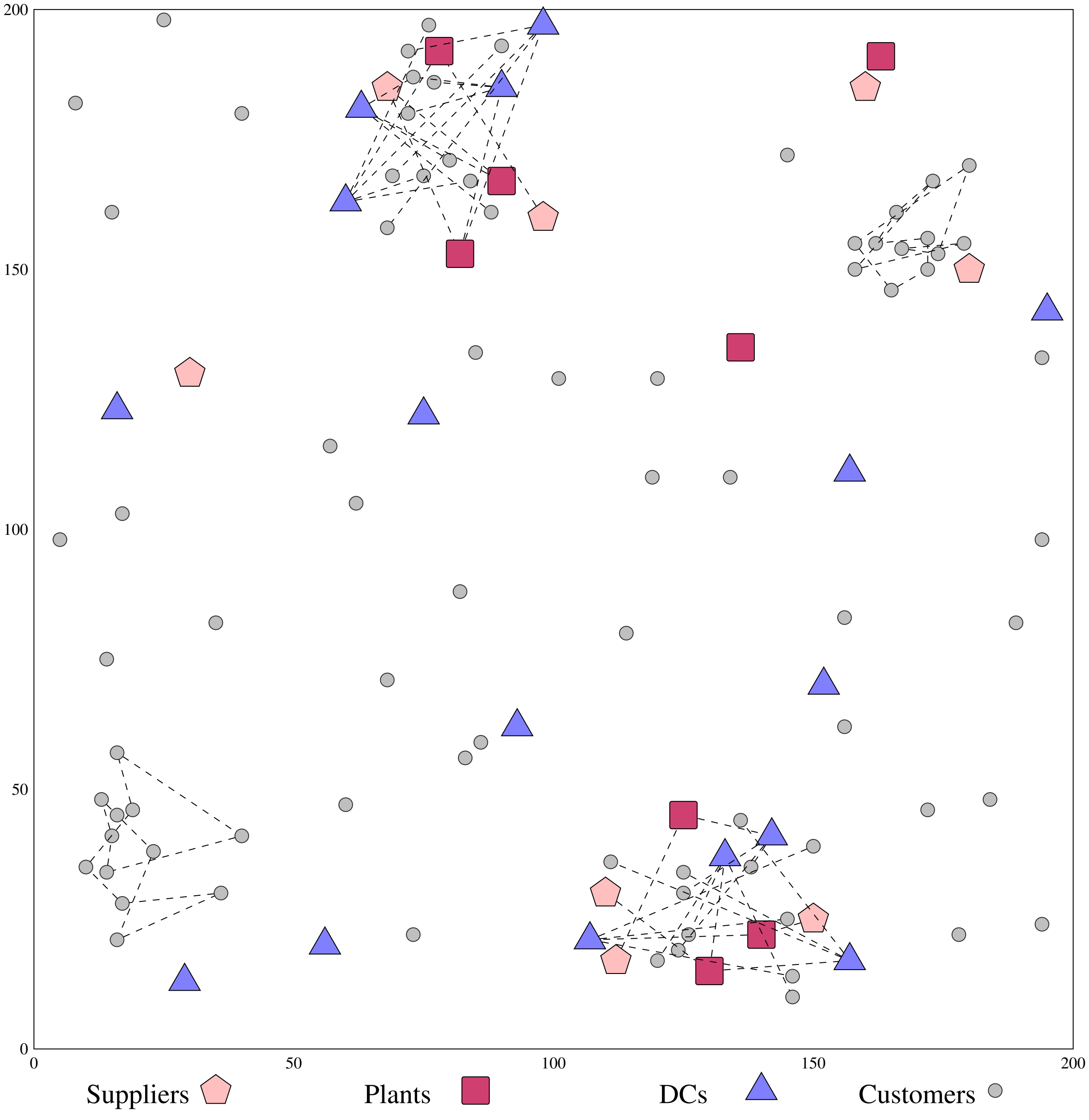

Figure 5.1: Example of supply chain pattern 2

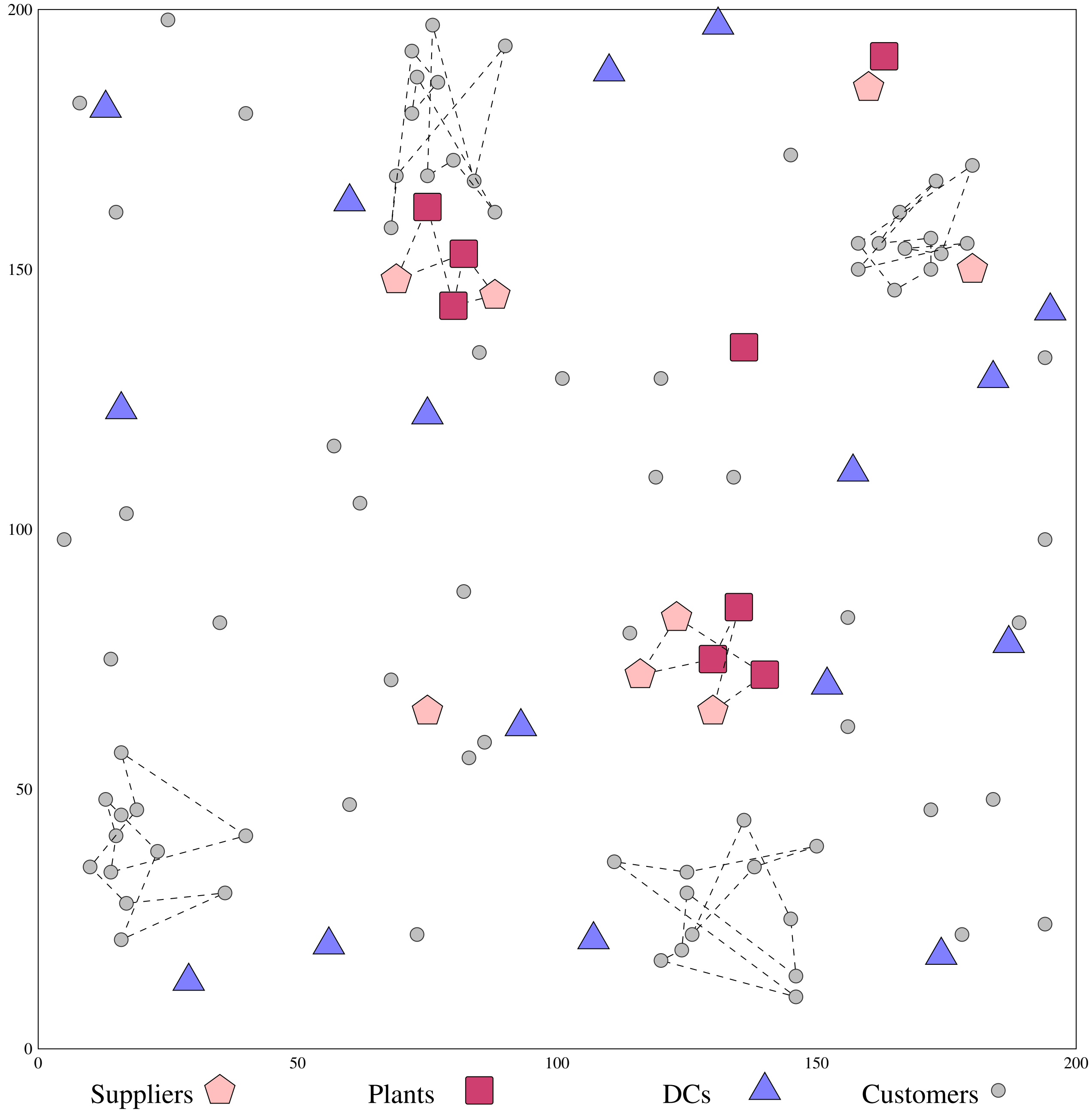

Figure 5.2: Example of supply chain pattern 3

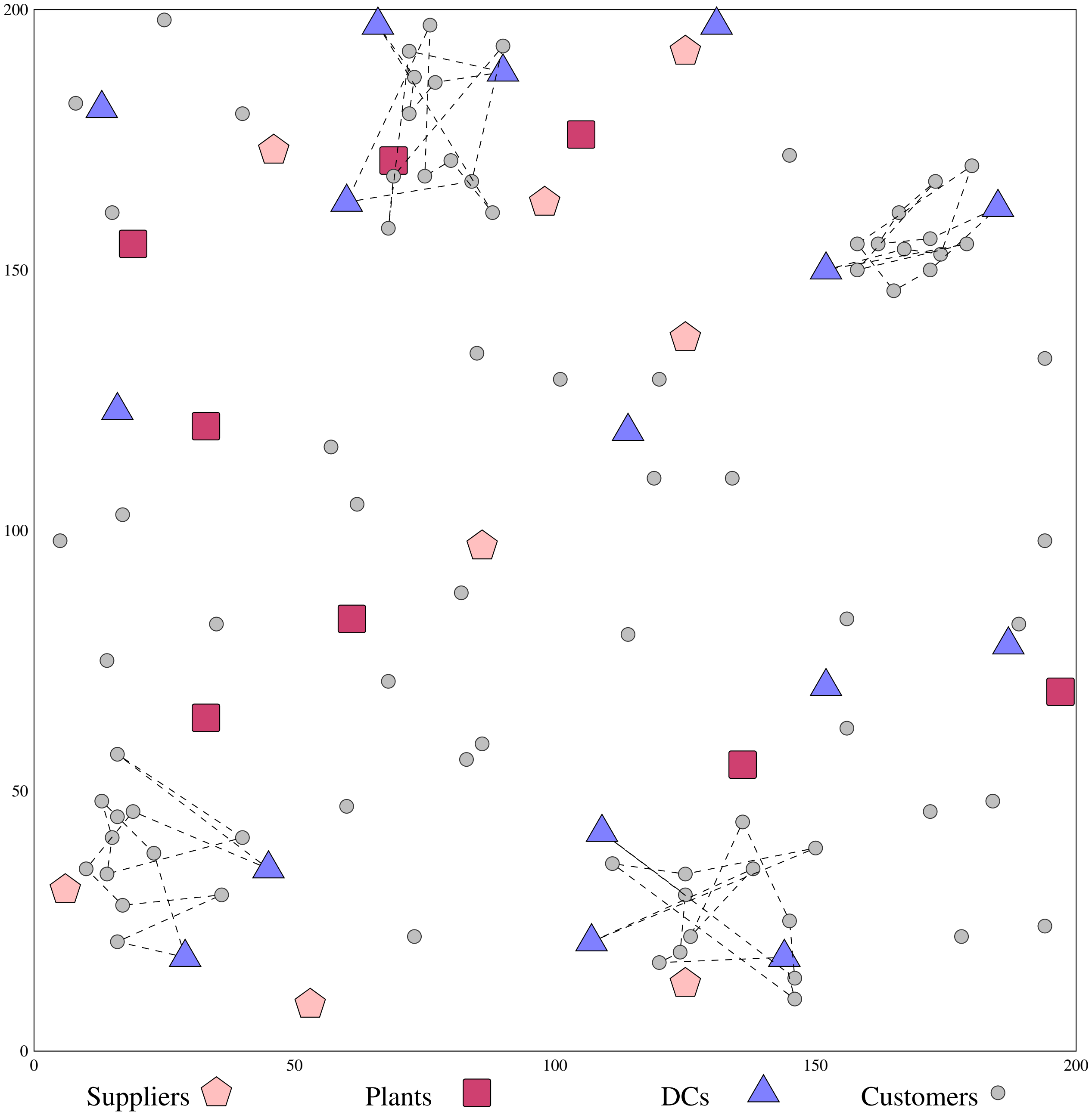

Figure 5.3: Example of supply chain pattern 4

amount of load on each shipment and that only for long-distance trips.

The fixed cost of mode 1 was assumed to be 10000. The variable cost of mode 2 was defined as 20% more expensive than the variable cost of mode 1. We also assumed that the fixed cost of mode 3 was zero and its variable was 80% of that of mode 1.

However, mode 1 can be used without any restriction whereas mode 2 is limited to the distribution to customers and mode 3 has a minimum product flow restriction and can be used only for a subset of long-haul trips. Admissible trips with mode 3 were generated by dividing the 200×200 grid into 25 sub-grids. Only a subset of sub-grids allows mode 3. Moreover, the two ends of the trip must be as far apart as distinct sub-grids that both allow mode 3.

Fixed cost of facility location

The fixed cost of opening facilities varies with the price of the real estate market in each region. Investment costs are significantly larger in sub-grids with a higher density of customers. We divided the 200×200 grid into 20×20 sub-grids of equal size and generated distinct fixed costs in each sub-grid, with a relative difference of about 60% between the cheapest and the most expensive sub-grids.

We assumed economies of scale when building large facilities. Thus the fixed costs are also roughly proportional to the square root of the facilities capacity which is calculated as the value $(c) \times (\sqrt{cap_f})$, where:

- c is randomly generated in the interval $[10000, 20000]$, $[20000, 35000]$, $[35000, 50000]$ or $[50000, 60000]$ depending on the price category of the sub-grid considered,
- cap_f is the capacity of the facility.

.

Variable costs

The variable transportation cost between two nodes depends on the arc length, the transportation modes and local factors. A variable transportation cost tc_{ij}^{1p} on arc $(i, j) \in A$ with mode 1 for product p was determined randomly in the interval $[0.8, 1.2] \times t_{ij} \times \tau$, where t_{ij} is the distance between nodes i and j, and τ is a parameter representing the cost in each layer of the supply chain. Due to the added value of products along the supply chain and the transportation of smaller lot sizes in the downstream part of the supply chain, we assumed slightly increasing transportation costs layer by layer. Thus, τ was randomly chosen in the interval $[1, 1.3]$ for the transportation between a supplier and a plant, in the interval $[1.2, 1.4]$ between plants and DCs and in the interval $[1.3, 1.5]$ for the distribution to customers. As explained before, the variable transportation costs for modes are proportional to that of mode 1.

The unit processing cost for a product $p \in P$ was generated as the sum of the purchase cost (in the interval $[130, 150]$), production cost (in the interval $[130, 150]$) and warehousing and logistics costs (in the interval $[100, 120]$). Then, for every node $n \in I, J, K$ and every product $p \in P$, we generated the corresponding costs, which were noised by multiplying them by a factor randomly chosen in the interval $[0.9, 1.2]$.

Since the variable costs (fixed transportation cost, variable transportation cost, and processing cost) influence the network configuration, we considered two levels of variable costs. Following Cordeau et al. [2006] and Sadjady and Davoudpour [2012], half of the instances were generated in such a way that variable costs represented $40\% - 50\%$ of the total network cost. In the other instances this cost represented $20\% - 30\%$ of the total cost. In the latter case, the fixed cost values were multiplied by 2.

Capacity of facilities

Assume that u is the sum of all customer demands. Then, the capacity of each DC was chosen randomly with a uniform distribution in the interval $[\frac{u}{|K_{max}|}, 1.1 \times \frac{u}{|K_{max}|}] \times 1.5$. The same formula was also applied to plants, with 2 instead of 1.5. Accordingly, the capacity of suppliers was chosen randomly with a uniform distribution in the interval $[\frac{u}{|I|}, 1.1 \times \frac{u}{|I|}] \times 3$.

Demand

As proposed in Yeh [2006], the customer demands were randomly generated according to a uniform distribution in the interval $[100, 300]$.

5.3 Conclusion

We generated different sizes of test instances to evaluate the LNS method. We also consider 4 different configuration patterns concerning the location of suppliers, plants, DCs, and customers. Overall, we generated 60 test instances. Due to the significant effect of the percentage of variable cost (processing cost, fixed and variable transportation costs) to the total network cost, we consider two levels of variable costs. In the former level, the variable costs represent $40 - 50\%$ of the total costs and $20 - 30\%$ in the latter level.

To generate the fixed cost for facilities, we considered two specifications for each facility: the capacity, and the geographical location of the facility. To make the data more realistic, we consider three different kinds of modes through the network: Internal truck, external truck, and train. We attempted to make differentiate between those by considering characteristics such as fixed cost, variable transportation cost and minimum flows limitation.

6

Computational experiments for the single-objective SCND model

In this chapter, we detail the computational experiments we performed in order to validate the proposed LNS. In the following we explain how the parameters of the LNS heuristic were set. Then, we detail the results of the heuristic, by analyzing the efficiency of each removal and repair operator, and comparing the numerical results and the computational time with a state of the art MILP solver. All algorithms are coded in C++ and performed on a computer with four Intel 3.0 GHz CPUs and 8 GB of RAM.

The rest of the chapter is organized as follows. In section 6.1, we present all experimental tests to tune required parameters of the algorithm. Different variations of the proposed LNS components such post optimization or the usefulness of cluster operators are also investigated in this section. Section 6.2 provides the results of comparison between the proposed method and the MILP solver. Lastly, the impact of the parameters and transportation modes on the supply chain configurations is investigated in 6.3

6.1 Parameters setting

We have chosen a representative subset of 15 instances to tune the algorithm and find reasonable parameters values. These instances are shown with $s1$ to $s15$ in the following sections. The optimality gap in all the following sections is calculated as follows:

$\%Gap = \frac{LNS-LB}{LB} \times 100$

where LNS denotes the best solution found by the LNS algorithm and LB represents the lower bound obtained by CPLEX. It is worth mentioning the LB presented by CPLEX can either be an optimal value or an actual strict lower bound. We also respect to the standard setting of the CPLEX software while running test instances using CPLEX.

6.1.1 Cooling rate and initial temperature

As an acceptance criterion, we use the principle of simulated annealing to accept a solution that is worse than the current solution. Given a current solution x, a new candidate solution x' with $f(x') > f(x)$ is accepted with a probability

$$e^{-(f(x')-f(x))/T}, \tag{6.1}$$

where $T > 0$ is the temperature. A standard exponential cooling rate is used, starting from an initial temperature and decreasing T according to the expression $T = T(1 - c)$, where c is the cooling rate. The initial temperature is tuned following Pisinger and Ropke [2007], in such a way that at first iteration, a solution which is 10% worse than the current solution is accepted with probability 0.5. Furthermore, we run a subset of instances with different cooling rates in order to tune it. We first tested a temperature reduction at each iteration. The Table 6.1 displays the results obtained with various values of parameter c, ranging from 0.001 to 0.05. We also tested a temperature reduction every 100 iteration, but this did not improve the results. From these experiments, we chose a cooling scheme with a cooling rate $c = 0.05$ at each iteration.

Table 6.1: Optimality Gap of LNS under different cooling rates

Test	*Cooling rate*				
Problems	0.001	0.002	0.005	0.01	0.05
s1	1.95	1.95	1.77	1.29	1.84
s2	1.75	3.23	2.24	2.24	1.75
s3	2.36	1.10	1.08	1.71	1.22
s4	1.00	0.65	1.04	1.04	0.88
s5	0.97	0.62	0.67	0.55	0.67
average	*1.60*	*1.51*	*1.36*	*1.36*	*1.27*
s6	2.26	2.65	1.06	1.70	1.06
s7	1.54	1.09	0.81	0.64	1.61
s8	1.34	0.43	1.49	0.75	0.43
s9	1.17	1.92	1.74	1.16	1.51
s10	1.86	1.61	1.81	1.74	2.09
average	*1.63*	*1.54*	*1.38*	*1.20*	*1.34*
s11	2.73	2.68	2.85	2.43	2.35
s12	1.80	2.08	2.36	2.39	1.63
s13	4.41	4.52	4.86	5.02	4.83
s14	0.78	1.00	0.91	1.15	1.27
s15	4.69	4.61	4.23	4.73	3.07
average	*2.88*	*2.98*	*3.04*	*3.14*	*2.63*
Total average	**2.04**	**2.01**	**1.93**	**1.90**	**1.75**

In formula (6.1), we also tried to replace the current iterate x by the best solution found in previous iterations. The objective of this trick was the reduce the prevent progressive deviation from the best solutions. The result displayed in Table 6.2 shows that this new acceptance criterion brings no significant difference. As a result, we respect to the standard formula according to formula (6.1) for the following test experiments.

6.1.2 Number of iterations

To tune this parameter, we let the LNS algorithm run for 30000 iterations. The number of best solutions found for each test problems during the search process show in Figure 6.1. The blue, red, and green columns show the total number of best solutions found during each 1000 iterations for test instances 1 to 5, 6 to 10, and 11-15, respectively. The maximum iteration number at which the algorithm finds new best solution is less than 14000. Thanks to given initial solution, for instances 1 to 5 all best solutions found in less than 2000 iterations. For instances 6 to 10, it happened in less than 8000 iterations. Therefore, to respect a good trade-off between the computational time and the quality of solutions, we choose 10000 as iterations for instances 1 to 10, and 15000 for instances 11 to 15.

Table 6.2: Optimality Gap of LNS under different SA acceptance criteria

Test Problems	*SA acceptance criteria* Best solution found	Current solution x
s1	0.82	0.82
s2	2.24	2.24
s3	1.10	1.08
s4	1.04	0.65
s5	0.62	0.55
average	*1.16*	*1.07*
s6	1.05	2.18
s7	0.64	0.96
s8	0.43	0.77
s9	0.92	1.33
s10	1.81	1.53
average	*0.97*	*1.35*
s11	1.72	2.03
s12	2.33	1.02
s13	4.44	4.45
s14	0.77	0.88
s15	3.20	2.56
average	*2.49*	*2.19*
Total average	**1.54**	**1.54**

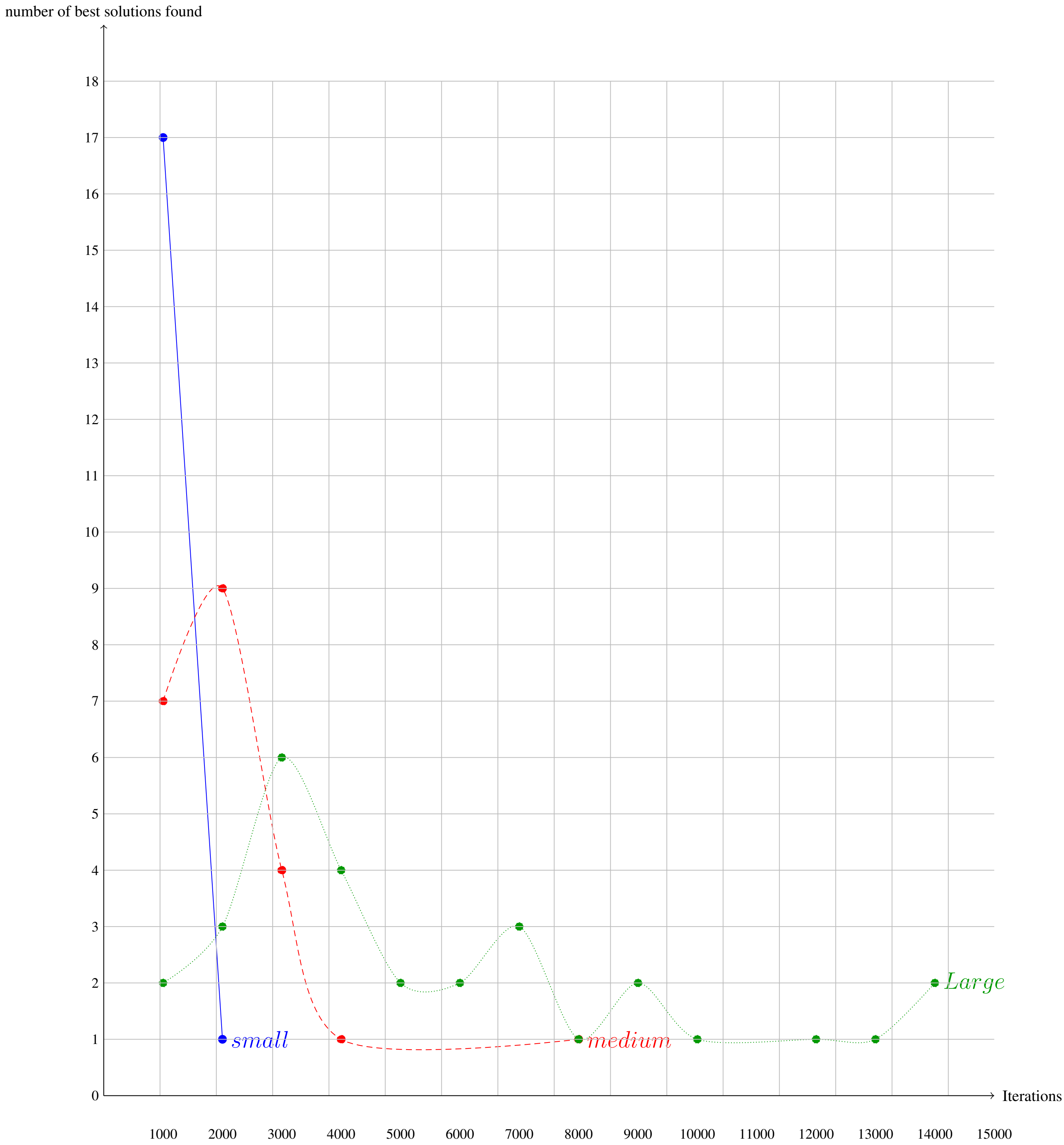

Figure 6.1: Number of best solutions found within process iterations

6.1.3 Network configuration

As mentioned before, the idea is that to identify the most promising network configurations that can facilitate LNS algorithm. To measure the efficiency of each network configuration, we need to explore various combinations. In another words, we need to make decision that which locations must be opened within each network configuration. We have chosen a number of effective operators to destroy and repair the solution, i.e. *capacity utilization* and *unit cost* to meet different combinations. To destroy solutions, we try three scenarios. In scenario 1, *capacity utilization* and *unit cost* operators are used. In scenario 2, *capacity utilization* is used and in scenario 3 *unit cost* is employed. We run each network configuration at least 75 times. From the result shown in Table 6.3, first scenario works slightly better than other scenarios.

Table 6.3: Optimality Gap of LNS under using different destroy operators in initial phase

Test Problems	*Scenario 1*	*Scenario 2*	*Scenario 3*
s1	1.84	1.95	2.28
s2	2.64	4.09	2.90
s3	2.02	2.02	1.44
s4	1.04	1.35	1.15
s5	0.97	0.56	0.60
s6	1.70	1.15	2.94
s7	2.09	1.11	1.58
s8	1.41	2.34	1.87
s9	1.90	1.81	3.17
s10	2.45	2.40	2.10
s11	3.25	3.12	2.98
s12	1.93	2.63	1.03
s13	4.47	5.32	5.65
s14	1.59	1.15	1.21
s15	5.07	5.32	5.33
average	2.29	2.42	2.42

We measure the most promising network configurations according to equation (4.1) in the initial phase and updating scores of each network configuration during the search process. To do this, we consider two approaches: (1) selecting the best solution found at each network configuration as a performance indicator, and (2) calculating the average value of the solutions within each network configuration. To evaluate the performance, we run a subset of instances regarding these approaches. From the result displayed in Table 6.4 we conclude that considering best objective found as an indicator for each network configuration yields explicitly better solutions.

We also wanted to show how the LNS algorithm concentrates on the most promising network configurations. Table 6.5 shows the number of visits of each network configuration during the execution of the LNS for a small-sized instance. The number of plants and DCs corresponding to a network configuration are written along the axes. The values inside the table represent the number of occurrences of each configuration. In this example, the optimal network configuration has 2 plants and 5 DCs. Three neighboring network configurations are also visited quite frequently. On the opposite side, bad network configurations are quickly abandoned by the heuristic.

Table 6.4: Tuning of the network configuration weights

Test Problems	*Gap% Best solution*	*Average solution*
s1	0.82	0.93
s2	1.68	2.24
s3	1.08	1.65
s4	0.65	0.68
s5	0.55	1.41
s6	2.18	2.89
s7	0.96	1.71
s8	0.77	1.87
s9	1.33	2.32
s10	1.53	2.66
s11	2.03	3.07
s12	1.02	2.49
s13	4.45	2.87
s14	0.88	1.68
s15	2.56	3.48
Average	1.50	2.13

Table 6.5: Number of occurrences of each network configuration

		# open plants		
		2	**3**	**4**
# open DCs	**5**	5615	2055	9
	6	2252	33	3
	7	25	5	0

6.1.4 Evaluation of the LNS operators

In order to evaluate the pertinence of the LNS operators, we selected a representative subset of 15 instances.

The first protocol compares the results obtained with and without each operator. First, we ran the LNS with all operators and obtained an objective value z_1. Then, we excluded each of the operators one by one while keeping the others. We obtained an objective value z_2. The individual contribution of each operator is measured by the quantity

$$\frac{z_2 - z_1}{z_1} \times 100.$$

The second protocol compares the results obtained with the random operator only and with the random operator + the assessed operator. More precisely, if we assess a removal operator, z_1 represents the value of the objective obtained with the random destruction + the assessed operator followed by all repair operators. z_2 represents the objective obtained with the random destruction operator only, followed by all repair operators. If we assess a repair operator, z_2 represents the objective obtained with all removal operators followed by random repair + the repair assessed operator. Value z_1 represents the objective obtained with all removal operators followed by the random repair operator only. The individual contribution of each operator is measured by the quantity

$$\frac{z_1 - z_2}{z_2} \times 100.$$

Table 6.6 shows the contribution of each operator measured by both protocols. We performed five runs on the 15 representative instances. Since the results were quite stable, we only report the average results.

Table 6.6: Average contribution of each removal and repair operator

Operator	*Contribution with protocol 1*	*Contribution with protocol 2*
1 Random removal	0.43	–
2 Total cost-based removal	0.22	-0.81
3 Capacity utilization	0.25	-0.98
4 Unit cost removal	0.31	-0.95
5 Horizontal cluster removal	0.25	-0.57
6 Vertical cluster removal	0.28	-0.45
1 Random repair	0.17	–
2 Total cost repair	0.22	-0.85
3 Best substitution	0.14	-0.34
4 Unit cost ratio	0.36	-1.04
5 Horizontal cluster	0.20	-0.24
6 Vertical cluster	0.25	-0.14
7 Cluster Customers-DC	0.42	-0.05
8 Top-down assignment	0.37	-0.22
9 Bottom-up assignment	0.24	-0.09
1 Swap	0.24	-0.67
2 History swap	0.47	0.06

The second column shows only positive numbers, which means that all operators contribute to the efficiency of the LNS. The third column shows that almost all operators, except *history swap*, give positive numbers, which means that they contribute to the efficiency of the LNS. The negative value for *history swap* is quite normal since this operator is a pure diversification factor, which is likely to work only when combined with other operators.

Table 6.7 analyzes the utility of each operator over five runs on a representative subset of 15 instances. For each operator, column 2 presents the average percentage of fruitful iterations, i.e. the iterations which result in a new best solution, an improvement of the current solution or a deterioration of the current solution, which is accepted by the acceptance criterion. Columns 3–5 show how this percentage is split into the three categories.

Table 6.7: Operator utility

Operator	% of useful iterations	best	improving	accepted
		(% of the results in column 2)		
1 Random removal	3.5	1.1	52.8	46.1
2 Total cost-based removal	3.9	1.1	56.5	42.4
3 Capacity utilization	4.0	1.3	57.7	40.9
4 Unit cost removal	4.1	2.0	58.0	40.0
5 Horizontal cluster removal	3.1	0.9	52.4	46.7
6 Vertical cluster removal	3.1	0.8	52.1	47.1
1 Random repair	2.9	1.0	53.4	45.6
2 Total cost-based	4.6	1.2	59.1	39.7
3 Best substitution	11.5	1.3	55.0	43.7
4 Unit cost ratio	4.6	2.0	60.5	37.5
5 Horizontal cluster	1.5	0.3	39.3	60.4
6 Vertical cluster	2.9	0.5	53.1	46.4
7 Cluster customers-DC	1.4	0.5	39.7	59.8
8 Top-down assignment	6.3	2.5	59.6	37.9
9 Bottom-up assignment	4.5	0.4	51.5	48.1
1 Swap	7.9	2.3	48.7	49.0
2 History swap	0.6	1.1	93.1	5.7
Average	*4.1*	*1.2*	*55*	*43*

These results show that no operator outperforms another. Some operators seem to have a negligible effect, but removing them may worsen the quality of the solution. For example, *vertical cluster removal* and *random repair* do not look very useful for yielding new best known solutions, but they may help in escaping from local optima. The main key performance factor is probably the simultaneous use of several operators, which enables the search procedure to be intensified or diversified. Identifying which interactions between operators favor good results is still an open question.

6.1.5 Effectiveness of cluster operators

We provide some operators focusing on cluster concept. However, having cluster of facilities in all cases is not practical. Moreover, we must justify the usefulness of using cluster operators while having cluster of facilities. Therefore, we evaluate performance of cluster operators in both cases.

To evaluate performance of cluster operators for cases that we don't have cluster of potential facilities, we run algorithm for the random network configuration. The result reported in Table 6.8. The second columns show the CPU time while keeping these operators. On the contrary, the third column report the CPU time while these operators are not used. The fourth and fifth columns show the optimality gap with and without cluster operators, respectively. The result reported in Table 6.8 show that there is no significant usefulness in using cluster operators while there is no cluster of facilities. The average gap while cluster operators are used is 1.88%. On the other side, the average gap without using cluster operators is 1.84%. There is also no significant difference between average CPU time in both cases. Using cluster operators yield 230 seconds as average CPU time, while without using cluster operators give 244 seconds Therefore, we can leave out cluster operators while there is no cluster in potential facilities.

Table 6.8: Using cluster operators for random network configuration

Test Problems	*CPU Time (in seconds)* *with cluster*	*without cluster*	*GAP%* *with cluster*	*without cluster*
s1	20	18	0.86	1.35
s2	31	29	1.51	1.83
s3	42	40	2.59	2.38
s4	54	53	1.14	0.76
s5	65	64	0.47	0.93
average	*42*	*41*	*1.31*	*1.45*
s6	78	79	1.13	1.13
s7	100	109	1.62	1.11
s8	142	140	1.10	0.61
s9	150	175	0.99	1.13
s10	216	216	2.34	2.05
average	*137*	*144*	*1.44*	*1.21*
s11	245	273	3.36	3.20
s12	330	373	2.66	2.35
s13	445	517	3.96	3.96
s14	688	686	2.39	2.68
s15	841	880	2.10	2.11
average	*510*	*546*	*2.89*	*2.86*
Total Average	**230**	**244**	**1.88**	**1.84**

To evaluate performance of cluster operators for cases that we have cluster of facilities, we run algorithm for the network configuration containing cluster of facilities. The result reported in Table 6.9. The second columns show the CPU time while keeping these operators. On the contrary, the third column report the CPU time while these operators are not used. The fourth and fifth columns show the optimality gap with and without cluster operators, respectively. The result reported in Table 6.9 prove the efficiency of cluster operators while there are clusters of facilities. The average gap while cluster operators are used is 1.77%. On the other side, the total average gap without using cluster operators is 2.04%. The average gap for test instances $1-5$, $6-10$, and $11-15$ reported in Table 6.9 confirm the same fact. In all cases, using cluster operators yield better average gap. Moreover, there is also no difference between average CPU time in both cases. Using cluster operators yield 222 seconds as average CPU time, while without using cluster operators give 221 seconds. Therefore, we keep cluster operators while there are some clusters in facilities.

6.1.6 Heuristic based on cost and depot

We developed a greedy heuristic to assign products flows. The idea is to assign the products at each layer to next layer via a cheap mode. Hereafter, we call the amount of products at each location to be assigned depot. One important issue in assigning products is to determine the order of locations' depots to be assigned, i.e. line 3 in algorithm 3. To do this, we tried two approaches:

- based on *Highest depot* giving higher priority to locations with more products (see algorithm 3),
- based on *Highest cost* giving higher priority to locations which impose more variable cost. To this end, we compute the $d_l^p \times min(v_{kl}^{mp})$ for each $l \in L$ and $p \in P$. Then we start assigning demands in descending order.

We run the algorithm regarding those mentioned approaches. The result presented in Table 6.10. The two first columns show the CPU time of the LNS heuristic regarding each approach. The second two columns represent the optimality gap regarding respective approaches. The average CPU time in column 2 is 47% less than that in column 3. The average optimality gap of a first method is 1.50% while the other one is 2.26%. Even for small-sized test instances the difference between gap optimality is more than 1%. Overall, the result reported in Table 6.10 shows that greedy heuristic based on highest depot outperforms

Table 6.9: Using cluster operators for network configurations including cluster

Test Problems	*CPU Time (in seconds)* with cluster	*CPU Time (in seconds)* without cluster	*GAP%* with cluster	*GAP%* without cluster
s1	9	9	0.82	1.29
s2	15	14	2.44	2.24
s3	20	19	1.38	1.72
s4	24	22	1.00	0.65
s5	26	25	0.74	0.93
average	*19*	*18*	*1.28*	*1.37*
s6	67	65	1.53	1.76
s7	83	79	0.98	1.67
s8	106	103	0.31	1.76
s9	127	126	1.70	1.25
s10	165	171	1.76	2.52
average	*110*	*109*	*1.26*	*1.79*
s11	308	306	2.58	2.25
s12	393	410	1.36	2.09
s13	516	545	4.86	4.44
s14	631	612	1.09	0.95
s15	834	809	4.03	5.05
average	*537*	*536*	*2.79*	*2.96*
Total average	**222**	**221**	**1.77**	**2.04**

the other one in terms of solution quality and CPU time. Hence, we keep this approach in the LNS method.

6.1.7 Calculating the product flows with an exact method

In line 9 of Algorithm 2, we use of a greedy heuristic to calculate the product flows. Since this subproblem is polynomial, we could also have solved it to optimality, for example by using the *simplex* or *dual simplex* algorithms. The differences in using those algorithms are presented in Table 6.11. Starting from scratch at each iteration is a disadvantage of using *simplex*. But since the location and transportation mode decisions are made, the small number of constraints and decision variables is the advantage of using the simplex method. An advantage of using *dual simplex* can be starting from the optimal basis of the last iteration. In fact, since a new solution can be developed by changing the value of location decisions y_i and transportation modes t_{ij}^m at the right-hand side of constraints (3.5), (3.6) and (3.8)–(3.9), *dual simplex* can be an efficient algorithm to get continuous variables. But having a large number of constraints and variables at each iteration can be a disadvantage of this algorithm.

To choose between both algorithms, we apply *simplex* and *dual simplex* instread of the greedy heuristic in Line 9 of Algorithm 2. The Table 6.12 shows the number of variables and constraints for each test instance.

The result represented in Fig 6.2 shows that *simplex* is much more efficient in term of CPU time. On test instances $s1$ to $s13$ *simplex* gives a slightly better CPU time. But on test instances $s14$ and $s15$, *simplex* strongly outperforms *dual simplex*. The maximum running time of *simplex* for the largest test instance is 7.74s, while it is 201s for *dual simplex*. Thus we select *simplex* as an exact method to calculate optimal product flows at each iteration. Note that there is no need to apply post optimization since optimal flows are provided.

Table 6.13 shows the results obtained with the heuristic and optimal calculation of product flows. Columns 2 and 3 show the CPU time of the exact and heuristic based LNS versions. Columns 4 and 5 present the optimality gap obtained by these approaches. The table show significant difference between these approaches in term of CPU time. The heuristic based LNS runs for 275 seconds on average, while the

Table 6.10: Comparing LNS and Cplex regarding two different assignment approaches of the greedy heuristic

Test Problems	*CPU Time (in seconds)*		*GAP%*	
	LNS with approach 1	*LNS with approach 2*	*LNS with approach 1*	*LNS with approach 2*
s1	24	39	0.82	2.77
s2	31	62	1.19	2.86
s3	42	85	1.42	2.59
s4	54	117	0.65	1.52
s5	64	136	0.81	1.24
Average	*43*	*87*	*0.98*	*2.20*
s6	80	178	2.18	1.65
s7	102	223	0.96	1.15
s8	126	313	0.77	1.08
s9	176	474	1.20	1.28
s10	219	532	1.53	2.61
Average	*140*	*344*	*1.33*	*1.55*
s11	266	582	2.03	2.61
s12	343	672	1.02	1.81
s13	503	759	4.45	4.78
s14	657	796	0.88	1.51
s15	711	892	2.56	4.43
Average	*496*	*740*	*2.19*	*3.03*
Total Average	**227**	**391**	**1.50**	**2.26**

Table 6.11: Comparing primal and dual simplex algorithms

	Advantage	Disadvantage
Primal method	The smaller number of constraints and variables (All constraints and variables related to open facilities are considered)	Starting from scratch
Dual simplex	Starting from optimal basis	The larger number of constraints and variables (including whole set of active and non-active variables and constraints)

Table 6.12: # of constraints and variables using Simplex and dual Simplex

Test	*Constraints*		*Variables*	
Problems	*Simplex*	*Dual Simplex*	*Simplex*	*Dual Simplex*
s1	650	2138	1300	8140
s2	829	2813	1870	11090
s3	936	3600	2130	14600
s4	1170	4424	2925	18295
s5	1401	5336	3755	22430
s6	1760	7525	5000	32525
s7	2252	10019	6760	44145
s8	2724	12982	8520	58110
s9	3470	16072	11550	72710
s10	4045	19570	13825	89350
s11	4706	23486	16480	108080
s12	5364	27806	19170	128830
s13	6391	32292	23605	150410
s14	7208	37346	27040	174830
s15	8071	42307	30705	198785

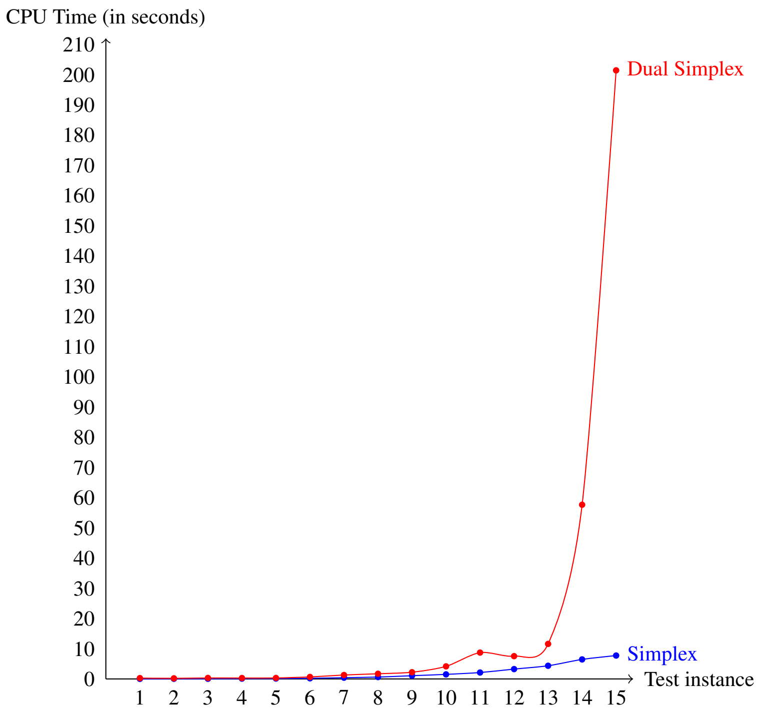

Figure 6.2: Comparing the CPU time of simplex and dual simplex algorithms

simplex based LNS lasts 6101 seconds on average (it is worth mentioning that the time criterion of 3 hours was reached for instances 9 to 15). This also influences the optimality gap on large test instances. When the problem size grows, the simplex based LNS cannot perform the maximal amount of authorized instances. In these situations, the heuristic based LNS yields better results. Overall, the average gap of the heuristic based LNS 1.54%, against 1.92% for the simplex based LNS. This justifies the use of a heuristic approach in Algorithm 2.

Table 6.13: Comparing simplex and heuristic based LNS

Test Problems	*CPU Time (in seconds) simplex*	*Heuristic*	*GAP% simplex*	*Heuristic*
s1	44	18	0.82	0.82
s2	79	29	1.66	2.24
s3	149	40	0.82	1.08
s4	313	51	0.65	0.65
s5	585	62	0.55	0.55
average	*234*	*40*	*0.90*	*1.07*
s6	1223	80	0.75	2.18
s7	3670	101	0.64	0.96
s8	9848	135	0.61	0.77
s9	$\geq 3h$	161	1.10	1.33
s10	$\geq 3h$	252	3.08	1.53
average	*7268*	*146*	*1.24*	*1.35*
s11	$\geq 3h$	406	3.12	2.03
s12	$\geq 3h$	498	2.58	1.02
s13	$\geq 3h$	638	5.96	4.45
s14	$\geq 3h$	751	1.29	0.88
s15	$\geq 3h$	908	5.25	2.56
average	*10800*	*640*	*3.64*	*2.19*
Average	**6101**	**275**	**1.92**	**1.54**

6.1.8 Determining the product flows and transportation modes with an MIP solver

An important question can be arisen is that how about determining the all the product flows and transportation modes variables with an MIP solver. More precisely, the goal is to find the optimal values of these variables in the post optimization phase. Table 6.14 displays the results obtained with the MIP solver (branch and bound algorithm) and combination of simplex algorithm and heuristic method. As stated before, MIP solver is used to obtain the optimal value of product flows and transportation modes. While, finding the only optimal value of product flows are guaranteed with the combination of heuristic and simplex algorithm. Columns 2 and 3 show the CPU time of the MIP and heuristic based LNS versions. Columns 4 and 5 present the optimality gap obtained by these approaches.

The results show significant difference between these approaches in term of CPU time. The heuristic based LNS runs for 275 seconds on average, while the MIP solver based LNS lasts 3882 seconds on average. This also influences the optimality gap. Apparently, in all instances the MIP solver based LNS yields slightly better results. Overall, the huge difference between two approaches in term of CPU time and reasonable difference in term of optimality gap justifies the use of a heuristic approach in Algorithm 2.

6.2 Computational results

The results of the proposed LNS heuristic were compared against the optimal solutions or lower bounds provided by Cplex 12.5 with a maximal computational time of 3 hours. The heuristic was run 10 times on

Table 6.14: Comparing MIP solver and heuristic based LNS in the post optimization phase

Test Problems	*CPU Time (in seconds)* MIP	Heuristic	*GAP%* MIP	Heuristic
s1	25	18	0.00	0.82
s2	37	29	1.18	2.24
s3	48	40	0.42	1.08
s4	71	51	0.29	0.65
s5	76	62	0.00	0.55
average	*51*	*40*	*0.38*	*1.07*
s6	159	80	0.31	2.18
s7	417	101	0.44	0.96
s8	844	135	0.43	0.77
s9	1162	161	0.34	1.33
s10	3921	252	0.76	1.53
average	*1300*	*146*	*0.46*	*1.35*
s11	3322	406	1.05	2.03
s12	6097	498	0.43	1.02
s13	10657	638	2.94	4.45
s14	10374	751	0.28	0.88
s15	21026	908	1.61	2.56
average	*10295*	*640*	*1.26*	*2.19*
Average	**3882**	**275**	**0.7**	**1.54**

each of the 60 instances. The computational results are presented in Tables 6.15–6.17. Columns 3 and 4 present the computational time (in seconds) for Cplex and the LNS heuristic, respectively. Columns 5, 6, and 7 present the minimal, average, and maximal gap (in %) between the results found by the LNS and Cplex. Columns 8, 9, and 10 in Tables 6.16–6.17 present the minimal, average, and maximal gap (in %) between the LNS and the lower bounds found by Cplex. These columns are filled only when Cplex cannot find any optimal solution after 3 hours of computation (in this case, column 3 contains an $*$).

In 23 out of the 60 instances, Cplex finds no optimal solution after 3 hours of computation. For these 23 instances, the average gap is 0.55% and 1.20% from the upper bound and 2.75% and 3.41% from the lower bound. If we ignore these 23 instances, the average value of the optimality gaps in columns 4 and 5 is 0.97% and 1.50%, respectively.

As an illustration, Figure 6.3 represents how the gap is reduced during the search process for test instance s15, pattern 4. The initial solution has a 6.78% gap from the lower bound. After 2000 iterations, the LNS outperforms the upper bound provided by Cplex. After 10500 iterations, the LB gap is 2.2%.

It can be observed from Tables 6.16–6.17 that the LB gap of the LNS ranges from 0.70% to 7.39% with an average value of 3.42%. For instance, in test set $s13$, pattern 1, the maximal LB gap is 7.39%, due to the difficulty of finding good lower bounds with Cplex. The UB gap ranges from -1.92% to 3.07% with an average value of 1.35%, which shows the efficiency of the proposed solution method. It is worth mentioning that the best, average, and worst results (columns 5–7, columns 8–10) and the non-significant difference between the results for each pattern are good indicators of the stability of our heuristic.

The maximum running time of the LNS is 923 seconds with an average of 269 seconds, which shows the ability of the heuristic to find good results within an acceptable time. Moreover, it can be observed that the CPU time of the LNS is not influenced by the pattern of data. For instance, Cplex could solve some test problems such as $s8$ and $s9$ to optimality, while it could not do so for other instances of the same size.

Table 6.15: Comparison between Cplex and the LNS (sets s1 to s5)

Set	CPU (in seconds)		UB GAP (%)		
	Cplex	LNS	Min	Avg.	Max
s1	37	16	0.86	1.52	1.82
	109	18	0.82	1.65	1.79
	82	18	0.59	0.78	0.91
	38	18	1.01	1.06	1.13
s2	651	26	1.51	2.25	2.57
	411	29	1.18	1.86	2.11
	502	29	1.75	2.45	2.78
	480	29	1.22	1.49	1.71
s3	326	36	2.38	2.74	2.96
	503	40	0.99	2.00	2.34
	662	40	0.68	0.99	1.18
	224	40	0.55	1.54	2.24
s4	1150	47	0.76	1.07	1.31
	1072	63	1.21	1.38	1.47
	668	52	1.45	1.79	2.04
	146	51	0.88	1.32	1.59
s5	686	57	0.59	1.09	1.41
	788	63	0.66	1.41	1.84
	597	62	0.57	0.71	0.97
	682	63	0.78	1.00	1.16
Average			1.02	1.50	1.78

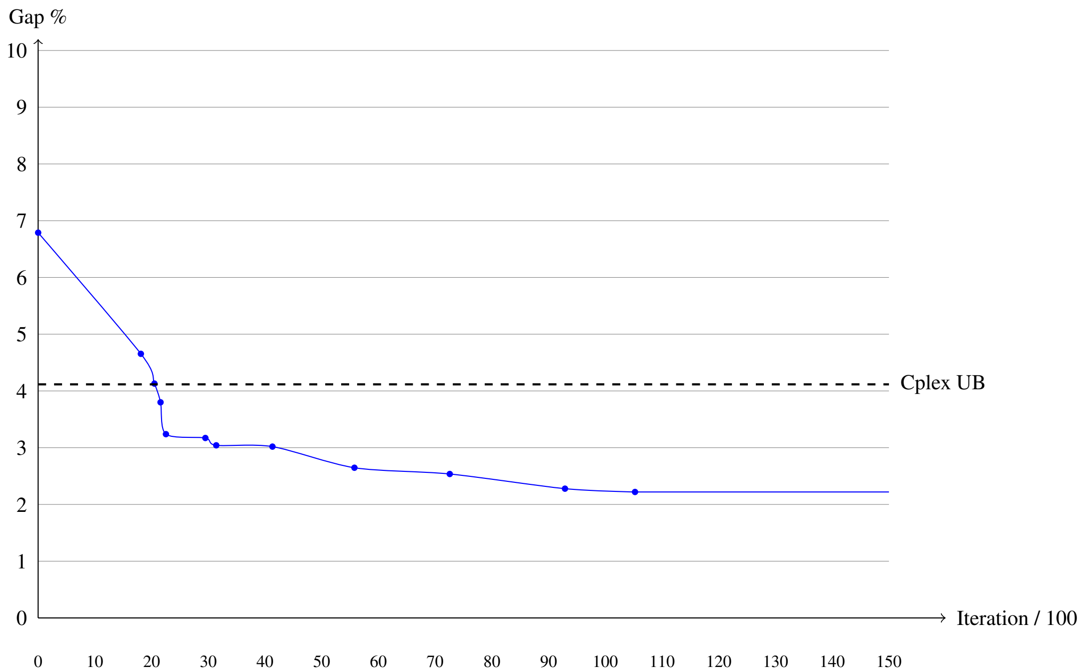

Figure 6.3: Example of LNS iterations (Test set s15, pattern 4)

Table 6.16: Comparison between Cplex and the LNS (sets s6 to s10)

Set	CPU (seconds)		UB GAP (%)			LB GAP (%)		
	Cplex	LNS	Min	Avg.	Max	Min	Avg.	Max
s6	909	69	1.13	1.84	2.06			
	1097	77	0.45	0.86	1.10			
	430	80	1.45	2.41	2.91			
	2826	78	1.91	2.52	2.81			
s7	4942	89	1.57	1.93	2.37			
	3534	101	0.64	1.27	1.94			
	7395	101	0.83	1.37	1.78			
	3115	97	0.90	1.30	1.65			
s8	1443	119	0.39	1.38	2.08			
	*	136	1.10	1.88	2.65	1.43	2.22	2.99
	7659	140	1.10	1.46	1.71			
	3905	135	0.48	1.24	1.67			
s9	4786	142	0.83	1.58	2.14			
	6265	169	0.79	1.10	1.54			
	*	161	1.07	1.79	2.48	1.15	1.88	2.57
	6180	165	1.41	1.93	3.07			
s10	*	194	0.60	1.62	2.34	1.73	2.76	3.48
	5029	213	0.65	1.00	1.49			
	*	252	1.06	1.47	1.81	1.67	2.09	2.43
	4464	212	0.51	0.90	1.39			
Average			0.94	1.54	2.05	1.50	2.23	2.86

Table 6.17: Comparison between Cplex and the LNS (sets s11 to s15)

Set	CPU (in seconds)		UB GAP (%)			LB GAP (%)		
	Cplex	LNS	Min	Avg.	Max	Min	Avg.	Max
s11	∗	348	1.14	1.44	2.36	4.51	4.83	5.3
	∗	406	0.97	1.80	2.47	1.85	2.69	3.37
	∗	410	1.43	1.92	2.72	1.60	2.09	2.89
	5481	381	0.49	1.14	2.29			
s12	∗	606	0.73	1.80	2.74	3.23	4.33	5.27
	∗	473	0.87	1.03	1.52	2.77	2.93	3.42
	∗	500	1.28	1.61	2.49	1.47	1.80	2.68
	∗	498	1.08	2.01	2.67	1.55	2.49	3.15
s13	∗	569	-0.42	0.65	1.88	5.03	6.16	7.39
	∗	638	0.28	0.88	1.57	4.01	4.64	5.33
	∗	608	-0.21	0.91	1.51	3.48	4.64	5.24
	∗	627	0.60	0.88	1.37	4.70	4.99	5.48
s14	∗	765	1.13	1.62	2.09	4.02	4.52	4.99
	∗	757	1.05	1.38	1.95	1.68	2.00	2.57
	∗	705	0.81	1.26	2.14	2.92	3.38	4.26
	∗	751	0.68	1.21	1.67	0.70	1.23	1.69
s15	∗	907	0.05	1.11	1.76	4.15	5.26	5.91
	∗	861	0.17	0.66	1.36	4.08	4.58	5.18
	∗	908	-0.86	0.27	0.63	3.41	4.59	4.95
	∗	923	-1.91	-1.63	-0.38	2.13	2.42	3.67
Average			0.47	1.10	1.83	3.02	3.66	4.35

6.3 Sensitivity analysis

6.3.1 comparing results with and without transportation mode

As stated before, few models in the literature incorporate transportation modes in designing a supply chain network. However, in real-life problems, using suitable transportation modes influences the logistics network efficiency. We ran the algorithm over a subset of instances with two options. Firstly, there is only one mode available between each pair of nodes. Secondly, it is possible to choose a suitable mode. The LNS heuristic was run 10 times for each test instance. The results presented in Table 6.18 show that considering different transportation modes has a strong influence on the network configuration. Columns 2 and 3 represent the percentage of different facilities between each scenario. Column 4 also shows the cost increment percentage occurred without considering transportation mode. The results show that the locations of 19% of plants and 24% of DCs have been changed.

Table 6.18: Influence of transportation modes on network configuration

Test	*Network configuration*		
Problems	*% of plants modified*	*% of DC modified*	*% of cost increase*
1	–	–	3.06
2	–	20	4.16
3	–	40	5.89
4	33	17	4.27
5	–	43	4.74
6	50	–	6.26
7	–	0.22	3.28
8	25	30	5.78
9	20	17	4.82
10	20	38	5.54
11	50	36	7.13
12	33	27	6.34
13	29	24	7.64
14	0	22	5.23
15	29	32	6.91
Average	0.19	0.24	5.4

6.3.2 Influence of demand

Since the demand can change during the horizon time, it is interesting to investigate the influence of decreasing and increasing demand on network configuration and see how far the best solution for the current demand is from optimality. We consider four scenarios for demand variations. Demand is to decrease 5%, and 10% and to increase by 5%, and 10%. For this matter, we run LNS algorithm 10 times for a subset of instances with demand decreased 5%, and 10% and increased by 5%, and 10%. The results are reported in Tables 6.19 – 6.22. Columns 2 and 3 show the amount of changes occurred at each location layer. Columns 4 and 5 display the number of facilities that we need to open or close in case. In some instances such as instances 1 and 7 in Table 6.22, there is no change in the current network configuration. On the contrary, the network configuration have been changed in one or two layers of locations in most of the instances. It seems that reducing 10% of demand has more influences on the network configurations rather than increasing one. In average, the plants and DCs are changed 25% and 33% with demand decreased 10%. But with demand increased 10%, the configuration of plants and DCs are changed 11% and 23%.

Table 6.19: Influence of a demand decrease (-10%) on network configuration

Test	*Network configuration*		*No of additional*	
Problems	*Plant changed*	*DCs changed*	*Plant to be opened*	*DC to be opened*
s1	0	0.25	0	0
s2	0	0.4	0	−1
s3	0	0.6	0	0
s4	0	0.16	0	0
s5	0	0.14	0	−1
s6	0	0.25	0	−1
s7	0.5	0.33	−1	−1
s8	0.25	0.4	0	−1
s9	0.4	0.25	−1	−1
s10	0.2	0.23	0	−1
s11	0.5	0.42	−1	−1
s12	0.66	0.4	−1	−1
s13	0.28	0.35	−1	−2
s14	0.42	0.33	−1	−2
s15	0.57	0.47	0	−1
Average	0.25	0.33	−0.40	−0.9

Table 6.20: Influence of a demand decrease (-5%) on network configuration

Test	*Network configuration*		*No of additional*	
Problems	*Plant changed*	*DCs changed*	*Plant to be opened*	*DC to be opened*
s1	0	0	0	0
s2	0	0.2	0	0
s3	0	0.6	0	0
s4	0	0.16	0	0
s5	0	0.28	0	−1
s6	0	0.12	0	0
s7	0	0.33	0	0
s8	0.25	0.4	0	0
s9	0.6	0.25	−1	−1
s10	0	0.23	0	−1
s11	0.66	0.28	−1	0
s12	0.16	0.26	0	0
s13	0.28	0.35	−1	−1
s14	0.14	0.27	0	−1
s15	0.42	0.42	0	0
Average	0.16	0.27	−0.20	−0.33

Table 6.21: Influence of a demand increase (+5 %) on network configuration

Test	*Network configuration*		*No of additional*	
Problems	*Plant changed*	*DCs changed*	*Plant to be opened*	*DC to be opened*
s1	0	0.25	0	0
s2	1	0.2	0	0
s3	0	0.4	0	1
s4	0.33	0.33	0	0
s5	0	0.14	0	0
s6	0.5	0.12	0	0
s7	0	0.1	0	1
s8	0.25	0.3	0	1
s9	0	0.08	0	0
s10	0.2	0.3	0	1
s11	0.16	0.28	0	1
s12	0.33	0.26	0	1
s13	0	0.23	0	1
s14	0.28	0.16	0	1
s15	0.42	0.52	1	1
Average	0.23	0.25	0.06	0.6

Table 6.22: Influence of a demand increase (+10%) on network configuration

Test	*Network configuration*		*No of additional*	
Problems	*Plant changed*	*DCs changed*	*Plant to be opened*	*DC to be opened*
s1	0	0	0	1
s2	0	0.2	1	0
s3	0	0.4	1	1
s4	0.33	0.33	0	1
s5	0	0.42	0	0
s6	0	0.12	0	1
s7	0	0	0	1
s8	0	0.2	1	1
s9	0.2	0.08	0	1
s10	0	0.15	1	1
s11	0.5	0.35	0	2
s12	0.16	0.26	1	2
s13	0	0.35	0	1
s14	0.14	0.16	1	2
s15	0.42	0.36	1	2
Average	0.11	0.23	0.46	1.13

6.3.3 Influence of varying variable cost on network configuration

We analyze the influence of the variable cost including processing cost, fixed and variable transportation costs on the network configuration by changing to 80%, 90%, 1.10%, and 1.20% of the current variable cost. The result reported in Tables 6.23 – 6.26 show the influence of the variable cost decreasing and increasing on the network configuration. Columns 2 and 3 represent the amount of changing at plants and DCs. Column 4 shows the cost deviation. It can be observed from the results, the current configuration of the plants are changed in the range of 9% to 14%. This range is changed from 19% to 23% for the DCs locations.

Table 6.23: Influence of a variable cost decrease (-20%) on network configuration

Test Problems	*Network configuration* *Plant changed*	*DCs changed*	*Cost reduction%*
s1	0.00	0.25	−7.35
s2	0.00	0.40	−5.83
s3	0.00	0.00	−4.63
s4	0.00	0.17	−3.93
s5	0.00	0.29	−4.39
s6	0.00	0.25	−7.03
s7	0.00	0.11	−4.72
s8	0.00	0.00	−7.28
s9	0.40	0.17	−6.19
s10	0.00	0.15	−6.48
s11	0.33	0.29	−6.34
s12	0.17	0.27	−3.68
s13	0.14	0.29	−3.35
s14	0.14	0.22	−4.21
s15	0.14	0.42	−4.31
Average	0.09	0.22	−5.32

Table 6.24: Influence of a variable cost decrease (-10%) on network configuration

Test Problems	*Network configuration* *Plant changed*	*DCs changed*	*Cost reduction%*
s1	0.00	0.25	−2.78
s2	0.00	0.20	−1.52
s3	0.00	0.00	−1.74
s4	0.33	0.33	−1.49
s5	0.00	0.00	−1.93
s6	0.00	0.13	−3.05
s7	0.00	0.22	−1.75
s8	0.00	0.00	−3.18
s9	0.20	0.17	−2.51
s10	0.00	0.15	−2.38
s11	0.50	0.29	−2.26
s12	0.33	0.20	−0.81
s13	0.14	0.24	−0.54
s14	0.14	0.28	−1.63
s15	0.29	0.37	−0.10
Average	0.13	0.19	−1.77

Table 6.25: Influence of variable cost increase (+10%) on network configuration

Test Problems	*Network configuration* *Plant changed*	*DCs changed*	*Cost reduction%*
s1	0.00	0.25	5.16
s2	0.00	0.20	5.84
s3	0.00	0.00	3.55
s4	0.33	0.33	3.15
s5	0.00	0.29	2.95
s6	0.00	0.13	5.61
s7	0.00	0.11	3.53
s8	0.25	0.20	4.37
s9	0.20	0.17	5.53
s10	0.00	0.31	5.92
s11	0.17	0.29	6.30
s12	0.33	0.13	3.95
s13	0.29	0.18	8.47
s14	0.14	0.22	3.37
s15	0.43	0.42	7.38
Average	0.14	0.21	5.00

Table 6.26: Influence of variable cost increase (+20%) on network configuration

Test Problems	*Network configuration* *Plant changed*	*DCs changed*	*Cost reduction%*
s1	0.00	0.00	8.31
s2	0.00	0.40	7.84
s3	0.00	0.40	6.42
s4	0.33	0.17	5.34
s5	0.00	0.14	5.15
s6	0.50	0.00	8.58
s7	0.00	0.22	5.98
s8	0.25	0.20	8.42
s9	0.20	0.17	9.15
s10	0.00	0.31	9.86
s11	0.17	0.29	10.48
s12	0.17	0.20	6.54
s13	0.14	0.29	12.14
s14	0.00	0.22	5.76
s15	0.29	0.37	11.46
Average	0.14	0.23	8.10

6.4 Conclusion

The performance of the LNS method has been compared with that of an MILP solver on 60 test instances with various sizes and different characteristics. The numerical results show the efficiency of our method in providing high quality solutions in reasonable time. In particular, our proposed method could outperform the MILP solver in a number of large instances, where the MILP solver could not obtain the optimal solutions in 3 hours. Our proposed method also provided a high quality solutions for the small test instances with a small gap% with the optimal values.

We also investigated the influence of important parameters such as demand, variable transportation cost, and transportation modes on the supply chain network configurations. We try a different variations of those parameter to analyse the stability of the supply chain configurations. The results show the supply chain configurations can be highly influenced by the variation of those parameters.

There is still space to improve the proposed solution methods. For instances, developing a more efficient algorithm for determining the transportation mode and product flows may improve both quality and computation time. Using an efficient heuristic may cause escaping from local optimum happen in the earlier iterations.

III

Sustainable SCND model

7

A bi-objective sustainable SCND model

In this chapter, we present a bi-objective sustainable supply chain network design model. As stated in chapter 2, minimizing the cost of the network is the most common objective in the SCND literature. A few papers have recently dealt with sustainable network design [Devika et al., 2014]. Lately and in particular, the increasing importance of environmental issues has prompted decision-makers to incorporate environmental factors fully into the decision process [Ilgin and Gupta, 2010]. Hence, we integrate environmental impacts into the model presented in chapter 3. As a result, we conduct a bi-objective SCND model to minimize cost and environmental impacts.

We consider CO_2 emission as the only environmental impact which is a very popular environment index and can be easily measured [Wang et al., 2011]. As mentioned before, the transport and industrial facilities account for 22% and 20% of global CO_2 emissions, respectively [OECD/IEA, 2012]. Therefore, we integrate those features as a source of CO_2 into our SCND model.

Overall, different types of SCND models have been developed to integrate environmental issues. Almost all the models are developed based on practical applications. Hence, employing a unique model applicable to different types of situations may not be conceivable. Nevertheless, various features such as multi-layer, technology levels and transportation modes could be recognized in the surveyed models. A comprehensive SCND model including all the mentioned features was rarely proposed in the literature.

Depending on the application or problem assumptions, different types of logistics network have been used in the related literature. In our study, similarly to Abdallah et al. [2013], Bouzembrak et al. [2013], Ramudhin et al. [2010], and Sadrnia et al. [2013] the proposed model consists of four layers: suppliers, plants, DCs and customers. Moreover, similarly to the works presented in Table 2.5 in chapter 2, we consider different available technology levels at the plants and DCs. Each technology represents a type of service with associated fixed and variable costs and CO_2 emissions. A higher-level technology may reduce carbon emissions, but is likely to require more investment cost. Therefore, the proper technology for each facility must be selected regarding total costs and emissions.

One of the closest work to our model is introduced by Devika et al. [2014]. They proposed a generic sustainable closed-loop SCND model including multi-level technologies. But they do not integrate transportation modes into the model. Overall, our model differentiates from others since it is able to adapt to different applications with less effort.

This chapter is organized as follows. Section 7.1 describes the proposed bi-objective mathematical model. Section 7.2 presents the notations for data, sets, parameters and decision variables. Finally, model formulation is provided in section 7.3.

7.1 Problem definition

As stated before, environmental issues have been integrated in SCND either using LCA approach or partial assessment. In our study, we use a partial assessment approach to integrate environmental issues. With respect to the literature presented in section 2.2.2, we assume that CO_2 emissions arise from two main sources:

- product processing, for which the amount of emissions are assumed to be proportional to the amount of products processed by the facility. It also depends on the type of operations (purchasing, manufacturing, and warehousing) and technology types.
- product transportation, for which the emissions are based on the distance travelled and the type of transportation mode used.

In this study, the logistics network design problem aims at minimizing total fixed and variable costs, and CO_2 emissions arising from facilities and transportation modes. There are several types of products in the network. Each customer has a fixed demand for each type of product. The suppliers, plants and DCs have limited production and throughput capacities. A set of potential technologies are available at plants and DCs. An appropriate transportation mode for shipping products between two nodes is selected regarding total costs, and emissions. Each transportation capability has a lower and upper capacity limitation.

The main issues to be addressed in the sustainable SCND model includes determining the number, location, and technology level at plants and DCs, suitable transportation mode, and product flows between facilities. The goal is to minimize two conflicting objectives: (1) the total cost (2) the total environmental impact expressed by the CO_2 emissions. Therefore, optimizing the model considered involves a reasonable trade-off between these two objectives depending on the decision makers preferences.

7.2 Data, sets, parameters and variables

For sake of clarity, all notations introduced in chapter 3 are presented again at the end of this section. Moreover, we introduce a set S of potential technologies for facilities. We present the following notations used in the sustainable SCND model:

- pe_i^{ps}: CO_2 emission caused by the manufacturing, or warehousing of one unit product $p \in P$ at $i \in J \cup K$ with technology level s.
- se_i^p: CO_2 emission caused by the purchasing and supply of one unit of semi-finished product $p \in P$ at $i \in I$.
- te_{ij}^{mp}: CO_2 emission caused by the transportation of one unit of product $p \in P$ along arc $(i, j) \in A$ by mode $m \in M$.

Binary variables y_j^s are set at 1 if a facility $j \in J \cup K$ with technology level s is open and 0 otherwise. We also introduce h_i^{ps} which represents the amount of product $p \in P$ manufactured/handled with technology level $s \in S$ at facility $j \in J \cup K$.

7.3 Mathematical formulation

Regarding the above notations, we propose a bi-objective Mixed Integer Linear Programming (MILP) model. The economic objective (7.1) encompasses all fixed and variable costs of the network. The first term is the sum of all opening fixed costs. The second and third terms correspond the cost of all commercial and industrial operations at facilities (purchasing, production, storage etc.). The fourth term represents the fixed costs of using each transportation mode between each pair of nodes. The last term refers to the variable transportation cost between each pair of nodes.

	Nomenclature presented in chapter 3
Sets	
I	a set of suppliers
J	a set of plants
K	a set of DCs
L	a set of customers
P	a set of products
M	a set of potential transportation modes
J^o	a subsets of open plants
K^o	a subsets of open DCs
V	a set of all suppliers, plants, DCs, and customers
A	the set of arcs defines all possible links between facilities
Parameters	
d_l^p	demand of customer $l \in L$ for product $p \in P$
cap_i	capacity of facility $i \in I \cup J \cup K$
v_{ij}^{mp}	variable transportation cost of a unit of product $p \in P$ on arc $(i, j) \in A$ by mode $m \in M$
a_i^p	unit processing cost of product $p \in P$ at $i \in I \cup J \cup K$
g_{ij}^m	fixed cost of transportation mode $m \in M$ along arc $(i, j) \in A$
$\underline{V}_{ij}^m$	minimum threshold volume for using transportation mode $m \in M$ along arc $(i, j) \in A$
$\bar{V}_{ij}^m$	capacity of transportation mode $m \in M$ along arc $(i, j) \in A$
c_j	fixed cost of opening facility $j \in J \cup K$
Binary variables	
t_{ij}^m	set at 1 if transportation mode $m \in M$ is selected to ship products along arc $(i, j) \in A$ and 0 otherwise
Continuous variables	
x_{ij}^{mp}	the flow of product $p \in P$ on arc $(i, j) \in A$ using transportation mode $m \in M$

$$min\ z_1 = \sum_{j \in J \cup K} \sum_{s \in S} c_j^s y_j^s + \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \sum_{p \in P} b_i^p x_{ij}^{mP} + \sum_{i \in J \cup K} \sum_{s \in S} \sum_{p \in P} a_i^{ps} h_i^{ps} + \sum_{(i,j) \in A} \sum_{m \in M} g_{ij}^m t_{ij}^m + \sum_{(i,j) \in A} \sum_{m \in M} \sum_{p \in P} v_{ij}^{mp} x_{ij}^{mp} \tag{7.1}$$

The environmental objective (7.2) consists of three terms. The first term corresponds to the CO_2 emissions due to purchasing and supplying of products from suppliers to plants. The second summation associated with manufacturing and warehousing CO_2 emissions at plants and DCs. The third term represents CO_2 emissions arising from transportation modes.

$$min\ z_2 = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \sum_{p \in P} se_i^p x_{ij}^{mP} + \sum_{i \in F} \sum_{s \in S} \sum_{p \in P} pe_i^{ps} h_i^{ps} + \sum_{(i,j) \in A} \sum_{m \in M} \sum_{p \in P} te_{ij}^{mp} x_{ij}^{mp} \tag{7.2}$$

Constraints (7.3) are the flow conservation constraints through the network.

$$\sum_{i \in V} \sum_{m \in M} x_{ij}^{mp} = \sum_{k \in V} \sum_{p \in P} \sum_{m \in M} x_{jk}^{mp} \qquad \forall j \in J \cup K, p \in P \tag{7.3}$$

Constraints (7.4) and (7.5) calculate the amount of product entering in each facility.

$$\sum_{s\in S} h_j^{sp} = \sum_{i\in I}\sum_{m\in M} x_{ij}^{mp} \qquad \forall j \in J, p \in P \tag{7.4}$$

$$\sum_{s\in S} h_k^{sp} = \sum_{j\in J}\sum_{m\in M} x_{jk}^{mp} \qquad \forall k \in K, p \in P \tag{7.5}$$

Constraints (7.6) ensure the satisfaction of customers demands.

$$\sum_{k\in K}\sum_{m\in M} x_{kl}^{mp} \geq d_l^p \qquad \forall l \in L, p \in P \tag{7.6}$$

Constraints (7.7)–(7.9) force the model to respect capacity constraint at suppliers, plants and DCs respectively. In addition, (7.8) and (7.9) state that the products can be shipped only to open facilities.

$$\sum_{j\in J}\sum_{m\in M}\sum_{p\in P} x_{ij}^{mp} \leq cap_i \qquad \forall i \in I \tag{7.7}$$

$$\sum_{p\in P} h_j^{sp} \leq cap_j\ y_j^s \qquad \forall j \in J, s \in S. \tag{7.8}$$

$$\sum_{p\in P} h_k^{sp} \leq cap_k\ y_k^s \qquad \forall k \in K, s \in S. \tag{7.9}$$

Constraints (7.10) ensure that at most one technology level is selected for each facility.

$$\sum_{s\in S} y_j^s \leq 1 \qquad \forall j \in J \cup K \tag{7.10}$$

Constraints (7.11) ensure that at most one transportation mode is selected between two connected nodes. Constraints (7.12) – (7.13) guarantee that the volume limitation of each given mode is respected.

$$\sum_{m\in M} t_{ij}^m \leq 1 \qquad \forall (i,j) \in A \tag{7.11}$$

$$\sum_{p\in P} x_{ij}^{mp} \leq \bar{V}_{ij}^m\ t_{ij}^m \qquad \forall (i,j) \in A, m \in M \tag{7.12}$$

$$\sum_{p\in P} x_{ij}^{mp} \geq \underline{V}_{ij}^m\ t_{ij}^m \qquad \forall (i,j) \in A, m \in M \tag{7.13}$$

Without loss of generality, we also consider restrictions on the number of open facilities. Constraints (7.14)–(7.15) bound the number of open plants and DCs respectively. These constraints can be discarded by setting minimal values at 0 and maximal values at $+\infty$.

$$J_{min} \leq \sum_{j\in J}\sum_{s\in S} y_j^s \leq J_{max} \tag{7.14}$$

$$K_{min} \leq \sum_{j\in K}\sum_{s\in S} y_j^s \leq K_{max} \tag{7.15}$$

Constraints (7.16) – (7.19) state binary and non-negativity restrictions on decision variables.

$$y_j^s \in \{0,1\} \qquad \forall j \in J \cup K, s \in S \tag{7.16}$$
$$t_{ij}^m = \{0,1\} \qquad \forall (i,j) \in A, m \in M \tag{7.17}$$
$$x_{ij}^{mp} \geq 0 \qquad \forall (i,j) \in A, p \in P, m \in M \tag{7.18}$$
$$h_i^{ps} \geq 0 \qquad \forall i \in J \cup K, p \in P, s \in S \tag{7.19}$$

This model has $((|J|+|K|)|P|)+(2(|S|-1)+|J|+|K|)$ additional constraints compared to the model presented in chapter 3. The first term shows the number of constraints for computing the amount of each product entering in each plant and DC. The second term is the number of constraints related to technology level at the plants and DCs.

The type of technology may also influence on the capacity of the facility. In fact, the facility with higher technology may lead to having more manufacturing and/or warehousing capacity. We can extend the introduced model to cope with this matter by changing the cap_j to cap_j^s in constraints (7.8) and cap_k to cap_k^s in constraints (7.9).

Chapters 8 and 9 explain the extended version of the LNS to a bi-objective method and the evaluation of its performance.

8

Bi-objective Large Neighborhood Search

Companies compete on several criteria such as commercial issues, environmental concern and service level. Companies could benefit from using multi-objective optimization (MOO) techniques when designing their distribution networks, to give extra flexibility to deal with key objectives simultaneously. For instance, minimizing the environmental impact of their activities along with improving customer service levels, while the overall cost is reducing at the same time. Instead of a single solution, multi-objective optimization techniques can offer a choice between several trade-off solutions, providing a decision maker with sufficient options necessary to balance all the important objectives [Harris et al., 2014, Guillén-Gosálbez, 2011a].

As concluded in chapter 2, there is a real need for developing efficient solution methods for rich SCND problems. In practice, solving relatively large instances may not be longer tractable with a MILP solver. Therefore, developing approximated approaches such as metaheuristic method is inevitable to find trade-off solutions [Zanjirani Farahani et al., 2010]. Two trends can be recognised in the literature dealing with multi-objective problems: (i) providing at most one trade-off solution in a single run, and (ii) providing multiple trade-off solutions in a single run.

As stated before, providing the trade-off solutions within one single run makes the metaheuristic approach more desirable. In this study we propose a metaheuristic approach to provide the trade-off solutions in one single run. We adopted the multi-directional local search (MDLS) framework recently introduced by Tricoire [2012]. Using the MDLS is able us conserve the proposed LNS structure and embed it into a bi-objective framework. In addition, since there is no dominant metaheuristic method in solving multi-objective sustainable SCND models (see section 2.5.2), we feel free to choose any method. The efficiency of the multi-directional local search framework has been proved on several known multi-objective problems such as the multi-objective knapsack problem, the bi-objective set packing problem and the bi-objective orienteering problem. Using the LNS method with the MDLS is the approach also described in Tricoire [2012]. To the best of our knowledge, this technique has never been used for solving SCND models. With this idea in our mind, our objective is to obtain high quality trade-off solutions.

The rest of this chapter is organized as follows. Basic definition and metaheuristic related to multi-objective optimization are recalled in sections 8.1 and 8.2 The algorithmic framework of the proposed bi-objective LNS (BOLNS) is presented in section 8.3.

8.1 Multi-objective optimization: basic definitions

It becomes more complicated to compare two solutions with respect to more than one objective. A common approach to compare two solutions is to consider a dominance rule: a solution dominates another one if it is better in at least one objective and not worse in all objectives. A solution is Pareto-optimal if there doesn't exist any solution that dominates it. Multi-objective optimization algorithms aim at finding Pareto-optimal set consisting of several trade-off solutions rather than only one optimal solution [Eberhart et al., 1996].

In this section, we recall the main concepts of multi-objective problems according to Zitzler et al. [2004]. We consider an arbitrary optimization problem with $|k|$ objectives, which are, without loss of generality, all to be minimized and all equally important, i.e., no additional knowledge about the problem is available. We assume that a solution to this problem can be described in terms of a decision vector $(x_1, x_2, \ldots, x_n)$ in the decision space $\mathbb{R}^n$. A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^k$ evaluates the quality of a specific solution by assigning it an objective vector $(y_1, y_2, \ldots, y_k)$ in the objective space $\mathbb{R}^k$.

In the case of a vector-valued evaluation function f, the situation of comparing two solutions x^1 and x^2 is more complex. Following the well known concept of Pareto dominance, an objective vector y^1 is said to dominate another objective vectors y^2 $(y^1 \succ y^2)$ if no component of y^1 is larger than the corresponding component of y^2 and at least one component is smaller. Accordingly, we can say that a solution x^1 is better to another solution x^2, i.e., x^1 dominates x^2 $(x^1 \succ x^2)$, if $f(x^1)$ dominates $f(x^2)$.

The set of optimal solutions in the decision space X is in general denoted as the Pareto set $X^* \subseteq \mathbb{R}^n$, and we will denote its image in objective space as Pareto front $Y^* = f(x^*) \subseteq \mathbb{R}^k$. With many multi-objective optimization problems, knowledge about this set helps the decision maker to choose the best compromise solution. This set can be partitioned into supported and non-supported solutions. For any k-objective problem and any given weight vector of size k, there exists a single-objective projected problem obtained by performing a linear combination of all weighted objectives. Supported solutions are then defined as those solutions for which there exists a weight vector, such that they are optimal for the associated single-objective projected problem [Tricoire, 2012].

Although there are different ways to approach a multi-objective optimization problem, e.g., by aggregation of the objectives into a single one, most work in the area of multi-objective optimization has concentrated on the approximation of the Pareto set. Therefore, we will assume in the following that the goal of the optimization is to find or approximate the Pareto set. Accordingly, the outcome of the algorithm described in section 8.3 is considered to be a set of mutually non-dominated solutions, or Pareto set approximation for short. The Pareto set approximation is used to estimate the approximated Pareto front. We also derive the so-called ideal point and nadir point that define the lower and upper bounds for the objective values of Pareto front [Ada Che et al., 2015].

8.2 An overview of recently published metaheuristic for SCND models

Many classical multi-objective optimization approaches such as weighted sum approach, ϵ-constraint method, and goal programming have been applied to provide one trade-off solution in a single run. Depending on the desired number of trade-off solutions, the algorithm must be run iteratively. Devika et al. [2014] presented a multi-objective sustainable SCND model. They develop three hybrid metaheuristic methods based on the adapted imperialist competitive algorithms and the variable neighborhood search. ϵ-constraint is used to provide trade-off solutions.

Researchers are more interested in methods having the ability of providing multiple trade-off solutions. This can be done by either doing a slight change in the classical methods or developing new approaches mostly based on the evolutionary algorithms. Table 8.1 presents selected papers that use meta-heuristic methods to solve multi-objective SCND problems. The meta-heuristic methods used are listed in column 2. The approach to tackle multi-objective problems is provided in column 3. Most of the studies reviewed provide methods with the ability of obtaining multiple trade-off solutions in a single run except the work provided by Devika et al. [2014]. Random weight approach and evolutionary algorithms are the most used methods to provide multiple trade-off solutions in a single run.

Table 8.1: Articles using multi-objective metaheuristics in SCND

Article	Meta-heuristic	Multi-objective method
Cardona-Valdés et al. [2014]	Tabu	Random weight regarding ideal points
Caballero et al. [2007]	Tabu	Random weight regarding ideal points
Eskandarpour et al. [2014]	VNS	Random weight
Eskandarpour et al. [2013]	VNS	Random weight
Du and Evans [2008]	Scatter search	Epsilon constraint
Devika et al. [2014]	Hybrid meta	Epsilon constraint
Olivares-Benitez et al. [2013]	Scatter search	Non-dominate sorting
Moncayo-Martínez and Zhang [2011]	Ant colony	Pareto Ant colony
Shankar et al. [2013a]	PSO	Non-dominate sorting algorithm
Shankar et al. [2013b]	PSO	Non-dominate sorting algorithm
Ganguly et al. [2011]	PSO	Pareto evolutionary algorithm
Jamshidi et al. [2012]	Memetic	Random weight and dynamic weight
Pishvaee et al. [2010b]	Memetic	Random weight
Liao et al. [2011]	Genetic	Non-dominate sorting algorithm
Dehghanian and Mansour [2009]	Genetic	Non-dominate sorting algorithm
Altiparmak et al. [2006]	Genetic	Random weight (two types)

One possibility to convert a multi-objective problem into a single objective is to use weighted sum functions, but it has the drawback that non-supported solutions are not captured by such a projection [Tricoire, 2012]. As a result, some researchers used an extended version of the weighted sum approach. The difference with the classical weighted sum is the ability to change the weight through search process. Several ways have been employed to determine the weight during the search process. Random weight approach is the most popular one that is applied by many researchers [Eskandarpour et al., 2013, 2014, Jamshidi et al., 2012, Pishvaee et al., 2010b, Altiparmak et al., 2006]. This approach explores the entire solution space in order to avoid local optima and thus gives a uniform chance to search all possible trade-off solutions along the Pareto front [Altiparmak et al., 2006]. In another approach, weights are determined based on the lower bounds for the objective function values of Pareto-optimal solutions [Cardona-Valdés et al., 2014, Caballero et al., 2007, Altiparmak et al., 2006]. The idea is to minimize the distance between trade-off solutions and ideal points. Cardona-Valdés et al. [2014], Caballero et al. [2007] applied tabu search within the framework of Multi-objective Adaptive Memory Programming (MOAMP). MOAMP framework includes two phases. In the first phase, a number of trade-off solutions are provided using weighted approach based on ideal points. In the second phase, the neighborhood of all trade-off solutions are explored to find additional non-dominated points.

Another class of meta-heuristic frequently used in solving Multi-objective SCND is population-based algorithms because of their ability to find multiple trade-off solutions in a single run [Zanjirani Farahani et al., 2010]. A strategy of elitism is widely applied to converge toward efficient non-dominated solutions. Elitism strategy allows some of the better solutions from the current generation to carry over to the next generation. In some studies, non-dominated sorting algorithm is used to incorporate multi-objective optimization into search process [Shankar et al., 2013a,b, Liao et al., 2011, Dehghanian and Mansour, 2009]. Olivares-Benitez et al. [2013] and Du and Evans [2008] deployed scatter search to explore solution space looking for the non-dominated solutions. To do this, they take advantage of the scatter search framework to systematically search diversification and intensification. Du and Evans [2008] used scatter search to assign capacity arrangement among the potential facility locations. Then the ϵ-constraint method is used to obtain a set of non-dominated solutions.

8.3 Algorithmic framework for BOLNS

In our approach, we use the single objective LNS within the framework of the Multi-objective Adaptive Memory Programming (MOAMP) which was first introduced by Caballero et al. [2007].

The main principle of MOAMP comes from this idea that efficient solutions of multi-objective problems are close enough together. It means that around a non-dominated solution we can often find another non-dominated solution. Thus, the MOAMP framework is composed of two major steps: first generating an initial Pareto set approximation and then improve the quality of this set using intensification process. In fact, MOAMP looks for mutually non-dominated solutions with an intensification process around an initial set of non-dominated solutions [Cardona-Valdés et al., 2014].

To obtain the Pareto set approximation, we propose a bi-objective LNS (BOLNS). We plan to gradually explore the solution space in terms of Pareto set approximation in a systematic way in three phases. Similarly to the work described in Caballero et al. [2007], we provide a set of initial Pareto set approximation in phase I. Then, we intensify the search around these points to improve the Pareto set approximation in phase II. As mentioned before, the phase II benefits from the efficient approach introduced by Tricoire [2012] to guide the search. Eventually, we apply the simplex algorithm to optimality determine the product flows and slightly improve the Pareto set approximation in phase III.

We also use the notion of *network configuration* to guide the search. This helps us efficiently controling the solution space in terms of the both objectives. To be more precise, having less open facilities can lead to less investment cost. But on the other hand, it can increase the environmental impact due to transportation. On the contrary, opening more facilities decreases the environmental impact, but it involves higher investment cost. Since the number of open facilities highly influences the cost and environmental impact, we benefit from the *network configuration* notion to effectively control these variables. The three phases method can be described as follows:

– **Phase I: look for an initial Pareto set approximation**
  The initial phase of the single objective LNS is executed separately for each objective. The output is an initial set of mutually non-dominated solutions, namely, Pareto set approximation.
– **Phase II: Intensification around the Pareto set approximation**
  The Pareto set approximation is improved by exploring the neighborhood of all the solutions in this set with a Multi-directional local search [Tricoire, 2012].
– **Phase III: optimization of product flows**
  After stabilizing the location and transportation mode decisions for all Pareto set approximation solutions in phase II, we determine the optimal product flows by applying the Simplex algorithm to all solutions in the set.

All visited solutions during the three phases are checked for inclusion into the Pareto set approximation. More precisely, we test whether solutions in the Pareto set approximation are dominated by a new solution and vice versa, i.e. whether this new solution is dominated by solutions in the Pareto set approximation. Eventually, the final output is the Pareto set approximation including the trade-off solutions between cost and environmental impact. These three phases are explained in more detail in the following subsections.

8.3.1 Phase I

The aim is to find an initial set of mutually non-dominated solutions which preferably represent a good coverage of the approximated Pareto front. Covering the approximated Pareto front helps the search in the second phase to explore different areas in the solution space. To this end, we benefit from the *network configuration* notion explained in chapter 4 to partition solution space into smaller domains. More precisely, we seek two efficient solutions for each network configuration, one regarding cost and the other one regarding CO_2 emissions. To obtain the efficient solutions for each network configuration regarding each objective, we employ initial phase of the single objective LNS described in chapter 4. Ultimately, we record two efficient solutions with each network configuration: one for cost objective and one for environmental objective. The initial Pareto set approximation is achieved by comparing the efficient solutions found for each network configuration and identifying a set of non-dominated solutions among the efficient solutions. The proposed approach in this phase is depicted in Algorithm 4.

First, Algorithm 4 is initialized with a empty list $\mathcal{S}$. The same approach presented in chapter 4 is used

Algorithm 4 Phase I

Require: $An intilal Pareto set approximation \mathcal{S} = \emptyset$
1: **for** Objective 1 **to** 2 **do**
2:     **for** Network configuration 1 **to** N **do**
3:         get a solution δ with Algorithm 5
4:         $\mathcal{S} \leftarrow \mathcal{S} \cup \{\delta\}$
5:     **end for**
6:     Obtain the score of each network configuration using formula (4.1) described in chapter 4
7: **end for**
8: Remove all dominated solutions from $\mathcal{S}$
9: **return** score of each network configuration regarding each objective, initial Pareto set approximation

to obtain the value of the best objective function obtained with the network configuration $n \in N$ (see Algorithm 5). After finding the value of the best respective objective for all network configurations, the same formula presented in chapter 4 is used to calculate the score of each network configuration regarding respective objective (line 6 of Algorithm 4). In the next step, all dominated solutions are removed (line 8 of Algorithm 4). The output is a Pareto set approximation including all the mutually non-dominated solutions as well as the score of each network configuration regarding each objective. Unlike the single objective LNS, each network configuration includes two scores. They indicate the quality of the network configuration regarding cost and environmental objectives. These scores will be used in phase II to choose a target network configuration for the next instance regarding respective objective.

For sake of clarity, the principle of Algorithm 5 explained in chapter 4 is described as follows. This algorithm is initialized with a simple greedy heuristic for each network configuration regarding each objective. It iteratively opens facilities with the least fixed cost for cost objective. Accordingly, it iteratively opens facilities with the least CO_2 emissions for environmental impact objective. A predetermined number of iterations is defined as the termination criteria. The same operators used in the single objective LNS is applied to destroy and repair the solution (line 4–5). Then, the allocation heuristic explained in Algorithm 3 is applied to determine the transportation modes and product flows between facilities (line 6). Depending on the respective objective, we use either variable cost or emission data in the allocation heuristic. The outcome is a best found solution for the respective network configuration (line 3 of Algorithm 4).

Algorithm 5 Find an efficient solution with a given network configuration

Require: $An Initial Solution \mathcal{S}$
1: $BestSolution \leftarrow \mathcal{S}$
2: $CurrentSolution \leftarrow \mathcal{S}$
3: **while** the termination criterion is not satisfied **do**
4:     $\mathcal{S} \leftarrow Destroy(\mathcal{S})$
5:     $\mathcal{S} \leftarrow Repair(\mathcal{S})$
6:     Apply Algorithm 3 described in chapter 4 to obtain transportation modes and product flows
7:     **if** $\mathcal{S} < BestSolution$ **then**
8:         $BestSolution \leftarrow \mathcal{S}$
9:         $CurrentSolution \leftarrow \mathcal{S}$
10:     **end if**
11: **end while**
12: **return** Best solution $\mathcal{S}$

8.3.2 Phase II

The goal of this phase is to intensify the search around each non-dominated solution found in phase I. The reason to implement this phase is that around a non-dominated solution, another one can be found [Caballero et al., 2007]. To explore the neighborhood of each non-dominated solution, we apply an efficient framework proposed by [Tricoire, 2012], namely, Multi-Directional Local Search (MDLS). MDLS is based on the principle of separately using independent single-objective local searches to iteratively improve the Pareto set approximation. The motivation for using this framework is the capability of using already implemented single objective optimization components.

We use different local searches, each of them working on a single objective. The idea comes from the fact that a solution can dominate another solution if it is better for at least one objective. Therefore, in order to find new efficient solutions, the search progresses in one direction at a time. An iteration of this method consists in (i) selecting a solution, (ii) performing local search on this solution for each objective, producing a new solution regarding each objective (iii) accepting or rejecting new solutions comparing with the Pareto set approximation [Tricoire, 2012].

Based on this framework, the aim of phase II is to search around all non-dominated solutions in two directions: cost and environmental objectives. To this purpose, we explore the neighbor solutions for each non-dominated solution using the single objective LNS. Figure 8.1 adapted from [Tricoire, 2012] illustrates this explanation. Let us suppose three mutually non-dominated solutions provided by phase I. We search around each non-dominated solution in the two directions: cost objective (Figure 8.1a) and environmental objective (Figure 8.1b). The circular portion represents the neighborhood considered around each non-dominated solution. Therefore, the final solution space to be searched around each non-dominated solution is the combination of steps (Figure 8.1a) and (Figure 8.1b) displayed in (Figure 8.1c).

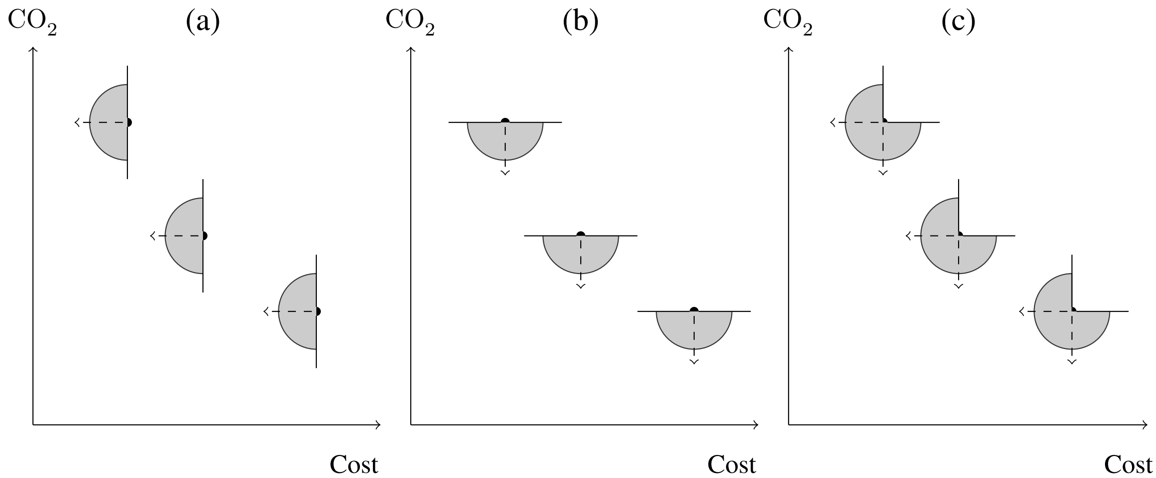

Figure 8.1: Relevant portions of solution space. (a) Relevant portion of solution space in favor of cost objective. (b) Relevant portion of solution space in favor of environmental objective. (c) Total relevant portion of solution space.

We iteratively perform this procedure around each non-dominated solution to identify possible new non-dominated solutions called local Pareto set approximation. Thus, the output is an improved set of mutually non-dominated solutions. We call it local Pareto set approximation. After exploring all non-dominated solutions, we update the Pareto set approximation by removing all dominated solutions from the local Pareto sets approximation. This principle is illustrated in Figure 8.2. The beginning of the search in the current iteration is started with the two mutually non-dominated solution displayed in Figure 8.2(a). Figure 8.2(b) shows the six neighbors obtained during the current iteration, three for each solution. Figure 8.2(c) presents the set of mutually non-dominated solutions at the end of this iteration, after dominance check.

The steps of phase II are depicted in Algorithm 6. As stated before, the algorithm starts with the Pareto set approximation resulting from phase I. The purpose is to update this set for a predefined number

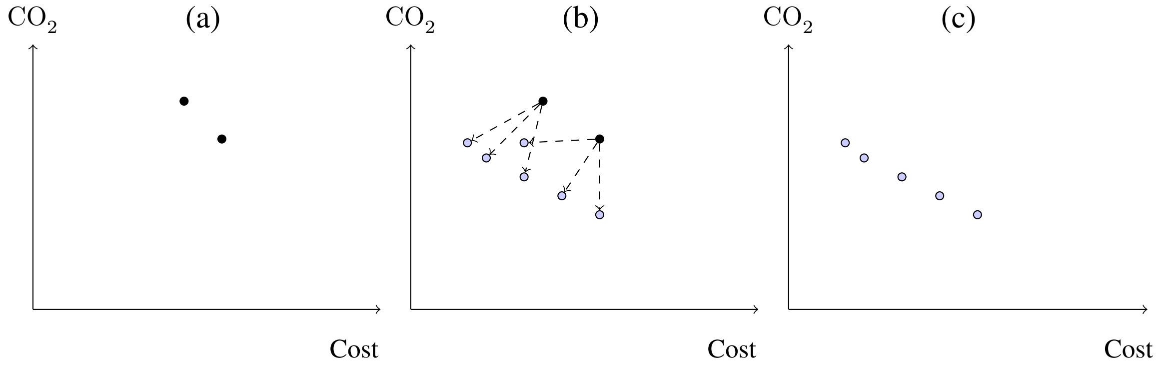

Figure 8.2: Updating Pareto set approximation in phase II. (a) Starting set of solutions. (b) Neighbors obtained during phase II around each solution. (c) Final Pareto set approximation.

of iterations (line 1). Hence, we intensify the search around each non-dominated solution of the Pareto set approximation. To this end, we first create a local Pareto set approximation for each non-dominated solution (line 2). The local Pareto set approximation is initialized with a non-dominated solution from the Pareto set approximation (line 3). A predefined number of inner iterations is considered as a stopping criteria (line 4). We start with a non-dominated solution which is randomly selected from a local Pareto set approximation (line 5). Then, the solution must be explored in the both directions (line 6). Let us suppose that a solution regarding cost objective must be explored. Each technology level is given a score representing the benefit of opening one given facility with this technology level. As a result, a technology with lesser fixed cost is given a higher score. All technology levels are ranked in order of scores. We choose the level of technology at facilities with a biased roulette wheel giving much higher probability to the technologies with higher scores (line 7). By selecting technology level is this way, we slightly diversify the solution space. To explore the neigborhood of the current solution regarding respective objective, the single-objective LNS is employed (line 8). We apply the same operators used in the single objective LNS to destroy and repair the solution. Similarly, the same algorithm is used to obtain proper transportation mode and product flows. Depending on the desired objective, either cost or CO_2 emission data is used. The desired network configuration is also chosen based on the score developed in phase 1.

After applying the LNS in both directions, the local Pareto set approximation is updated (line 9). Then a new solution from the local Pareto set approximation is selected to guide the search. We continue this procedure until reaching a predefined number of iterations. In this time the final local Pareto set approximation is stored to compare with the Pareto set approximation. After obtaining all local Pareto sets approximation, we compare those with the Pareto set approximation to update it (line 13). After updating the Pareto set approximation, a new iteration will start.

8.3.3 Phase III

The main goal of phase II is to obtain optimal product flows and to slightly improve the best solutions provided by phase II. To this purpose, we use a post optimization step using a linear programming solver instead of the allocation heuristic to obtain. Applying this phase reduces the number of non-dominated solutions since neighboring solutions can merge. Figure 8.3 illustrates this in schematic way. Figure 8.3(a) displays the Pareto set approximation resulting from phase II. Figure 8.3(b) shows the three non-dominated neighbors obtained during phase III. Figure 8.3(c) presents the set of non-dominated solutions at the end of phase III.

To obtain optimal product flows, we apply the Simplex algorithm to the Pareto set approximation solutions in the both directions. We prefer using the Simplex algorithm rather than dual Simplex algorithm because of its better performance in term of CPU time. First, we apply the allocation heuristic described in chapter 4 to each solution to fix the transportation modes decisions regarding the desired objective. Once

Algorithm 6 Phase II

Require: a set F of non-dominated solutions , the score of the network configurations for each objective

while the termination criterion is not satisfied **do**
  create F local Pareto sets approximation L^F
  for every solution $f \in F$ **do**
    while the termination criterion is not satisfied **do**
      $\mathcal{S} \leftarrow$ Select a solution(L^f)
      for Objective 1 **to** 2 **do**
        choose a technology level using a biased roulette wheel
        apply single-objective LNS
        update(L^f, S)
      end for
    end while
  end for
  update(F, L^F)
end while
return Pareto set approximation

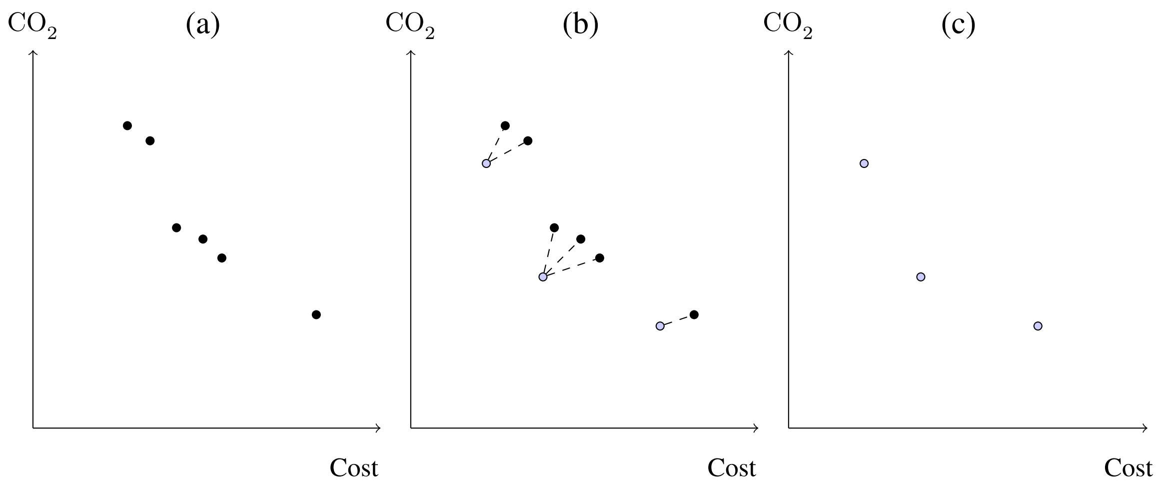

Figure 8.3: Influence of phase III on the Pareto set approximation. (a) Pareto set approximation at the end of phase II. (b) Neighbors obtained during phase III. (c) Final Pareto set approximation.

all binary variables have been fixed, the products flows are obtained using the simplex algorithm with an LP solver.

9

Computational experiments for the bi-objective SCND model

In this chapter, we evaluate the performance of the BOLNS presented in chapter 8 through a comparison with that of the well known ε-constraint method, denoted as EC. The remaining of this chapter is organized as follows. The generation of instances is described in section 9.1. Section 9.2 is dedicated to the ε-constraint method. In particular, it details the way to generate the different values of parameter ε and the computational results obtained with the solver IBM Ilog Cplex 12.5. The tuning of parameters for the BOLNS is discussed in section 9.3. The evaluation of each phase of the bi-objective LNS is investigated in section 9.4. We describe the performance measures used to assess the quality of the BOLNS in section 9.5. Section 9.6 compares the approximated Pareto fronts obtained with the BOLNS and those provided by the EC. Note that the solutions provided by the EC are Pareto optimal only if each single objective problem is solved to optimality. Due to the complexity of the problem, it is not the case for all medium-sized and large-sized instances. Thus, some solutions provided by the BOLNS may dominate those provided by the ε-constraint method. To illustrate the results, an example of sustainable supply chain topology is presented in section 9.7. Finally, section 9.8 presents the conclusion of this chapter.

9.1 Description of data for bi-objective SCND model

In this section, we explain the procedure used to generate data for the bi-objective SCND. In addition to the environmental data, the fixed and processing costs in plants and DCs are changed in the bi-objective SCND in comparison with the single objective SCND. It is because of introducing the technology levels into the mathematical model. It is worth mentioning that the following data are generated only for experimental purpose. Although we try to stick to realistic values, they do not represent a real situation.

9.1.1 Test instances

All instances of different sizes were generated as explained in chapter 5. We consider two available technology levels at each facility. We chose one pattern for each distinct size. Therefore, we kept 15 instances out of the 60 described in chapter 5.

Table 9.1 displays the value of all parameters for each size of instance. The values are the same as in Table 5.1, but we have only one instance of each size.

Table 9.1: Characteristics of test instances

Test instance	*Pattern*	$\|I\|$	$\|J\|$	$\|K\|$	$\|L\|$	$\|J_{max}\|$	$\|K_{max}\|$
T1	2	6	6	12	60	3	6
T2	3	7	7	14	70	4	7
T3	1	8	8	16	80	4	8
T4	4	9	9	18	90	5	9
T5	1	10	10	20	100	5	10
T6	3	12	12	24	120	6	12
T7	2	14	14	28	140	7	14
T8	4	16	16	32	160	8	16
T9	1	18	18	36	180	9	18
T10	3	20	20	40	200	10	20
T11	2	22	22	44	220	11	22
T12	4	24	24	48	240	12	24
T13	2	26	26	52	260	13	26
T14	4	28	28	56	280	14	28
T15	3	30	30	60	300	15	30

9.1.2 Environmental factors

The CO_2 emissions arise from two sources: processing, and transportation. Hence, we categorize emissions into two groups: facilities and transportation emissions. We generate the CO_2 emissions in such a way that CO_2 emissions arising from facilities represent $60\% - 75\%$ of total emissions.

Facilities emissions Technology level at facilities influences the amount of processing CO_2 emissions, fixed opening cost, and processing cost. Let us suppose there are two potential technologies (l_1, l_2) at each facility . l_1 is the lowest technology level and l_2 is the highest technology level. The relative characteristics of technology levels l_1 and l_2 are displayed in Table 9.2. We assume that lower technology level results in higher processing cost and CO_2 emissions with lower investment cost. On the contrary, higher technology level results in lower processing cost and CO_2 emissions at the price of higher investment cost.

Table 9.2: Characteristics of technology levels

Technology level	l_1	l_2
Fixed cost	$=$	$+20\%$
Processing cost	$=$	-10%
Processing emission	$=$	-20%

To estimate the processing CO_2 emissions at suppliers and facilities, we choose a random number φ as a conversion factor in (kg CO_2 equiv./ton of product) in the interval $[2.5, 4.5]$ for each type of product. These generated numbers are associated with the lower technology level at facilities (i.e. plants and DCs). The conversion factor for the upper technology level at each facility is obtained by $0.8 \times \varphi$. We also assume that the weight of each product is 1 kg.

The size of facility have significant impact on the CO_2 emissions in facilities. However, we could not find a unique approach in the literature to generate data. Harris et al. [2011] consider a relatively linear relation between size of a facility and CO_2 emissions. As the size of a facility increases the fixed emission increases. On the contrary, Abdallah et al. [2012] take into account the relationship between the size and energy requirement as a convex function. We Thus decided to exclude the size of facility from the model.

Transportation emissions We use the data provided by the French Environment and Energy Management Agency (ADEME) to extract the emissions for transportation modes. We assume that 3PL have the ability to pool shipments from several companies, and thus they operate with full truckload vehicles. In comparison, internal fleet of trucks operate with half truck load. According to Table 32 and 35 presented by ADEME [2010], we consider the conversion factors of 0.065 and 0.055 kg per km.ton for full and half truckload respectively Similarly, 0.006 kg per km.ton is considered for train mode. Finally, the total emission on each arc is calculated by multiplying the arc length by the conversion factor and the amount of products shipped.

9.1.3 Fixed and processing costs

In addition to the characteristics mentioned in chapter 5 such as the size of facility and the price of the real estate market, the fixed cost of opening facilities is influenced by the technology level.

Similarly to the single objective SCND model, we assume economies of scale when building large facilities. Thus, the fixed cost of a facility is calculated as the value $(c + \gamma_l) \times (\sqrt{cap_f})$, where:

- γ_l is set at 30000 for technology level l_1 and 36000 for technology level l_2,
- c is randomly generated in the interval $[10000, 20000]$, $[20000, 35000]$, $[35000, 50000]$ or $[50000, 60000]$ depending on the price category of the sub-grid considered,
- cap_f is the capacity of the facility.

Similarly to the mono-objective case, we estimate the processing cost at suppliers and facilities with a random number in the interval $[130, 150]$ for each type of product. These generated numbers are associated with the lower technology level at facilities.

9.2 Epsilon constraint method

We generate approximated Pareto fronts using the Epsilon Constraint (EC) to compare with those obtained with the BOLNS method. To do this, we employed the EC method to provide a Pareto set approximation including several Pareto optimal solutions for small-sized instances. Accordingly, the EC is used to develop the Pareto set approximation including a number of non-dominated solutions for large-sized instances. We used the same procedure presented by Du and Evans [2008] to generate different values of ε. For each value of ε, an MILP solver is employed to solve the problem.

First, we must construct a payoff table for a given minimization bi-objective problem. To this purpose, we solve the model regarding each objective function, separately. Let X^c denote an optimal solution for the cost objective and X^e denote an optimal solution for the environmental objective. $z_1^*(X^c)$ and $z_2(X^c)$ represent the cost and economic objective values of solution X^c. Accordingly, $z_1(X^e)$ and $z_2^*(X^e)$ represent the cost and economic objective values of solution X^e, respectively. Now, we can construct the payoff table. This table facilitates finding ranges for the both objectives in the non-dominated set:

$z_1^*(X^c) \leq z_1(X) \leq z_1(X^e), z_2^*(X^e) \leq z_2(X) \leq z_2(X^c)$.

After constructing the payoff table, the bi-objective problem is converted to a single objective by modeling the environmental objective as a constraint. The range of the second objective $z_2(X)$ in the constraint will be bounded by a value ε. Indeed, the upper bound of ε is $z_2(X^c)$, and the lower bound of ε is $z_2^*(X^e)$.

Let γ denote the number of different values of ε. The following formula is used to generate the value of each ε.

$\varepsilon = z_2^*(X^e) + [h/(\gamma - 1)][z_2(X^c) - z_2^*(X^e)]$,

where $h = 0, 1, 2, \ldots, (\gamma - 1)$.

The larger the γ is, the more candidate solutions will be produced. We consider $\gamma = 10$ in our experiments. We observed that the solution minimizing the environmental objective generally present a huge overcost compared with the 9 other solutions. In order to improve the coverage of the cost space, we generated an eleventh solution by solving an additional MILP with the constraint $z_2(X) \leq z_2^* - \vartheta$, where ϑ is a small value. Hence, the EC methods provides an approximated Pereto front with 11 mutually non dominated solutions.

After solving the problem regarding each value of ϑ, 11 candidate solutions are obtained for each test instance. At the end, from these candidate solutions a set of the non-dominated solutions is chosen as approximated Pareto front. Figure 9.1 shows the approximated Pareto front for the instance T8. Solving the cost objective model for 11 different values of ε for environmental impact resulted in having 11 mutually non-dominated solutions including 2 extreme points and 9 intermediate non-dominated solutions. The approximated Pareto front for the rest of the instances is similar.

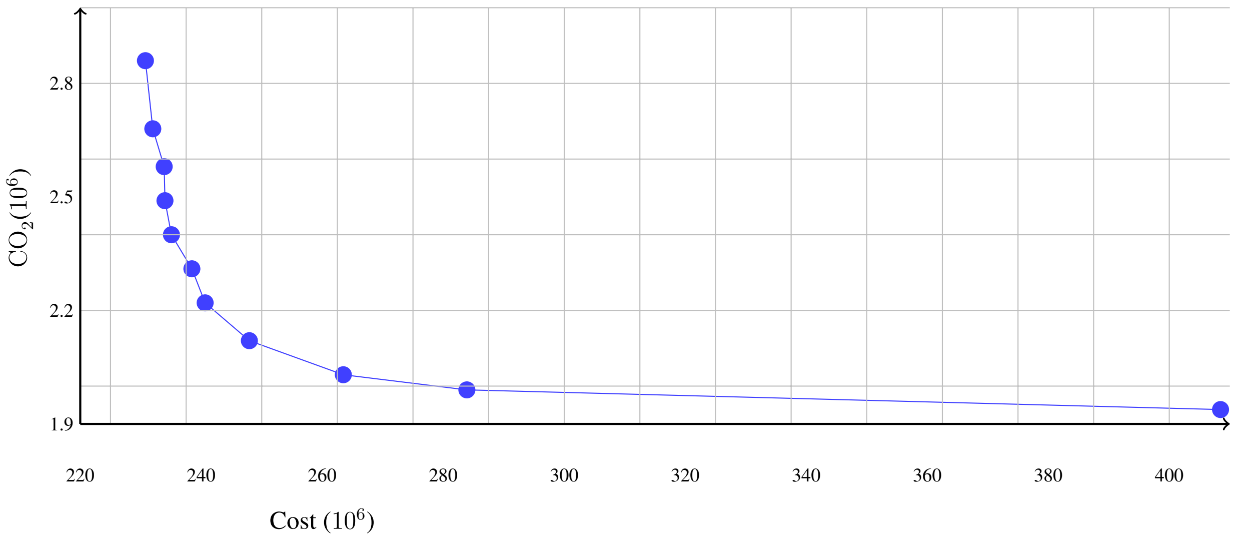

Figure 9.1: Approximated Pareto front for instance T8

We used Cplex 12.5 concert technology to solve the instances with a time limit of 3 hours for each value of ε. For some instances 11 Pareto optimal solutions could be obtained within the 3h. But as the instances get larger, finding an approximated Pareto front including Pareto optimal solutions becomes more intractable. In these cases, the solution found is considered as a candidate non-dominated solution.

Table 9.3 displays the results obtained for all instances. Column 2 shows the number of non-dominated solutions for each test instance. Column 3 presents the total run time for each test instance. Columns 4 shows the number which the problem could not be solved within the time limitation. The average Gap% between the best solution found and the lower bound is reported in column 5.

Table 9.3: Information about the obtained approximated Pareto fronts with ε constraint

Instance	*No of Pareto points*	*Total time (s)*	*points reached limit*	*Gap %*
T1	11	757	–	–
T2	11	9268	–	–
T3	11	12916	–	–
T4	11	23621	–	–
T5	11	34713	1	0.07
T6	9	58866	2	0.35
T7	11	79168	4	2.49
T8	11	$33h$	11	5.82
T9	10	$33h$	11	5.06
T10	11	$33h$	10	4.09
T11	11	$33h$	11	3.01
T12	9	$33h$	11	6.54
T13	11	$33h$	11	5.59
T14	11	$33h$	11	3.26
T15	9	$33h$	11	5.75

As it is shown in column 2, the number of non-dominated solutions is less than 11 for some instances. It is sometimes less than 11 since a solution may be dominated by another solution. It is clear that Cplex has more difficulty to solve problems to optimality for medium and large sized instances. Therefore, using a metaheuristic algorithm is recommended to find approximated Pareto front in reasonable time.

9.3 Parameter Settings

The tuning of the BOLNS relies on few parameters. First, we need to tune the number iterations in phase II. We have selected three instances from small to large sizes. We run each test instance for 250 iterations of phase II. The cumulative number of new non-dominated solutions found during each 10 iterations is shown in Figure 9.2. It seems that small, medium, and large instance converge after about 100, 250, 250 iterations, respectively. Therefore, we stop the algorithm after 100 iterations for instances $T1$ to $T5$ and 250 iterations for instances $T6$ to $T15$.

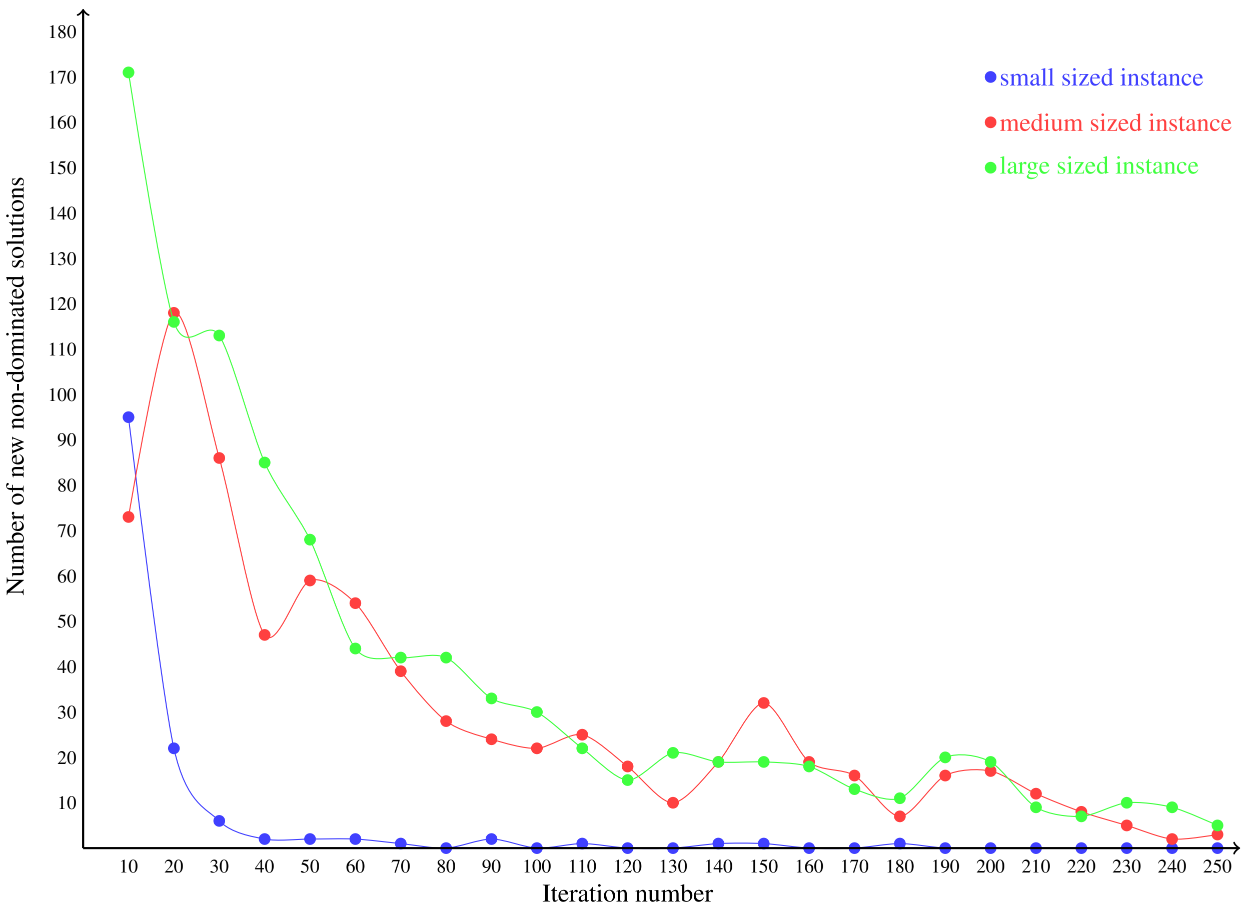

Figure 9.2: Number of new non-dominated solutions found within phase II

The second parameter is the number of LNS iterations in phase II. We tested this parameter by considering five values: 20, 40, 60, 80, and 100. The obtained approximated Pareto fronts and the CPU times are shown in Figures 9.3 and 9.4. If we consider the quality of the Pareto front, considering larger number of iterations yields slightly better solutions. However, it is more time consuming. To keep a satisfying balance between the CPU time and quality, we choose 60 LNS iterations.

Finally, one may wonder why Phase III is called only at the end of the BOLNS algorithm. Applying phase III reduces the number of mutually non-dominated solutions obtained with phase II. Therefore, calling Phase III periodically during the execution of Phase II would speed up the algorithm. We consider five scenarios to test this issue. We call phase III every 5, 10, 50, 100 iterations, or only at the end of phase II. The results are displayed in Figure 9.5. We conclude that calling phase III at the end of algorithm provides a better approximated Pareto front. It seems advisable to keep many solutions in the approximated Pareto

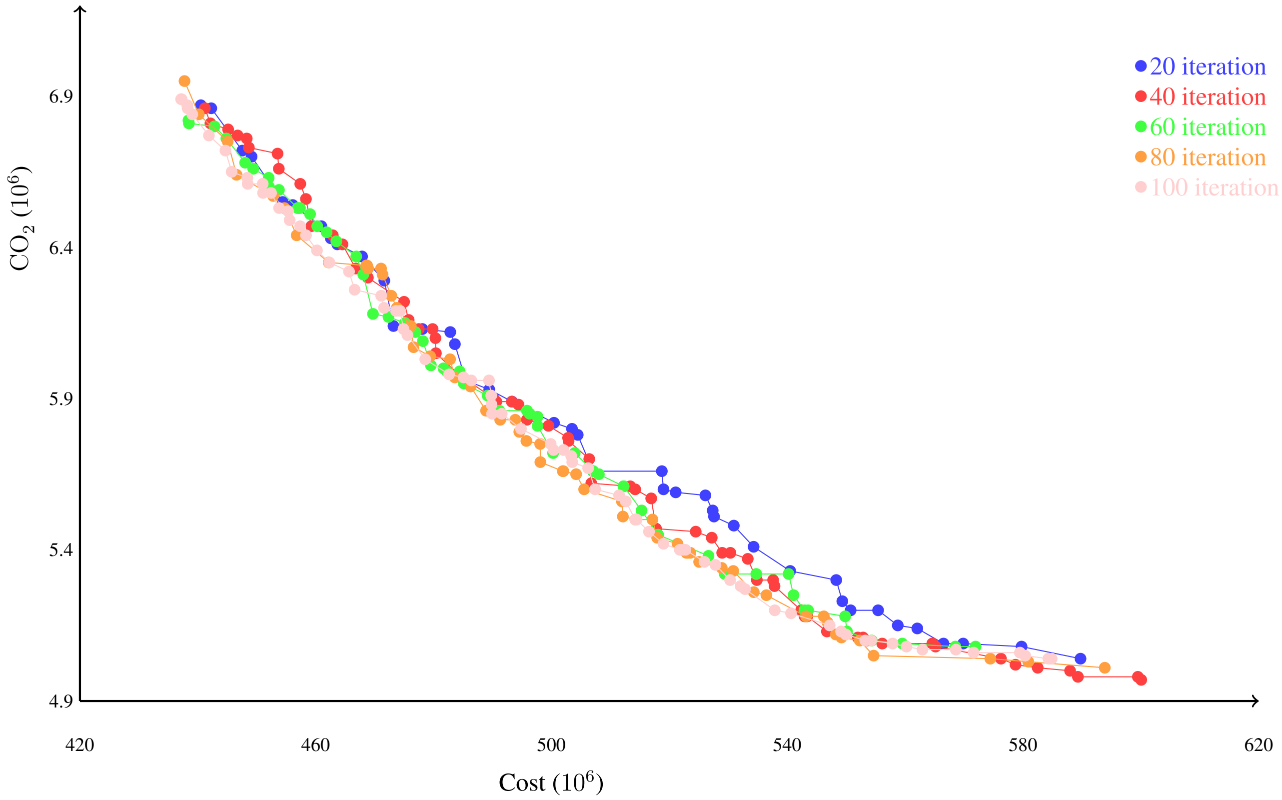

Figure 9.3: Comparison of the approximated Pareto fronts for instance T10

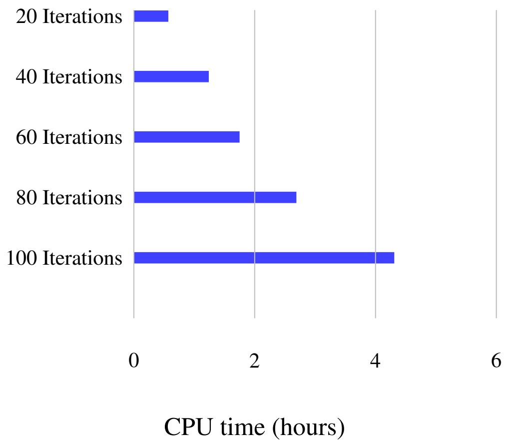

Figure 9.4: CPU time consumed by each scenario

front through the search. A counterpart is that this scenario is much more time consuming than the others, as shown in Figure 9.6.

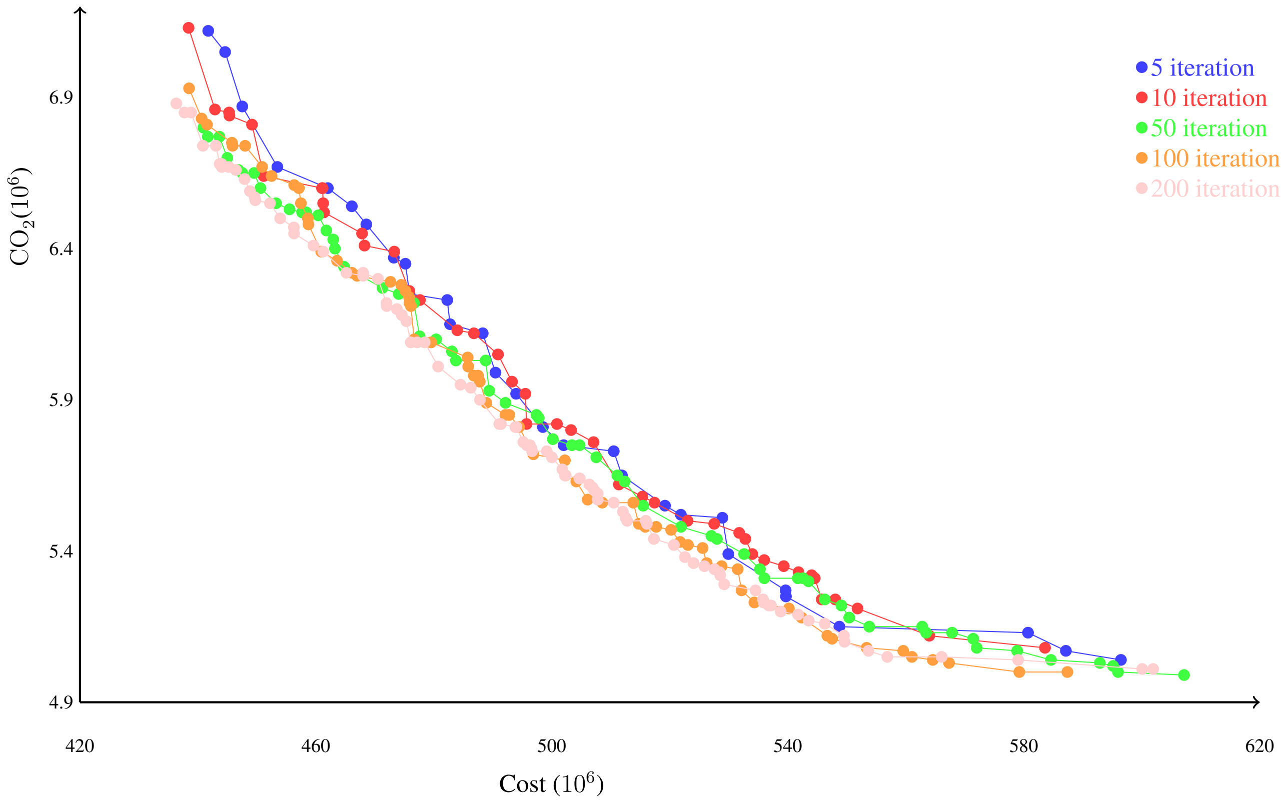

Figure 9.5: Impact of the frequency of phase III (instance T10)

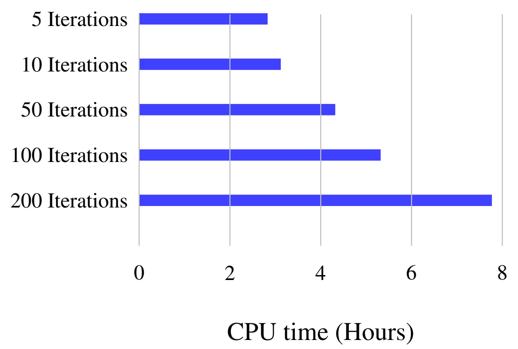

Figure 9.6: CPU time consumed by each scenario during the tuning of phase III

9.4 Evaluating the performance of each phase

Since each phase starts from the Pareto set approximation found during the previous one, each phase improves the approximated Pareto front found by the preceding one. Table 9.4 measures the contribution of each phase. It reports the average number of mutually non-dominated solutions found and the running CPU time in seconds at the end of each phase over five times runs.

The results show a few mutually non-dominated solutions are found in the first phase. Then the number of non-dominated solutions is considerably increased using bi-directional local search in the second phase. Eventually, the number of Pareto set approximation is decreased in the third phase with respect to those obtained in the second phase. As stated earlier, because of the optimal value of products flows, some of the solutions can be dominated by neighboring solutions. Figure 9.7 displays the approximated Pareto front yielded by each phase over one run of instance T8. In phase I, 15 mutually non-dominated solutions are found. At the end of phase II, the Pareto set approximation includes 136 solutions. Since most of them are close together, some points merge during phase III. The final Pareto set approximation provided by phase III has 68 solutions.

Regarding computing times, phases I and III require considerably less time than phase II. In average, more than 96% of the running time is spent in phase II.

Table 9.4: Contribution of each phase of the BOLNS

Test	*Phase I*		*Phase II*		*Phase III*	
instance	*Points*	$CPU(s)$	*Points*	$CPU(s)$	*Points*	$CPU(s)$
T1	5.2	1	33.2	255	17.6	1
T2	5.6	1	122.4	1430	58.8	9
T3	8.4	2	69.2	997	48.4	7
T4	10.8	2	130.6	2439	66.4	21
T5	6.8	3	80.0	1513	47.0	21
T6	11.0	6	111.4	4783	72.2	48
T7	12.4	17	207.2	11526	82.4	172
T8	14.6	36	117.6	8412	64.4	172
T9	12.4	46	117.4	10579	58.0	273
T10	22.4	77	154.4	19503	73.2	518
T11	26.0	92	140.0	22362	66.0	585
T12	23.2	135	126.0	29364	72.6	645
T13	17.2	254	103.0	24511	46.4	750
T14	32.7	394	153.0	33351	89.5	817
T15	29.3	486	139.3	37654	74.7	910

9.5 Performance measures

An important issue in multi-objective optimization is to evaluate the performance of the methods. In particular, when the outcome of the method is an approximated Pareto front, evaluating the quality of this approximation Pareto front is a challenging issue [Zitzler et al., 2003]. Various measures exist in the literature of multi-objective optimization. The outcome of each measure is a value reflecting one aspect of those sets. Although each measure provides information of one aspect of the respective approximated Pareto fornt, these measures all have drawbacks. In fact, using several measures at the same time can provide a fair comparison rather than one single measure [Tricoire, 2012]. In the next sections, we describe three classic performance measures used to compare the BOLNS with the EC.

9.5.1 The hypervolume measure

The hypervolume measure introduced by Zitzler et al. [2003] represents the size of the space covered by a set of non-dominated solutions with respect to a reference point. In our study, we use nadir point as a reference point. With this measure, a set with a larger hypervolume is better [Zitzler et al., 2003]. Figure 9.8 displays the region covered by three non-dominated solutions and bounded above by the nadir point.

In order to compare two methods A and B, we first compute the hypervolume value for both approximated Pareto fronts provided by methods A and B. Let us denoted by H_A and H_B the hypervolume of methods A and B, respectively. The gap (H) between those sets is calculated as follows:

$H = \frac{(H_A - H_B)}{H_B} \times 100.$

A positive value of H shows the superiority of method A. The larger the value, the better method A.

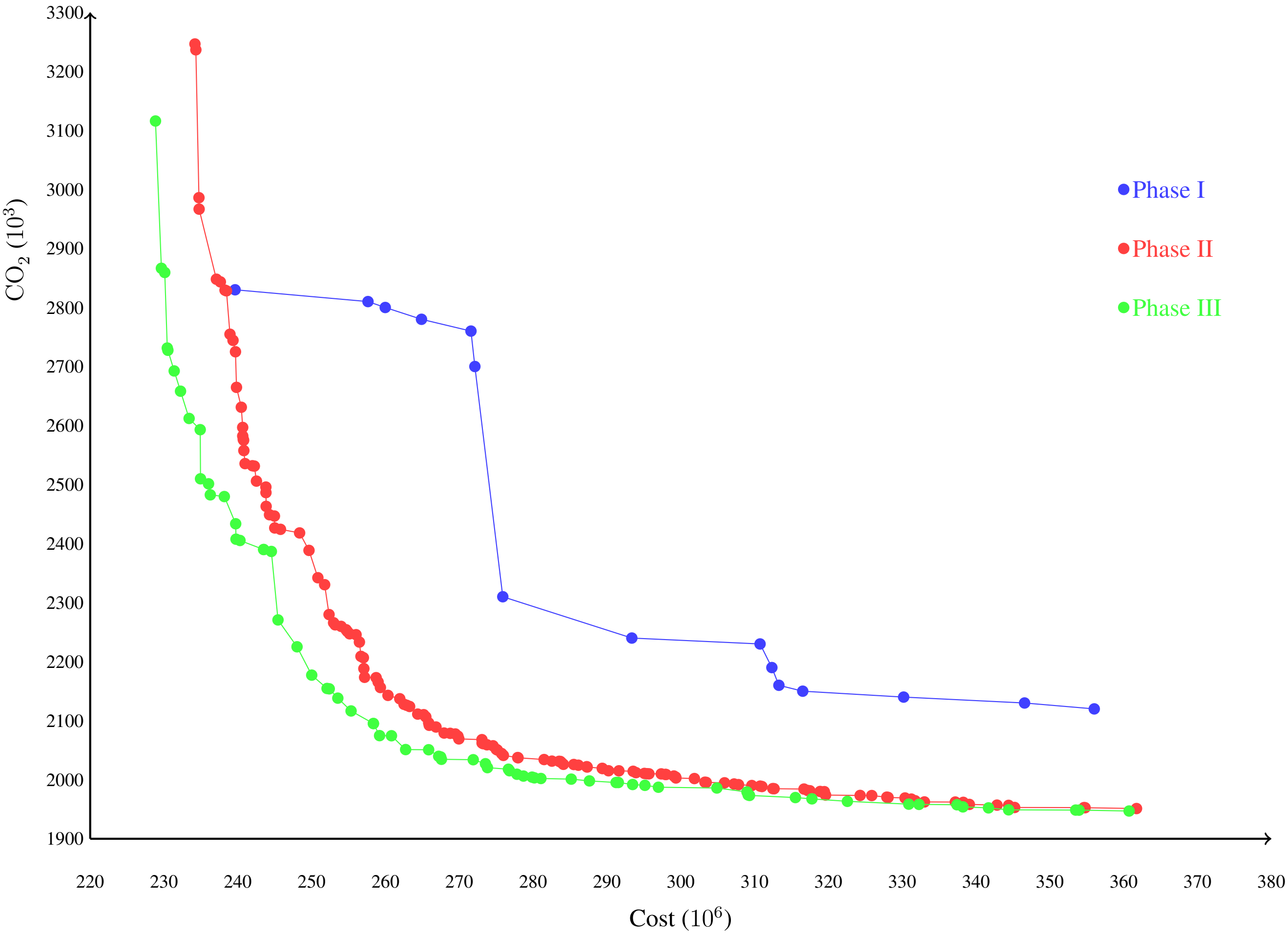

Figure 9.7: Mutually non-dominated solutions found by each phase of the BOLNS for test instance T8

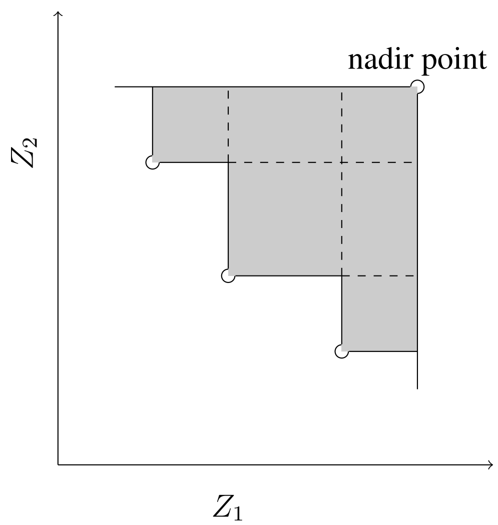

Figure 9.8: The hypervolume measure in the bi-objective case [Cardona-Valdés et al., 2014]

9.5.2 The unary epsilon indicator

The unary epsilon indicator, introduced by Zitzler et al. [2003], provide a number indicating how far are two approximated Pareto fronts from each other. For a minimization problem with k objectives a non-dominated solution with the objective vector $z^1 = (z_1^1, z_2^1, \dots, z_k^1) \in Z$ is said to $\epsilon-$dominate another non-dominated solution with objective vector $z^2 = (z_1^2, z_2^2, \dots, z_k^2) \in Z$, if and only if $\forall 1 \leq i \leq k$

$z_i^1 \leq \epsilon \times z_i^2$,

for a given $\epsilon > 0$. In practice, to find the ϵ in such a way that the approximated Pareto front A dominates the approximated Pareto front B by a factor of ϵ in all objectives, the following formula is applied:

$\epsilon(A, B) = \max_{Z^1 \in A} \min_{Z^2 \in B} \max_{1 \leq i \leq k} \frac{Z_i^1}{Z_i^2}$

With this measure, the smallest value is 1 and smaller values are better.

9.5.3 The ratio of approximated Pareto front

The ratio of approximated Pareto front, introduced by Altiparmak et al. [2006], shows the percentage of solutions from a approximated Pareto front not dominated by any member of another set. This performance measure is calculated as follows. Suppose two approximated Pareto fronts corresponding to methods A and B, respectively. Ratio of approximated Pareto front of A refers the the solutions from set A not dominated by any solution in $A \cup B$. This ratio $RP_A$is calculated as follows:

$RP_A = \frac{|A - \{X \in A | \exists Y \in A \cup B : Y \succeq X\}|}{|A|}$

where $Y \succeq X$ means solution X is dominated by solution Y. As PR_A increases, the number of Pareto set approximation not dominated by any member of the set $A \cup B$ increases.

9.6 Computational results

To compare the approximated Pareto fronts found by BOLNS and EC, the BOLNS is run 5 times and EC is used with a time limit of 3 hours per each value of ε. We impose 11 different values of ε for each instances using EC.

Table 9.5 reports the CPU time and the number of non-dominated solutions found by each method. The second and third columns present the average number of mutually non-dominated solutions. The fourth and fifth columns show the average CPU time (in seconds). The results show the BOLNS is able to generate a large amount of mutually non-dominated solutions. The average number of non-dominated solutions provided by the BOLNS is 62.5. The average CPU time of the BOLNS for all test instances is 14345 seconds, whilst EC took 77694 seconds in average. From test instances 8 to 15, EC can not find an optimal solution for all values of ε within the time limit of 3 hours. To obtain more solutions by this approach, we would need to run Cplex for more values of ε, which requires more time.

We consider three performance measures to evaluate the performance of the approximated Pareto fronts: the average ratio of approximated Pareto front (Ratio (R)), unary epsilon, and the Hypervolume. Table 9.6 reports the corresponding results. The second and third columns show the average ratio (R). The fourth and fifth columns display the value of unary epsilon indicator for BOLNS and EC. The last column shows the gap% between the hypervolume value of BOLNS and EC. To measure the Ratio (R) and the unary (ϵ) indicators, the approximated Pareto fronts provided by both BOLNS and EC are compared with a common reference set. This reference set consists of the set of all non-dominated solutions provided by these methods.

As it is expected, the ratio R of approximated Pareto solutions provided by EC is superior to BOLNS. By definition, a solution from the BOLNS set is dominated in a one to one comparison with an optimal point provided by EC. The average ratio of BOLNS for all instances is 0.56 versus 0.92 of EC. As the size of instances increases, the average ratio of the approximated Pareto fronts of BOLNS increases. On the contrary, the average ratio of approximated Pareto fronts of EC decreases.

Table 9.5: Number of non-dominated solutions found and CPU time (seconds)

Test instance	Points		*CPU (s)*	
	BOLNS	EC	BOLNS	EC
T1	17.6	11	256	757
T2	58.8	11	1440	9268
T3	48.4	11	1006	12916
T4	66.4	11	2462	23621
T5	47.0	11	1537	34713
T6	72.2	9	4838	58866
T7	82.4	11	11715	79168
T8	64.4	11	8621	118814
T9	58.0	10	10898	118811
T10	73.2	11	20098	114396
T11	66.0	11	23039	118819
T12	72.6	9	30144	118809
T13	46.4	11	25516	118817
T14	89.5	11	34562	118825
T15	74.7	9	39050	118816
$Average$	62.5	9.5	14345	77694

Table 9.6: Ratio (R), unary epsilon , Hypervolume (H)(average values over 5 runs)

Test instance	R		unary		$H\%$
	BOLNS	EC	BOLNS	EC	
T1	0.11	1	1.34	1.53	−6.94
T2	0.36	1	1.50	1.60	−1.42
T3	0.57	1	1.47	1.60	−0.92
T4	0.37	1	1.64	1.70	0.86
T5	0.46	1	1.32	1.59	−0.25
$average$	0.38	1	1.45	1.60	−1.73
T6	0.53	1	1.89	1.91	0.48
T7	0.54	1	1.43	1.63	1.49
T8	0.71	0.91	1.61	1.78	1.80
T9	0.66	0.91	1.54	1.77	2.61
T10	0.62	0.96	1.63	1.80	1.76
$average$	0.62	0.96	1.63	1.80	1.63
T11	0.68	0.82	1.47	1.50	1.23
T12	0.73	0.82	1.52	1.59	0.89
T13	0.69	0.82	1.47	1.47	1.08
T14	0.64	0.91	1.62	2.02	1.04
T15	0.76	0.64	1.47	1.51	1.15
$average$	0.70	0.80	1.51	1.62	1.08
$average$	0.56	0.92	1.53	1.67	0.32

In terms of both unary and hypervolume criteria, BOLNS is superior to EC. Indeed, BOLNS gives a slightly better value in average (1.53 versus 1.67). The main reason for the superiority of BOLNS to EC is that end points of the approximated Pareto front of BOLNS are closer to the ideal point. Figures (9.9 – 9.11) display the approximated Pareto fronts of both methods for three sample instances.

The BOLNS also outperforms the approximated Pareto front of the EC in term of hypervolume in medium and large sized instances. The main reason is that the number of non-dominated solutions is larger than the one provided by the EC. Therefore, the volume of these fronts relative to the nadir point is naturally bigger than the approximated Pareto fronts of the EC.

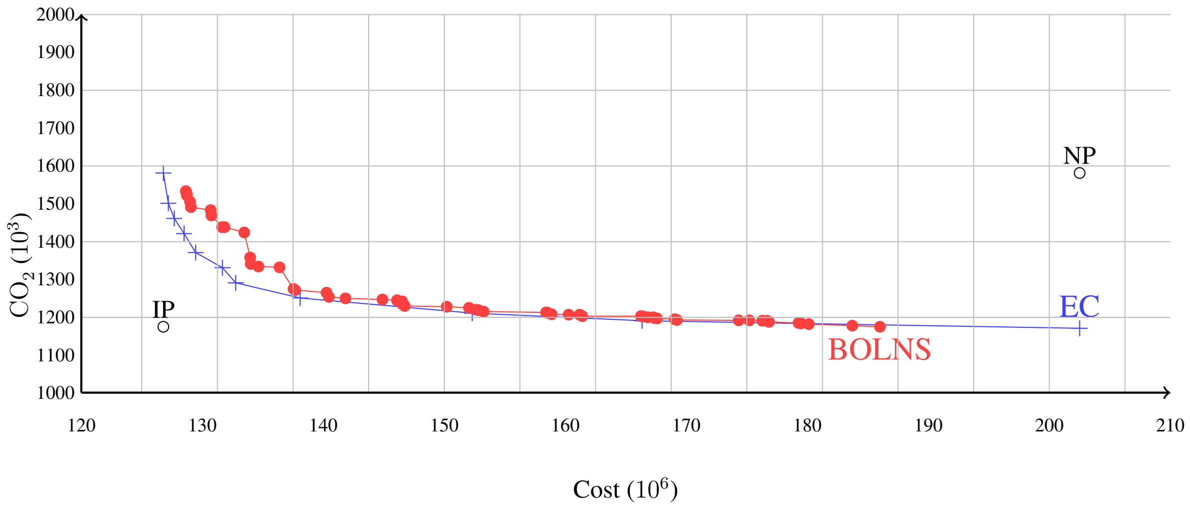

Figure 9.9: Comparison of the Pareto fronts for instance T3

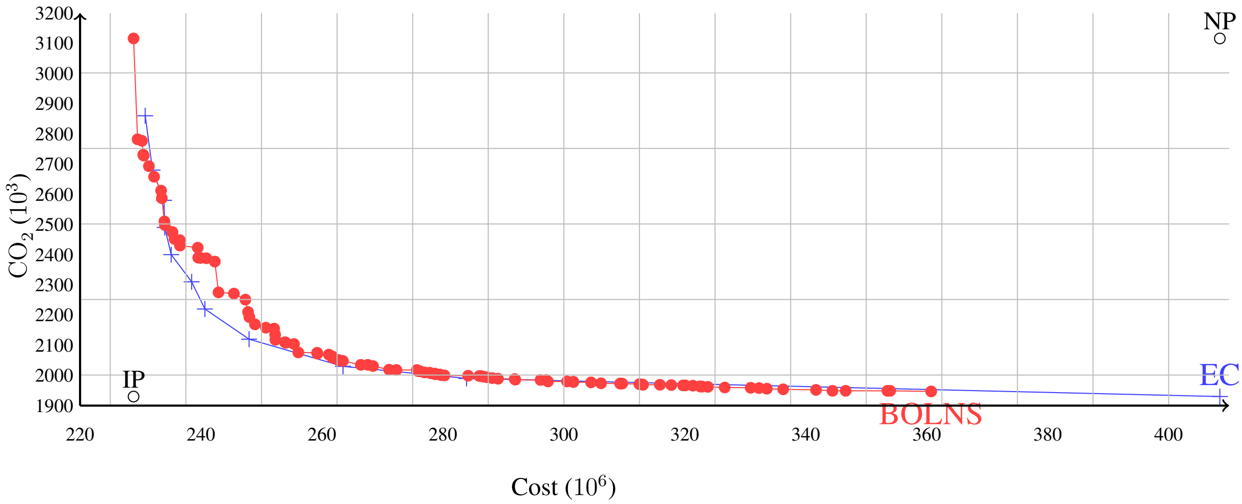

Figure 9.10: Comparison of the Pareto fronts for instance T8

Finally, we assess the capability of the BOLNS to provide good quality ends of the approximated Pareto fronts. To do so, we solved each single objective problems with Cplex, with a time limit of 3 hours, and compares the results with each end of the approximated Pareto front provided by the BOLNS. As in Tables 6.15 and 6.16, we calculate two types of gaps. The UB gap measures the relative distance between the objective function found by the BOLNS and the best solution found by Cplex. The LB gap measures the relative distance between the BOLNS and the lower bound provided by Cplex (when no optimal solution can be found). The results are presented in Table 9.7.

Columns 2 and 3 present the minimal and average UB gaps (in %) over 5 runs for the economic objective. Columns 4 and 5 present the minimal and average LB gaps (in %) over 5 runs for the economic

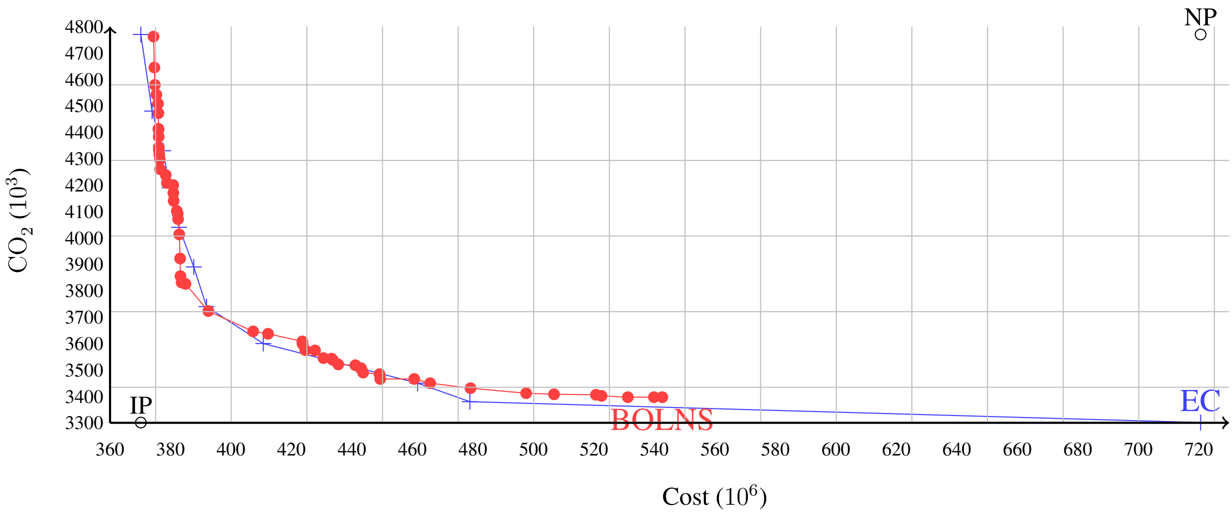

Figure 9.11: Comparison of the Pareto fronts for instance T13

objective. Columns 6 to 9 report the same information, but for the environmental objective.

Table 9.7: Comparison between BOLNS and EC for the ends of Pareto fronts

Test	Cost objective				Environmental objective			
	UB GAP %		LB GAP %		UB GAP %		LB GAP %	
instance	*Min*	*Avg.*	*Min*	*Avg.*	*Min*	*Avg.*	*Min*	*Avg.*
T1	0.80	0.82	–	–	2.88	3.10	–	–
T2	1.06	1.06	–	–	1.98	2.02	–	–
T3	1.47	1.47	–	–	0.20	1.07	–	–
T4	1.30	1.35	–	–	1.31	1.33	–	–
T5	0.93	1.06	–	–	1.31	1.31	–	–
T6	1.22	1.47	–	–	0.94	1.12	–	–
T7	0.41	0.44	–	–	0.92	1.08	–	–
T8	−0.83	−0.05	4.03	4.86	0.46	0.63	0.90	1.08
T9	1.09	1.26	4.15	4.32	1.11	1.24	1.31	1.44
T10	0.86	0.95	1.95	2.04	0.88	1.27	–	–
T11	0.96	1.97	1.55	2.56	1.17	1.77	1.58	2.18
T12	1.16	2.37	4.51	5.77	0.44	1.39	1.89	2.85
T13	1.13	1.40	5.09	5.36	2.38	3.91	3.21	4.75
T14	0.49	1.39	1.98	2.90	0.85	1.88	1.28	2.31
T15	0.95	1.26	4.45	4.77	1.20	2.08	1.58	2.46
Average	0.87	1.21	3.46	4.07	1.20	1.68	1.74	2.61

In 8 and 7 out of the 15 instances, Cplex does not find any optimal solution concerning cost and environmental objectives after 3 hours of computation. It can be concluded that the average gape from UB and LB for both objectives are quiet acceptable. Note that minimizing the economic objective seems more difficult for Cplex than minimizing the environmental objective.

9.7 Supply chain topology

The supply chain topology can vary from one non-dominated solution to another one. As an example, consider a network of 9 suppliers, 9 potential plants, 18 potential DCs, and 90 customers (instance 4). The approximated Pareto front is shown in Figure 9.12. The final configurations shown in Figures 9.13 – 9.15 present the open plants and DCs regarding the cost objective (solution A), an intermediate solution (solution

B), and the environmental objective (solution C), respectively. The technology level used at each facility is displayed with letter l_1 and l_2 in the figures.

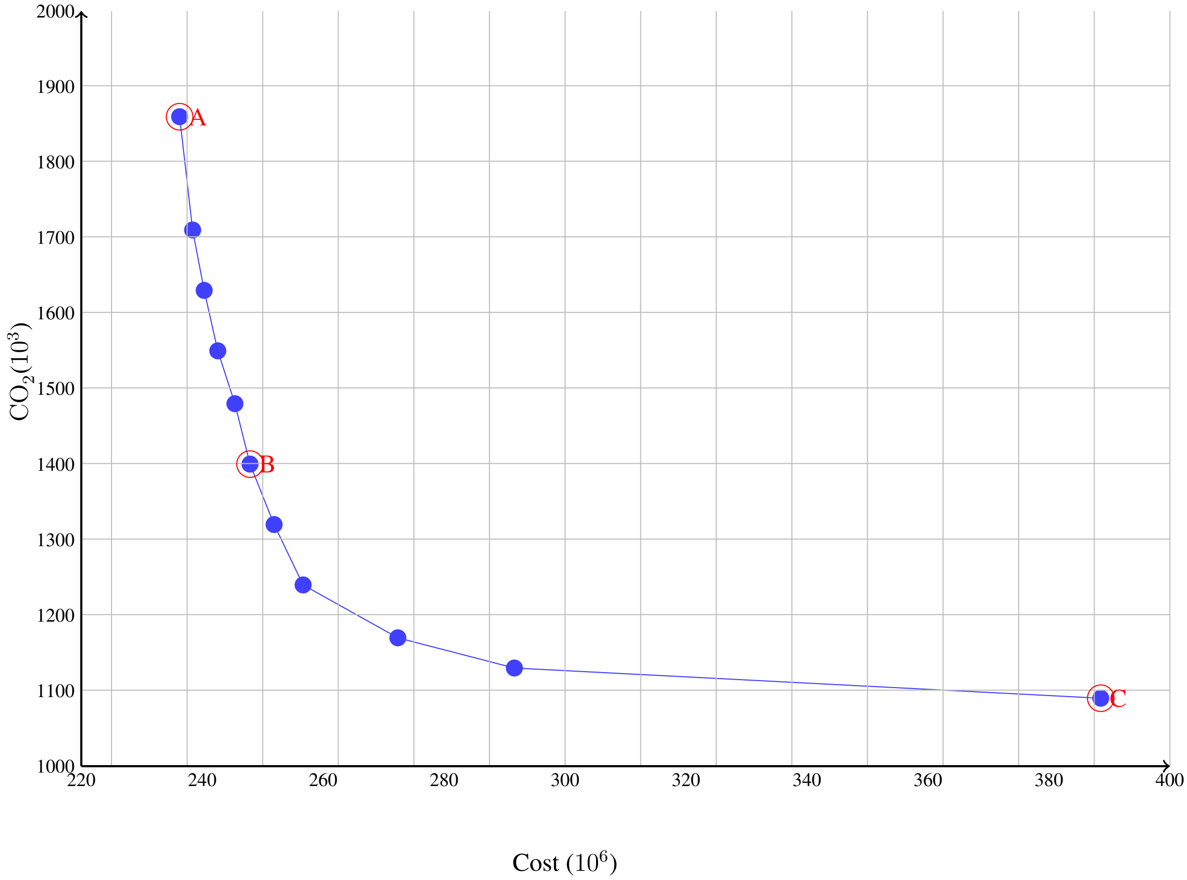

Figure 9.12: Approximated Pareto front for instance T4

The number of open plants and DCs is not the same in all topologies. There are 4 plants and 6 DCs in solution A, but 5 plants and 9 DCs in solution C. Since the cost objective doesn't matter for solution C, the maximum allowed number of facilities are opened. The number of plants and DCs are the same in solutions A and B. But, unlike the solution A, the technology with the lowest fixed cost is used in most of the facilities in solution A.

As stated before, we consider different ranges of the location fixed cost from the cheapest to the most expensive one (C_1 to C_4). Table 9.8 shows the distribution of the number of open plants and DCs for each range of location fixed cost. In solution A, all facilities are located in cheap regions. But, in the other topologies in which the economic objective has less importance, some more expensive locations are chosen to open facilities.

Table 9.8: Distribution of the fixed cost types for each topology ($A - C$)

Type of price	*Plants*			*DCs*		
	A	*B*	*C*	*A*	*B*	*C*
C_1	2	2	–	3	1	–
C_2	2	2	3	3	3	2
C_3	–	–	2	–	1	4
C_4	–	–	–	–	1	3

Another interesting issue is to investigate the situation of each facility within all non-dominated solutions. Figure 9.16 displays the total number of times that each facility (plant and DC) is selected to be opened for all 11 non-dominated solutions presented in Figure 9.12. Surprisingly enough, there is one plant

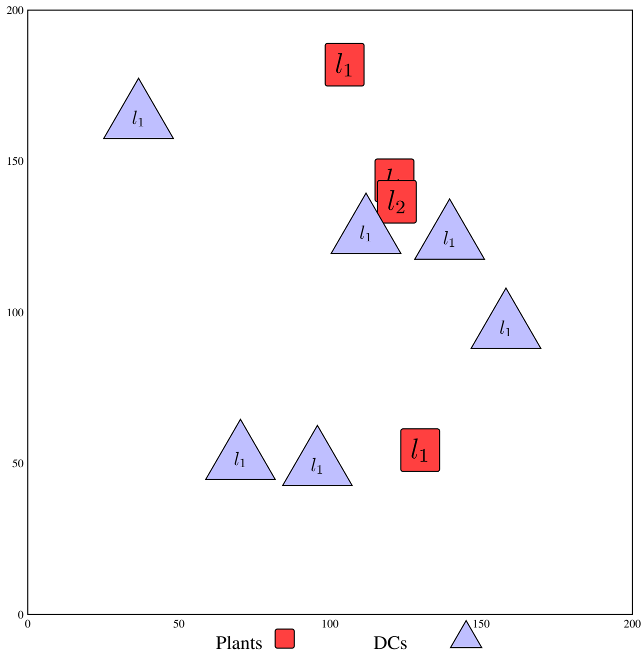

Figure 9.13: Supply chain topology in solution A

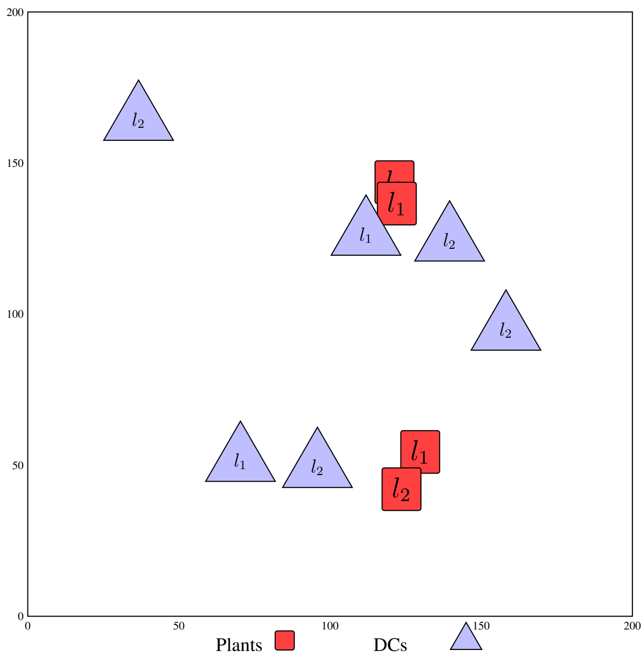

Figure 9.14: Supply chain topology in solution B

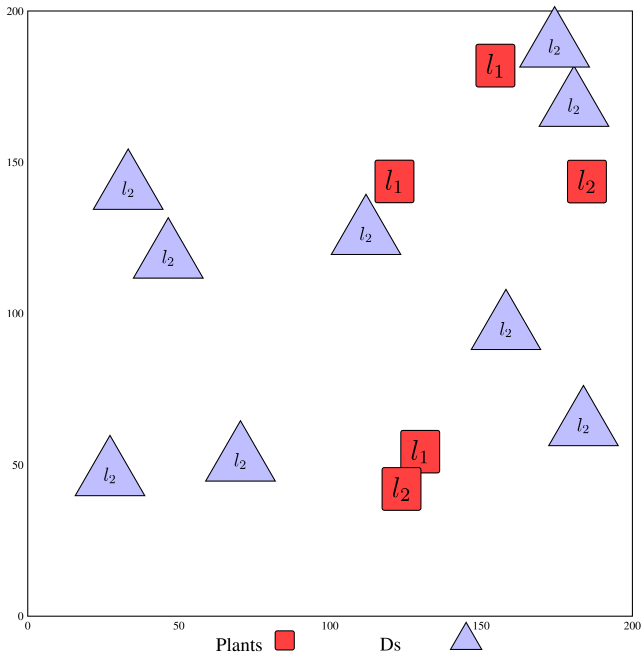

Figure 9.15: Supply chain topology in solution C

and one DC which are opened for all non-dominated solutions. In other words, they are interesting locations in terms of both objectives. On the contrary, there are five DCs and one plant which are closed at all solutions.

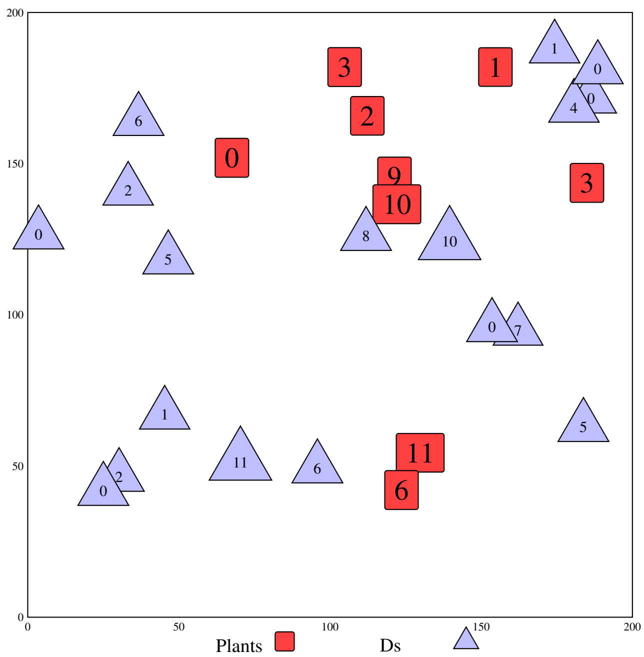

Figure 9.16: Number of times each location is opened for all non-dominated solutions

9.8 Conclusion

The goal of this chapter was to evaluate the performances of the BOLNS. To this purpose, we compared the approximated Pareto front provided by the BOLNS that provided by EC according to three measures. The BOLNS produced results competitive with the EC, particularly for the large size instances.

There is still space to improve the efficiency of the BOLNS, especially in term of CPU time. More than 96% of the CPU time is spent in phase II in average. This may happen because of the large amount of the non-dominated active solutions. Updating this set at each iteration is costly. Having a more efficient heuristic for determining transportation modes and product flows may reduce the number of the non-dominated solutions and consequently the CPU time.

IV

Concluding remarks and further research directions

10

Conclusion

In this research, we studied sustainable supply chain network design problems and proposed relevant models and solution methods based on Large Neighborhood Search to provide high quality solutions in a reasonable time. We benefited from the Large Neighborhood Search concept to provide flexible methods for solving both single and multi-objective SCND models.

The work presented in this thesis contains three major contributions: The first contribution was to provide an optimization-oriented review of the literature on SCND problems integrating sustainable development factors. Supply chain network design models and methods have been the subject of several recent literature review surveys, but none of them explicitly includes sustainable development as a main challenge for the considered problem. It is not even presented in the forthcoming book by Laporte et al. [Forthcoming]. The aim was to bridge this gap. We analyzed 87 papers in the field of supply chain network design, focusing on mathematical models that include economic factors as well as environmental and/or social factors. Environmental supply chain network design problems are analyzed with a special emphasis on Life-Cycle Assessment (LCA). We classified the modeling approaches used, in terms of the nature of the models (deterministic or stochastic, linear or non linear) and the number of objective functions (single or multiple). Then we identified the main solution methods used for single objective and multi-objective models. Finally, we review the variety of real-life applications and sector specific issues. We concluded the work with a proposal for future research directions such as developing methodologies for quantifying the social aspect and approaches for better measuring environmental damage through the entire product life-cycle.

The second contribution was to propose an LNS approach to solve a four-layer multi-product supply chain design model. We proposed an LNS heuristic for solving an SCND model with four layers, multiple commodities and transportation modes. Location decisions are focused on the two intermediate levels, i.e. plants and DCs. The main goal of this study was to assess the efficiency of the LNS approach on this type of model. Several challenges emerged. Firstly, the SCND model includes binary and continuous variables, which must be treated separately in the LNS algorithm. Our hierarchical approach was to determine the locations with the LNS operators and to determine continuous variables by solving a linear programming subproblem in each iteration. Then, in most SCND problems, the number of active facilities in an optimal solution is unknown a priori. Thus, the classic LNS framework is guided to explore several network configurations. Lastly, our model includes two types of binary variables: the location variables and the choice of transportation modes. In our heuristic, location decisions were fixed using LNS and transportation modes and products flows were determined a posteriori by a greedy heuristic.

The third contribution was to develop a bi-objective LNS approach to solve the four-layer multi-product supply chain design model with respect to cost and CO_2 emissions minimization. We developed a bi-objective LNS method for the sustainable SCND model. Our method contains three phases. In the first phase, we obtain a number of mutually non-dominated solutions. In the second and third phase, we tried to intensify the search around the solutions found in the first phase. This enabled us to identify additional non-dominated solutions. In the third phase, the simplex algorithm was used to slightly improve the quality of the solutions. With the aim to extend our single objective LNS framework to a bi-objective one, we benefited from a flexible framework, called Multi-Directional Local Search (MDLS), proposed by Tricoire [2012]. The numerical results show the stability of the methods and their efficiency, in terms of both quality of solution and computation time. We believe that a great benefit comes from integration the notion of *Network configuration* and a variety of operators within the LNS approach.

Since the considered problems involves strategic decisions with impact in the mid-to long term, they obtains solutions relatively fast. Therefore various scenarios can be easily analyzed with changing parameters of demand, cost, or CO_2 emissions concerning uncertainty, before determining a final decision. We believe our results are general in nature and will remain valid independent of the scenario chosen. The experimental results showed that the methods can be used to solve realistic instances of large size. Furthermore, the reasonable computation times make the proposed methods more applicable in contexts where solutions must be obtained quickly.

Of course, further research can still be considered. Sustainable SCND problems are complex in nature because they have to address the specific characteristics of the three dimensions of sustainable development. Social aspects should be given more attention in future research to achieve a sustainable SCND. However, developing methodologies for quantifying the social aspects is a challenging task. Their consideration at the stage of scenarios definition before optimization may remain an effective alternative within a decision making process.

As frequently mentioned, strategic decisions such as network design have a significant influence on tactical and operational constraints and decisions. However, the coordination of the different levels has been almost ignored in the sustainable SCND literature. More attention should be given to integrated strategic and tactical models. Tactical decisions may have significant impacts on costs and impacts for example changes in delivery schedules impacting on vehicle fill rates and therefore efficiency of transport.

Many challenging problems and solution methods have been published separately by authors within the management, industrial engineering or operations research literature. For example, we observed that all LCA-based approaches use modeling tools and solvers whereas operations research focused papers sometimes use very sophisticated algorithms to solve problems with poor environmental or economic modeling. Solving rich environmental SCND real-life problems within acceptable time is probably still beyond the capabilities of current mathematical solvers. This requires combining realistic modeling and efficient solution techniques and thus reinforced collaboration between researchers from various communities.

By nature, strategic decisions such as facility location should last for a considerable amount of time. In fact, due to the large investments generally associated with this type of decisions, stability with respect to the topology of the supply chain network is a highly desirable feature. Nevertheless, it is important to consider the possibility of making future adjustments in the network topology to allow gradual changes in the supply chain structure and in the capacities of the facilities. In this case, a planning horizon divided into several time periods is typically considered and strategic decisions are to be planned for each period [Melo et al., 2009]. Therefore, further research will include the adaptation of our algorithm to models with multiple periods.

Other realistic assumptions like bill of material (BOM) and single source assignment can be included into the model. BOM contains a comprehensive list of raw materials, components and assemblies required to manufacture a product. The proposed LNS approach can be equipped to these assumptions by adapting the proposed greedy heuristic to find the products flows.

Lastly, uncertainty and risk should also be better considered in sustainable SCND models. The uncertainty of parameters can influence the overall performance of logistics network in both environmental and economical aspects. These parameters can be arisen either from the uncertain nature of logistics network design such as transportation cost and demand [Pishvaee et al., 2012b] or environmental damage assessment method [Guillén-Gosálbez and Grossmann, 2010]. Therefore, considering it during the design phase of supply chain may avoid imposing high risks to firms [Pishvaee et al., 2012b]. Stochastic and fuzzy programming are the most widely used methods to deal with uncertainty in SCND models. Furthermore, the consideration of realistic management features such as supplier selection and risk management have indeed been frequently considered in supply chain and procurement research, but quantitative sustainable SCND models incorporating these features are not so much. The LNS algorithm worth trying as the solution method of such problems.

Bibliography

T. Abdallah, A. Farhat, A. Diabat, and S. Kennedy. Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment. *Applied Mathematical Modelling*, 36(9): 4271–4285, 2012. 20, 30, 31, 38, 39, 48, 50, 126

T. Abdallah, A. Diabat, and J. Rigter. Investigating the option of installing small scale pvs on facility rooftops in a green supply chain. *International Journal of Production Economics*, 146(2):465–477, 2013. 13, 33, 34, 35, 39, 109

A. Ada Che, J. Feng, H. Chen, and C. Chu. Robust optimization for the cyclic hoist scheduling problem. *European Journal of Operational Research*, 240(3):627 – 636, 2015. 116

ADEME. *Guide des facteurs d'émissions*. Agence De l'Environnement et de la Maîtrise de l'Énergie, 2010. 127

P. Ahi and C. Searcy. An analysis of metrics used to measure performance in green and sustainable supply chains. *Journal of Cleaner Production*, 86:360–377, 2015. 34

E. Akçali, S. Çetinkaya, and H. Üster. Network design for reverse and closed-loop supply chains: An annotated bibliography of models and solution approaches. *Networks*, 53(3):231–248, 2009. 25

O. Akgul, N. Shah, and L. G. Papageorgiou. An optimisation framework for a hybrid first/second generation bioethanol supply chain. *Computers & Chemical Engineering*, 42(0):101–114, 2012. 30, 31, 40, 41, 45, 48, 50, 51, 52

L. Alçada-Almeida, J. Coutinho-Rodrigues, and J. Current. A multiobjective modeling approach to locating incinerators. *Socio-Economic Planning Sciences*, 43(2):111–120, 2009. 32, 33, 35, 41, 45, 47, 50, 52

F. Altiparmak, M. Gen, L. Lin, and T. Paksoy. A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers & Industrial Engineering*, 51(1):196 – 215, 2006. 14, 117, 134

F. Altiparmak, M. Gen, L. Lin, and I. Karaoglan. A steady-state genetic algorithm for multi-product supply chain network design. *Computers & Industrial Engineering*, 56(2):521 – 537, 2009. 21

S. H. Amin and G. Zhang. A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return. *Applied Mathematical Modelling*, 37(6):4165–4176, 2013. 32, 33, 34, 35, 36, 39, 40, 41, 42, 43, 45, 48

N. Aras, T. Boyaci, and V. Verter. Designing the reverse logistics network. In M. Ferguson and G. Souza, editors, *Closed Loop Supply Chains: New Developments to Improve the Sustainability of Business Practices*, pages 67–98. Taylor and Francis, CRC Press, 2010. 25

M. O. Arioglu Salmona, A. Selam, and O. Vayvay. Sustainable supply chain management: a literature review. In *ICOVACS 2010, International Conference on Value Chain Sustainability*, 2010. 25

A. Ashby, M. Leat, and M. Hudson-Smith. Making connections: a review of supply chain management and sustainability literature. *Supply Chain Management: An International Journal*, 17(5):497–516, 2012. 25

C. Autry, T. Goldsby, J. Bell, M. Moon, C. Munson, M. Watson, S. Lewis, P. Cacioppi, and J. Jayaraman. *The definitive guide to modern supply chain management (collection)*. Pearson Education, 2013. 19

I. Awudu and J. Zhang. Uncertainties and sustainability concepts in biofuel supply chain management: A review. *Renewable & Sustainable Energy Reviews*, 16(2):1359–1368, 2012. 25

A. Azapagic. Life cycle assessment and its application to process selection, design and optimisation. *Chemical Engineering Journal*, 73(1):1–21, 1999. 28

A. P. Barbosa-Póvoa. Process supply chains management - where are we? where to go next? *Frontiers in Energy Research*, 2(23):1–13, 2014a. 21

A. P. Barbosa-Póvoa. Process supply chains management - where are we? where to go next? *Frontiers in Energy Research*, 2(23), 2014b. 25, 26

B. Baud-Lavigne, B. Agard, and B. Penz. Environmental constraints in joint product and supply chain design optimization. *Computers and Industrial Engineering*, 76(0):16–22, 2014. 33, 35, 41, 45, 48

B. M. Beamon. Supply chain design and analysis: models and methods. *International Journal of Production Economics*, 55(3):281–294, 1998. 11, 25

S. Beheshtifar and A. Alimoahmmadi. A multiobjective optimization approach for location-allocation of clinics. *International Transactions in Operational Research*, pages n/a–n/a, 2014. doi: 10.1111/itor.12088. 37, 42, 45, 50

C. BenoÃőt-Norris. Data for social lca. *The International Journal of Life Cycle Assessment*, 19(2):261–265, 2014. 36

C. Berger, G. Savard, and A. Wizere. EUGENE: an optimization model for integrated regional solid waste management planning. *International Journal of Environment and Pollution*, 12(2-3):280–307, 1999. 33, 35, 40, 41, 48, 50, 53

A. Bernardi, S. Giarola, and F. Bezzo. Spatially explicit multiobjective optimization for the strategic design of first and second generation biorefineries including carbon and water footprints. *Industrial & Engineering Chemistry Research*, 52(22):7170–7180, 2013. 30, 31, 32, 41, 44, 45, 48, 50

P. Beske, A. Land, and S. Seuring. Sustainable supply chain management practices and dynamic capabilities in the food industry: A critical analysis of the literature. *International Journal of Production Economics*, In Press, 2013. 25

J. Bloemhof-Ruwaard, L. Van Wassenhove, H. Gabel, and P. Weaver. An environmental life cycle optimization model for the European pulp and paper industry. *Omega*, 24(6):615–629, 1996. 30, 31, 39, 50

A. Bojarski, J. Laínez, A. Espuña, and L. Puigjaner. Incorporating environmental impacts and regulations in a holistic supply chains modeling: An lca approach. *Computers and Chemical Engineering*, 33(10):1747–1759, 2009. 30, 31, 41, 45, 48, 50, 52

N. Bostel, P. Dejax, and Z. Lu. *Logistics Systems: Design and Optimization*, chapter The Design, Planning and Optimization of Reverse Logistic Networks. Springer, 2005. 24

T. Boukherroub, J. Fondrevelle, A. Guinet, and A. Ruiz. Multi-criteria decision making for the supply chain design: A review with emphasis on sustainable supply chains. In *Creative logistics for an uncertain world*. Proceedings of the 4th International Conference on Information Systems, Logistics and Supply Chain, 2012. 25, 26

Y. Bouzembrak, H. Allaoui, G. Goncalves, and H. Bouchriha. A multi-modal supply chain network design for recycling waterway sediments. *International Journal of Environment and Pollution*, 51(1):15–31, 2013. 13, 33, 35, 36, 37, 39, 48, 50, 109

M. Brandenburg, K. Govindan, J. Sarkis, and S. Seuring. Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research*, 233(2):299–312, 2014. 24, 25, 28

I. Burton. Our Common Future - World Commission on Environment and Development. *Environment*, 29 (5):25–29, 1987. 24

R. Caballero, M. González, F. Guerrero, J. Molina, and C. Paralera. Solving a multiobjective location routing problem with a metaheuristic based on tabu search. application to a real case in Andalusia. *European Journal of Operational Research*, 177(3):1751 – 1763, 2007. 14, 117, 118, 120

Y. Cardona-Valdés, A. Álvarez, and J. Pacheco. Metaheuristic procedure for a bi-objective supply chain design problem with uncertainty. *Transportation Research Part B: Methodological*, 60(0):66 – 84, 2014. 7, 21, 61, 117, 118, 133

D. Carlsson and R. Rönnqvist. Supply chain management in forestry – case studies at Södra cell AB. *European Journal of Operational Research*, 163(3):589 – 616, 2005. Supply Chain Management and Advanced Planning. 61

C. Caruso, A. Colorni, and M. Paruccini. The regional urban solid waste management system: A modelling approach. *European Journal of Operational Research*, 70(1):16–30, 1993. 32, 33, 35, 36, 37, 41, 45, 50

P. Castka and M. A. Balzarova. Iso 26000 and supply chains - on the diffusion of the social responsibility standard. *International Journal of Production Economics*, 111(2):274–286, 2008. 57

A. Chaabane, A. Ramudhin, and M. Paquet. Designing supply chains with sustainability considerations. *Production Planning & Control*, 22(8):727–741, 2011. doi: 10.1080/09537287.2010.543554. 33, 35, 41, 45, 48, 50

A. Chaabane, M. Paquet, and M. Chaker. Sustainable supply chains and responsiveness trade-offs in supply chain planning. In *Creative logistics for an uncertain world*. Proceedings of the 4th International Conference on Information Systems, Logistics and Supply Chain, 2012a. 20

A. Chaabane, A. Ramudhin, and M. Paquet. Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics*, 135(1):37–49, 2012b. 30, 31, 37, 40, 41, 48, 50, 53, 58

E. Chardine-Baumann and V. Botta-Genoulaz. A framework for sustainable performance assessment of supply chain management practices. *Computers & Industrial Engineering*, 76(0):138–147, 2014. 36, 56

L. Chen, J. Olhager, and O. Tang. Manufacturing facility location and sustainability: A literature review and research agenda. *International Journal of Production Economics*, 149(0):154–163, 2014. The Economics of Industrial Production. 24, 25, 26, 28

S. Chopra and P. Meindl. *Supply chain management*. Pearson Prentice-Hall, 2. ed., internat. ed. edition, 2004. 19

P. J. Copado-Méndez, C. Blum, G. Guillén-Gosálbez, and L. Jiménez. Large neighbourhood search applied to the efficient solution of spatially explicit strategic supply chain management problems. *Computers & Chemical Engineering*, 49(11):114–126, 2013. 12, 68

J. Cordeau, F. Pasin, and M. Solomon. An integrated model for logistics network design. *Annals of Operations Research*, 144:59–82, 2006. 61, 75, 80

G. Corsano, A. Vecchietti, and J. Montagna. Optimal design for sustainable bioethanol supply chain considering detailed plant performance model. *Computers & Chemical Engineering*, 35(8, SI):1384–1398, 2011. 33, 35, 38, 39, 47, 48, 50, 51

P. Costi, R. Minciardi, M. Robba, M. Rovatti, and R. Sacile. An environmentally sustainable decision model for urban solid waste management. *Waste Management*, 24(3):277–295, 2004. 32, 33, 35, 38, 39, 48, 50, 52, 53

M. S. Daskin, L. V. Snyder, and R. Berger. Facility location in supply chain design. In A. Langevin and D. Riopel, editors, *Logistics Systems: Design and Optimization*, pages 39–65. Springer US, 2005. 11, 19, 25

S. Datta. Multi-criteria multi-facility location in niwai block, rajasthan. *IIMB Management Review*, 24(1): 16–27, 2012. 37, 39, 45, 47, 50, 54

P. Davis and T. Ray. A branch-and-bound algorithm for the capacitated facilities location problem. *Naval Research Logistics*, 16:331–344, 1969. 67

A. De Meyer, D. Cattrysse, J. Rasinmäki, and J. V. Orshoven. Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. *Renewable and Sustainable Energy Reviews*, 31(0):657–670, 2014. 25, 26

F. Dehghanian and S. Mansour. Designing sustainable recovery network of end-of-life products using genetic algorithm. *Resources, Conservation and Recycling*, 53(10):559–570, 2009. 30, 31, 36, 37, 41, 45, 46, 47, 48, 50, 53, 117

R. Dekker, M. Fleischmann, K. Interfuth, and L. van Wassenhove, editors. *Reverse logistics: quantitative models for closed loops supply chains*. Springer-Verlag, 2004. 24

R. Dekker, J. Bloemhof, and I. Mallidis. Operations Research for green logistics - An overview of aspects, issues, contributions and challenges. *European Journal of Operational Research*, 219(3):671–679, 2012. 25, 26

L. Der-Horng and D. Meng. A heuristic approach to logistics network design for end-of-lease computer products recovery. *Transportation Research Part E*, 44(3):455 – 474, 2008. 21, 67

K. Devika, A. Jafarian, and V. Nourbakhsh. Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques. *European Journal of Operational Research*, 235(3):594–615, 2014. 13, 25, 26, 33, 35, 36, 37, 41, 45, 46, 50, 53, 109, 116, 117

A. Diabat, T. Abdallah, A. Al-Refaie, D. Svetinovic, and K. Govindan. Strategic closed-loop facility location problem with carbon market trading. *IEEE Transactions on Engineering Management*, 60(2): 398–408, 2013. 33, 35, 39, 48, 50

F. Du and G. Evans. A bi-objective reverse logistics network analysis for post-sale service. *Computers & Operations Research*, 35(8):2617 – 2634, 2008. 20, 21, 117, 127

V. Dua and E. N. Pistikopoulos. An algorithm for the solution of multiparametric mixed integer linear programming problems. *Annals of Operations Research*, 99(1–4):123–139, 2000. 47

G. Dueck. New optimization heuristics: The great deluge algorithm and the record-to-record travel. *Journal of Computational Physics*, 104:86–92, 1993. 68

J. Duque, A. Barbosa-Povoa, and A. Novais. Design and planning of sustainable industrial networks: application to a recovery network of residual products. *Industrial & Engineering Chemistry Research*, 49(9):4230–4248, 2010. 30, 31, 41, 45, 48, 50

R. C. Eberhart, P. Simpson, R. Dobbins, and R. W. Dobbins. *Computational intelligence PC tools*. Boston: Academic Press, 1996. 116

S. Elhedhli and R. Merrick. Green supply chain network design to reduce carbon emissions. *Transportation Research Part D: Transport and Environment*, 17(5):370–379, 2012. 33, 34, 35, 38, 39, 44, 48

J. Elia, R. Baliban, X. Xiao, and C. Floudas. Optimal energy supply network determination and life cycle analysis for hybrid coal, biomass, and natural gas to liquid (CBGTL) plants using carbon-based hydrogen production. *Computers & Chemical Engineering*, 35(8):1399–1430, 2011. 29, 30, 31, 38, 39, 48, 50, 51

J. A. Elia, R. C. Baliban, and C. A. Floudas. Nationwide energy supply chain analysis for hybrid feedstock processes with significant co2 emissions reduction. *AIChE Journal*, 58(7):2142–2154, 2012. ISSN 1547-5905. doi: 10.1002/aic.13842. URL `http://dx.doi.org/10.1002/aic.13842`. 30, 31, 39, 48, 50

J. A. Elia, R. C. Baliban, and C. A. Floudas. Nationwide, regional, and statewide energy supply chain optimization for natural gas to liquid transportation fuel (GTL) systems. *Industrial & Engineering Chemistry Research*, 53(13):5366–5397, 2014. 30, 31, 39, 48, 50

E. Erkut, A. Karagiannidis, G. Perkoulidis, and S. A. Tjandra. A multicriteria facility location model for municipal solid waste management in north greece. *European Journal of Operational Research*, 187(3): 1402–1421, 2008. 33, 35, 41, 42, 45, 48, 50, 53

M. Eskandarpour, S. Zegordi, and E. Nikbakhsh. A parallel variable neighborhood search for the multi-objective sustainable post-sales network design problem. *International Journal of Production Economics*, 145(1):117–131, 2013. 21, 32, 33, 35, 42, 45, 46, 50, 117

M. Eskandarpour, E. Nikbakhsh, and S. Zegordi. Variable neighborhood search for the bi-objective post-sales network design problem: A fitness landscape analysis approach. *Computers & Operations Research*, 52(B):300–314, 2014. 21, 117

E. Eskigun, R. Uzsoy, P. V. Preckel, G. Beaujon, S. Krishnan, and J. D. Tew. Outbound supply chain network design with mode selection, lead times and capacitated vehicle distribution centers. *European Journal of Operational Research*, 165(1):182 – 206, 2005. 61

M. Fleischmann, J. Bloemhof-Ruwaard, R. Dekker, E. Laan, J. van Nunen, and L. Van Wassenhove. Quantitative models for reverse logistics: A review. *European Journal of Operational Research*, 103(1):1–17, 1997. 24

G. Galante, G. Aiello, M. Enea, and E. Panascia. A multi-objective approach to solid waste management. *Waste Management*, 30(8–9):1720–1728, 2010. 32, 33, 35, 41, 45, 47, 48, 50, 52

S. Ganguly, N. Sahoo, and D. Das. Mono- and multi-objective planning of electrical distribution networks using particle swarm optimization. *Applied Soft Computing*, 11(2):2391 – 2405, 2011. 117

I. Giannikos. A multiobjective programming model for locating treatment sites and routing hazardous wastes. *European Journal of Operational Research*, 104(2):333–342, 1998. 53

S. Giarola, A. Zamboni, and F. Bezzo. Spatially explicit multi-objective optimisation for design and planning of hybrid first and second generation biorefineries. *Computers & Chemical Engineering*, 35(9): 1782–1797, 2011. 30, 31, 41, 48, 50, 51, 52

S. Giarola, N. Shah, and F. Bezzo. A comprehensive approach to the design of ethanol supply chains including carbon trading effects. *Bioresource Technology*, 107:175–185, 2012a. 30, 31, 39, 40, 48, 50, 51

S. Giarola, A. Zamboni, and F. Bezzo. Environmentally conscious capacity planning and technology selection for bioethanol supply chains. *Renewable Energy*, 43:61–72, 2012b. 30, 31, 41, 48, 50, 51

M. Goedkoop and R. Spriensma. The eco-indicator 99, a damage oriented method for life cycle impact assessment: Methodology report. (third edition). Technical report, PRé Consultants, 2000. 30

M. Goedkoop, R. Heijungs, M. Huijbregts, A. De Schryver, J. Struijs, and R. Van Zelm. ReCiPe 2008, a life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level. first edition. report i: Characterisation. Technical report, Rijksinstituut voor Volksgezondheid en Milieu, The Netherlands, 2009. 31

K. Govindan, A. Jafarian, R. Khodaverdi, and K. Devika. Two-echelon multiple-vehicle location-routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*, 152:9–28, 2013. 33, 35, 36, 40, 41, 45, 46, 50

V. D. R. Guide and L. N. Van Wassenhove. Closed-loop supply chains: An introduction to the feature issue (part 1). *Production and Operations Management*, 15(3):345–350, 2006a. 24

V. D. R. Guide and L. N. Van Wassenhove. Closed-loop supply chains: An introduction to the feature issue (part 2). *Production and Operations Management*, 15(4):471–472, 2006b. 24

G. Guillén-Gosálbez. A novel milp-based objective reduction method for multi-objective optimization: Application to environmental problems. *Computers & Chemical Engineering*, 35(8):1469 – 1477, 2011a. 115

G. Guillén-Gosálbez. A novel MILP-based objective reduction method for multi-objective optimization: Application to environmental problems. *Computers & Chemical Engineering*, 35(8):1469–1477, 2011b. 46

G. Guillén-Gosálbez and I. Grossmann. Optimal design and planning of sustainable chemical supply chains under uncertainty. *AICHE Journal*, 55(1):99–121, 2009. 30, 31, 42, 43, 44, 45, 47, 48, 50, 52

G. Guillén-Gosálbez and I. Grossmann. A global optimization strategy for the environmentally conscious design of chemical supply chains under uncertainty in the damage assessment model. *Computers and Chemical Engineering*, 34(1):42–58, 2010. 30, 31, 43, 44, 45, 46, 47, 48, 50, 52, 147

G. Guillén-Gosálbez, J. Caballero, and L. Jiménez. Application of life cycle assessment to the structural optimization of process flowsheets. *Industrial & Engineering Chemistry Research*, 47(3):777–789, 2008. 30, 31, 42, 45, 47, 48, 50

G. Guillén-Gosálbez, F. Mele, and I. Grossmann. A bi-criterion optimization approach for the design and planning of hydrogen supply chains for vehicle use. *AICHE Journal*, 56(3):650–667, 2010. 30, 31, 32, 40, 41, 45, 46, 48, 50, 51

A. Gupta and J. Könemann. Approximation algorithms for network design: a survey. *Surveys in Operations Research and Management Science*, 16(1):3–20, 2011. 21

S. Gupta and O. Palsule-Desai. Sustainable supply chain management: review and research opportunities. *IIMB Management Review*, 23(4):234–245, 2011. 25

R. Hahn. Iso 26000 and the standardization of strategic management processes for sustainability and corporate social responsibility. *Business Strategy and the Environment*, 22(7):442–455, 2013. 57

S. L. Hakimi. Optimum locations of switching centers and the absolute centers and medians of a graph. *Operations Research*, 12(3):450–459, 1964. 19

N. A. Harraz and N. M. Galal. Design of sustainable end-of-life vehicle recovery network in Egypt. *Ain Shams Engineering Journal*, 2(3-4):211–219, 2011. 33, 34, 35, 37, 41, 45, 48, 50

I. Harris, M. Naim, A. Palmer, A. Potter, and C. Mumford. Assessing the impact of cost optimization based on infrastructure modelling on CO_2 emissions. *International Journal of Production Economics*, 131(1): 313–321, 2011. 33, 34, 35, 126

I. Harris, C. L. Mumford, and M. N. Naim. A hybrid multi-objective approach to capacitated facility location with flexible store allocation for green logistics modeling. *Transportation Research Part E: Logistics and Transportation Review*, 66(0):1 – 22, 2014. 115

E. Hassini, C. Surti, and C. Searcy. A literature review and a case study of sustainable supply chains with a focus on metrics. *International Journal of Production Economics*, 140(1):69–82, 2012. 25

I. Heckmann, T. Comes, and S. Nickel. A critical review on supply chain risk âĂŞ definition, measure and modeling. *Omega*, 52(0):119–132, 2015. 56

A. Hugo and E. Pistikopoulos. Environmentally conscious long-range planning and design of supply chain networks. *Journal of Cleaner Production*, 13(15):1471–1491, 2005. 30, 31, 41, 45, 47, 50, 52

A. Hugo, P. Rutter, S. Pistikopoulos, A. Amorelli, and G. Zoia. Hydrogen infrastructure strategic planning using multi-objective optimization. *International Journal of Hydrogen Energy*, 30(15):1523–1534, 2005. 30, 31, 40, 41, 50, 51

M. Ilgin and S. Gupta. Environmentally conscious manufacturing and product recovery (ECMPRO): a review of the state of the art. *Journal of Environmental Management*, 91:563–591, 2010. 28, 109

IPCC. *Fourth Assessment Report: Climate Change 2007: Working Group I Report: The Physical Science Basis*. Geneva: IPCC, 2007. 31

ISO. Environmental management-life cycle assessment-principles and framework, 2006. 7, 28, 29

R. Jamshidi, S. Fatemi Ghomi, and B. Karimi. Multi-objective green supply chain optimization with a new hybrid memetic algorithm using the taguchi method. *Scientia Iranica*, 19(6):1876–1886, 2012. 21, 33, 34, 35, 41, 45, 46, 117

T. Johnsen, J. Miemczyk, and M. Macquet. Sustainable purchasing and supply management. *Supply Chain Management*, 17(5):478–496, 2012. 25

O. Jolliet, M. Margni, R. Charles, S. Humbert, J. Payet, G. Rebitzer, and R. Rosenbaum. Impact 2002+: A new life cycle impact assessment methodology. *The International Journal of Life Cycle Assessment*, 8 (6):324–330, 2003. 30

A. Jorgensen. Social LCA – a way ahead? *The International Journal of Life Cycle Assessment*, 18:296–299, 2013. 57

A. Jorgensen, A. Bocq, L. Nazarkina, and M. Hauschild. Methodologies for social life cycle assessment. *The International Journal of Life Cycle Assessment*, 13:96–103, 2008. 57

D. Kannan, A. Diabat, M. Alrefaei, K. Govindan, and G. Yong. A carbon footprint based reverse logistics network design model. *Resources, Conservation and Recycling*, 67(0):75–79, 2012. 33, 35, 38, 39, 48, 50

C. Kanzian, M. KÃijhmaier, J. Zazgornik, and K. Stampfer. Design of forest energy supply networks using multi-objective optimization. *Biomass and Bioenergy*, 58(0):294–302, 2013. 33, 35, 41, 45, 50

S. Kirkpatrick, C. Gelatt, and M. Vecchi. Optimization by simulated annealing. *Science*, 220:671–680, 1983. 68

A. Klose and A. Drexl. Facility location models for distribution system design. *European Journal of Operational Research*, 162(1):4–29, 2005. 19

A. Kostin, G. Guillén-Gosálbez, F. Mele, and L. Jiménez. Identifying key life cycle assessment metrics in the multiobjective design of bioethanol supply chains using a rigorous mixed-integer linear programming approach. *Industrial & Engineering Chemistry Research*, 51(14):5282–5291, 2012. 30, 31, 32, 41, 45, 46, 48, 50

H. Krikke. Impact of closed-loop network configurations on carbon footprints: a case study in copiers. *Resources, Conservation and Recycling*, 55(12):1196–1205, 2011. 33, 35, 38, 39, 48, 50

H. Krikke, J. Bloemhof-Ruwaard, and L. N. Van Wassenhove. Concurrent product and closed-loop supply chain design with an application to refrigerators. *International Journal of Production Research*, 41(16): 3689–3719, 2003. 33, 34, 35, 41, 45, 48, 50, 54

A. Kumar, V. Jain, and S. Kumar. A comprehensive environment friendly approach for supplier selection. *Omega*, 42(1):109–123, 2014. 34

H. Lam, W. Wendy Ng, R. Ng, E. Ng, M. K. Abdul Aziz, and D. Ng. Green strategy for sustainable waste-to-energy supply chain. *Energy*, 57(0):4–16, 2013. 32, 33, 35, 41, 48, 50

G. Laporte, S. Nickel, and F. Saldanha da Gama. *Location science*. Springer, Forthcoming. 145

S. Liao, C. Hsieh, and P. Lai. An evolutionary approach for multi-objective optimization of the integrated location-inventory distribution network problem in vendor-managed inventory. *Expert Systems with Applications*, 38(6):6768 – 6776, 2011. 117

J. D. Linton, R. Klassen, and V. Jayaraman. Sustainable supply chains: an introduction. *Journal of Operations Management*, 25(6):1075 – 1082, 2007. 20

L. F. Lira-Barragán, J. M. Ponce-Ortega, M. Serna-González, and M. M. El-Halwagi. An MINLP model for the optimal location of a new industrial plant with simultaneous consideration of economic and environmental criteria. *Industrial & Engineering Chemistry Research*, 50(2):953–964, 2011. 33, 35, 38, 39, 47, 48

L. F. Lira-BarragÃąn, J. M. Ponce-Ortega, F. NÃąpoles-Rivera, M. Serna-GonzÃąlez, and M. M. El-Halwagi. Incorporating property-based water networks and surrounding watersheds in site selection of industrial facilities. *Industrial & Engineering Chemistry Research*, 52(1):91–107, 2013. 35, 36, 39, 47, 48

P. Liu, A. Whitaker, E. N. Pistikopoulos, and Z. Li. A mixed-integer programming approach to strategic planning of chemical centres: A case study in the UK. *Computers & Chemical Engineering*, 35(8): 1359–1373, 2011. 33, 35, 39, 42, 48, 50

M. J. M. and V. B. G. Global supply chain design: A literature review and critique. *Transportation Research Part E: Logistics and Transportation Review*, 41(6):531 – 550, 2005. 11, 19, 25

J. Malczewski and W. Ogryczak. An interactive approach to the central facility location problem: locating pediatric hospitals in Warsaw. *Geographical Analysis*, 22(3):244–258, 1990. 37, 41, 45, 46, 50, 54

I. Mallidis, R. Dekker, and D. Vlachos. The impact of greening on supply chain design and cost: a case for a developing region. *Journal of Transport Geography*, 22:118–128, 2012. 33, 35, 38, 39, 47, 48, 50, 54

M. Marufuzzaman, S. D. Ek¸sioğlu, and R. Hernandez. Environmentally friendly supply chain planning and design for biodiesel production via wastewater sludge. *Transportation Science*, 48(4):555–574, 2014. 33, 35, 41, 45, 48, 50

S. M. Masoumik, S. H. Abdul-Rashid, E. Udoncy Olugu, and R. A. R. Ghazilla. Sustainable supply chain design: A configurational approach. *The Scientific World Journal*, 2014:16 pages, 2014. 25

E. Melachrinoudis. The location of undesirable facilities. In H. A. Eiselt and V. Marianov, editors, *Foundations of Location Analysis*, volume 155 of *International Series in Operations Research & Management Science*, pages 207–239. Springer US, 2011. 24

F. Mele, G. Guillén-Gosálbez, and L. Jimenez. Optimal planning of supply chains for bioethanol and sugar production with economic and environmental concerns. In J. Jezowski and J. Thullie, editors, *19th European Symposium on Computer Aided Process Engineering*, volume 26, pages 997–1002. Elsevier, 2009. 29, 30, 31, 32, 41, 45, 48, 50

F. Mele, A. Kostin, G. Guillén-Gosálbez, and L. Jiménez. Multiobjective model for more sustainable fuel supply chains. a case study of the sugar cane industry in argentina. *Industrial & Engineering Chemistry Research*, 50(9):4939–4958, 2011. 30, 31, 32, 41, 45, 48, 50

M. Melo, S. Nickel, and F. Saldanha-da Gama. A tabu search heuristic for redesigning a multi-echelon supply chain network over a planning horizon. *International Journal of Production Economics*, 136(1): 218 – 230, 2012. 21

M. T. Melo, S. Nickel, and F. Saldanha-da Gama. Facility location and supply chain management - a review. *European Journal of Operational Research*, 196(2):401–412, 2009. 11, 19, 21, 25, 146

A. Messac, A. Ismail-Yahaya, and C. Mattson. The normalized normal constraint method for generating the Pareto frontier. *Structural and multidisciplinary optimization*, 25(2):86–98, 2013. 47

J. Miemczyk, T. Johnsen, and M. Macquet. Sustainable purchasing and supply management: A review of definitions and measures at the dyad, chain and network levels of analysis. *Supply Chain Management: An International Journal*, 17(5):478–496, 2012. 25

R. Minciardi, M. Paolucci, M. Robba, and R. Sacile. Multi-objective optimization of solid waste flows: Environmentally sustainable strategies for municipalities. *Waste Management*, 28(11):2202–2212, 2008. 33, 35, 41, 45, 48, 50, 52

M. Mohammadi, S. Torabi, and R. Tavakkoli-Moghaddam. Sustainable hub location under mixed uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, 62(0):89–115, 2014. 33, 35, 36, 43, 45, 46, 47, 48

L. A. Moncayo-Martínez and D. Z. Zhang. Multi-objective ant colony optimisation: A meta-heuristic approach to supply chain design. *International Journal of Production Economics*, 131(1):407 – 420, 2011. 117

G. Montibeller, V. Belton, F. Ackermann, and L. Ensslin. Reasoning maps for decision aid: an integrated approach for problem-structuring and multi-criteria evaluation. *Journal of the Operations research Society*, 59(5):575–589, 2008. 47

B. Mota, M. I. Gomes, A. Carvalho, and A. P. Barbosa-Povoa. Towards supply chain sustainability: economic, environmental and social design and planning. *Journal of Cleaner Production*, -(in press):–, 2014. doi: http://dx.doi.org/10.1016/j.jclepro.2014.07.052. 30, 31, 36, 37, 41, 45, 48, 50

E. Muñoz, E. Capón-García, J. Laínez, A. Espuña, and L. Puigjaner. Considering environmental assessment in an ontological framework for enterprise sustainability. *Journal of Cleaner Production*, 47:149–164, 2013. 30, 31, 42, 47, 48

A. Nikolopoulou and M. Ierapetritou. Optimal design of sustainable chemical processes and supply chains: a review. *Computers & Chemical Engineering*, 44:94–103, 2012. 25, 26, 34, 52

OECD/IEA. CO_2 emissions from fuel combustion 2012-highlights. Technical report, OECD/IEA, 2012. URL `https://www.iea.org/co2highlights/co2highlights.pdf`. (accessed March 28, 2014). 13, 22, 32, 109

E. Olivares-Benitez, R. Ríos-Mercado, and J. González-Velarde. A metaheuristic algorithm to solve the selection of transportation channels in supply chain design. *International Journal of Production Economics*, 145(1):161–172, 2013. 21, 61, 67, 71, 117

S. H. Owen and M. S. Daskin. Strategic facility location: a review. *European Journal of Operational Research*, 111(3):423–447, 1998. 11, 25

C. Papapostolou, E. Kondili, and J. Kaldellis. Development and implementation of an optimisation model for biofuels supply chain. *Energy*, 36(10):6019–6026, 2011. 32, 33, 35, 36, 38, 39, 48, 50

R. Pati, P. Vrat, and P. Kumar. A goal programming model for paper recycling system. *Omega*, 36(3): 405–417, 2008. 20, 33, 34, 35, 41, 45, 47, 48, 50, 53

R. Pati, R. Jans, and R. Tyagi. Green logistics network design: A critical review. In *24th Annual POMS conference*, Denver, USA, 2013. 25

M. Pérez-Fortes, J. Laínez-Aguirre, P. Arranz-Piera, E. Velo, and L. Puigjaner. Design of regional and sustainable bio-based networks for electricity generation using a multi-objective MILP approach. *Energy*, 44(1):79–95, 2012. 30, 31, 37, 41, 44, 45, 48, 50, 51

C. Pieragostini, M. C. Mussati, and P. Aguirre. On process optimization considering LCA methodology. *Journal of Environmental Management*, 96(1):43–54, 2012. 28

T. Pinto-Varela, A. Barbosa-Póvoa, and A. Novais. Bi-objective optimization approach to the design and planning of supply chains: Economic versus environmental performances. *Computers & Chemical Engineering*, 35(8):1454–1468, 2011. 30, 31, 32, 41, 43, 44, 45, 48, 50, 53

A. Pires, G. Martinho, and N.-B. Chang. Solid waste management in European countries: A review of systems analysis techniques. *Journal of Environmental Management*, 92(4):1033–1050, 2011. 52

M. Pishvaee and J. Razmi. Environmental supply chain network design using multi-objective fuzzy mathematical programming. *Applied Mathematical Modelling*, 36(8):3433–3446, 2012. 30, 31, 43, 45, 48, 50, 53

M. Pishvaee, R. Zanjirani Farahani, and W. Dullaert. A memetic algorithm for bi-objective integrated forward/reverse logistics network design. *Computers & Operations Research*, 37(6):1100–1112, 2010a. 21, 44

M. Pishvaee, J. Razmi, and S. Torabi. Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets and Systems*, 206(0):1–20, 2012a. 32, 33, 35, 37, 42, 43, 45, 48, 50, 53

M. Pishvaee, S. Torabi, and J. Razmi. Credibility-based fuzzy mathematical programming model for green logistics design under uncertainty. *Computers & Industrial Engineering*, 62(2):624–632, 2012b. 30, 31, 43, 45, 47, 48, 50, 53, 58, 146, 147

M. S. Pishvaee, R. Zanjirani Farahani, and W. Dullaert. A memetic algorithm for bi-objective integrated forward/reverse logistics network design. *Computers & Operations Research*, 37(6):1100 – 1112, 2010b. 117

D. Pisinger and S. Ropke. A general heuristic for vehicle routing problems. *Computers & Operations Research*, 34(8):2403–2435, 2007. 70, 73, 84

S. Pokharel and A. Mutha. Perspectives in reverse logistics: a review. *Resources, Conservation and Recycling*, 53(4):175–182, 2009. 24

H. Pourmohammadi, M. Rahimi, and M. Dessouky. Sustainable reverse logistics for distribution of industrial waste/byproducts: A joint optimization of operation and environmental costs. *Supply Chain Forum: an International Journal*, 9(1):2–17, 2008. 33, 34, 35, 36, 41, 47, 48, 50, 53

C. Pozo, R. Ruiz-Femenia, J. Caballero, G. Guillén-Gosálbez, and L. Jimenez. On the use of principal component analysis for reducing the number of environmental objectives in multi-objective optimization: Application to the design of chemical supply chains. *Chemical EngineeringScience*, 69(1):146–158, 2012. 30, 31, 41, 44, 45, 46, 48, 50

J. Quariguasi Frota Neto, J. Bloemhof-Ruwaard, J. van Nunen, and E. van Heck. Designing and evaluating sustainable logistics networks. *International Journal of Production Economics*, 111(2):195–208, 2008. 30, 31, 40, 41, 45, 47, 50

R. Rahmaniani and A. Ghaderi. A combined facility location and network design problem with multi-type of capacitated links. *Applied Mathematical Modelling*, 37(9):6400–6414, 2013. 61

T. R. P. Ramos, M. I. Gomes, and A. P. Barbosa-Pv́oa. Planning a sustainable reverse logistics system: Balancing costs with environmental and social concerns. *Omega*, 48:60–74, 2014. 24

A. Ramudhin, A. Chaabane, and M. Paquet. Carbon market sensitive sustainable supply chain network design. *International Journal of Management Science and Engineering Management*, 5(1):30–38, 2010. 13, 33, 35, 41, 45, 47, 48, 50, 53, 109

C. ReVelle and H. Eiselt. Location analysis: A synthesis and survey. *European Journal of Operational Research*, 165(1):1–19, 2005. 19

S. Ropke and D. Pisinger. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science*, 40(4):455âĂŞ472, 2006. 70

S. Ropke and D. Pisinger. Large neighborhood search. In M. Gendreau and J.-Y. Potvin, editors, *Handbook of Metaheuristics*, pages 399–419. Springer New York, 2nd edition, 2010. 67

R. Ruiz-Femenia, G. Guillén-Gosálbez, L. Jiménez, and J. Caballero. Multi-objective optimization of environmentally conscious chemical supply chains under demand uncertainty. *Chemical Engineering Science*, 95:1–11, 2013. 30, 31, 42, 43, 45, 48, 50

T. L. Saaty. How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, 48(1):9–26, 1990. 37, 47

H. Sadjady and H. Davoudpour. Two-echelon, multi-commodity supply chain network design with mode selection, lead-times and inventory costs. *Computers & Operations Research*, 39(7):1345 – 1354, 2012. 61, 80

A. Sadrnia, N. Ismail, N. Zulkifli, M. K. A. Ariffin, H. Nezamabadi-pour, and H. Mirabi. A multiobjective optimization model in automotive supply chain networks. *Mathematical Problems in Engineering*, 2013 (Article ID 823876):10 pages, 2013. 13, 33, 35, 41, 45, 50, 109

M. M. Saffar, H. G. Shakouri, and J. Razmi. A new bi-objective mixed integer linear programming for designing a supply chain considering co2 emission. *Uncertain Supply Chain Management*, 2(4):275–292, 2014. 33, 35, 43, 45

M. M. Saffar, H. G. Shakouri, and J. Razmi. A new multi objective optimization model for designing a green supply chain network under uncertainty. *International Journal of Industrial Engineering Computations*, 6(1):15–32, 2015. 33, 35, 43, 45

G. Sahin and H. Süral. A review of hierarchical facility location models. *Computers & Operations Research*, 34(8):2310–2331, 2007. 11, 19, 25

J. E. Santibañez Aguilar, J. B. González-Campos, J. M. Ponce-Ortega, M. Serna-González, and M. M. El-Halwagi. Optimal planning and site selection for distributed multiproduct biorefineries involving economic, environmental and social objectives. *Journal of Cleaner Production*, 65(0):270–294, 2014. 30, 31, 37, 41, 45, 48, 50

J. Sarkis, Q. Zhu, and K. Lai. An organizational theoretic review of green supply chain management literature. *International Journal of Production Economics*, 130(1):1–15, 2011. 25

G. Schrimpf, J. Schneider, H. Stamm-Wilbrandt, and G. Dueck. Record breaking optimization results using the ruin and recreate principle. *Journal of Computational Physics*, 159:139–171, 2000. 21, 67

N. Seman, N. Zakuan, A. Jusoh, and M. Arif. Green supply chain management: A review and research direction. *International Journal of Managing Value and Supply Chains*, 3(1), 2012. 25

S. Seuring. A review of modeling approaches for sustainable supply chain management. *Decision Support Systems*, 54(4):1513–1520, 2013. 24, 25, 28

S. Seuring and M. Müller. From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, 16(15):1699–1710, 2008. 24, 25, 36

B. L. Shankar, S. Basavarajappa, J. Chen, and R. Kadadevaramath. Location and allocation decisions for multi-echelon supply chain network - a multi-objective evolutionary approach. *Expert Systems with Applications*, 40(2):551 – 562, 2013a. 117

B. L. Shankar, S. Basavarajappa, R. Kadadevaramath, and J. Chen. A bi-objective optimization of supply chain design and distribution operations using non-dominated sorting algorithm: A case study. *Expert Systems with Applications*, 40(14):5730 – 5739, 2013b. 117

P. Shaw. Using constraint programming and local search methods to solve vehicle routing problems. In *Proceedings of the 4th International Conference on Principles and Practice of Constraint Programming*, pages 417–431, 1998. 21, 67

D. Simchi-Levi, P. Kaminsky, and E. Simchi-Levi, editors. *Managing the Supply Chain: The Definitive Guide for the Business Professional*. McGraw-Hill, 2004. 19

L. V. Snyder. Facility location under uncertainty: A review. *IIE Transactions*, 38:547–564, 2004. 40

M. Soysal, J. M. Bloemhof-Ruwaard, M. P. Meuwissen, and J. G. van der Vorst. A review on quantitative models for sustainable food logistics management. *International Journal on Food System Dynamics*, 3 (2):136–155, 2012. 25

S. Srivastava. Green supply-chain management: A state-of-the-art literature review. *International Journal Of Management Reviews*, 9(1):53–80, 2007. 20, 25

S. K. Srivastava. Network design for reverse logistics. *Omega*, 36(4):535–548, 2008. 24

P. Subramanian, N. Ramkumar, T. Narendran, and K. Ganesh. PRISM: PRIority based SiMulated annealing for a closed loop supply chain network design problem. *Applied Soft Computing*, 13(2):1121 – 1135, 2013. 21

S. A. Terouhid, R. Ries, and M. M. Fard. Towards sustainable facility location - a literature review. *Journal of Sustainable Development*, 5(7), 2012. 25, 26

M. Tiwari, N. Raghavendra, S. Agrawal, and S. Goyal. A hybrid Taguchi-immune approach to optimize an integrated supply chain design problem with multiple shipping. *European Journal of Operational Research*, 203(1):95–106, 2010. 61

F. Tricoire. Multi-directional local search. *Computers & Operations Research*, 39(12):3089 – 3101, 2012. 14, 21, 115, 116, 117, 118, 120, 132, 146

G. Tuzkaya, B. Gülsün, and S. Önsel. A methodology for the strategic design of reverse logistics networks and its application in the Turkish white goods industry. *International Journal of Production Research*, 49(15):4543–4571, 2011. 33, 35, 36, 37, 41, 44, 45, 46, 50, 54

M. Verma, M. Gendreau, and G. Laporte. Optimal location and capability of oil-spill response facilities for the south coast of Newfoundland. *Omega*, 41(5):856–867, 2013. 35, 36, 39, 40, 48, 50

F. Wang, X. Lai, and N. Shi. A multi-objective optimization for green supply chain network design. *Decision Support Systems*, 51(2):262–269, 2011. 13, 21, 32, 33, 35, 42, 45, 47, 48, 109

H. Wang and H. Hsu. A closed-loop logistic model with a spanning-tree based genetic algorithm. *Computers & Operations Research*, 37(2):376–389, 2010. 21

W. Wilhelm, D. Liang, B. Rao, D. Warrier, X. Zhu, and S. Bulusu. Design of international assembly systems and their supply chains under NAFTA. *Transportation Research Part E: Logistics and Transportation Review*, 41(6):467 – 493, 2005. 61

L. A. Wright, S. Kemp, and I. Williams. Carbon footprinting: towards a universally accepted definition. *Carbon Management*, 2(1):61–72, 2011. 34

M. Wu, Y. Hsu, and L. Huang. An integrated approach to the design and operation for spare parts logistic systems. *Expert Systems with Applications*, 38(4):2990–2997, 2011. 61

T. Xifeng, Z. Ji, and X. Peng. A multi-objective optimization model for sustainable logistics facility location. *Transportation Research Part D: Transport and Environment*, 22:45–48, 2013. 33, 35, 41, 45, 46

M. Yaghini, M. Momeni, and M. Sarmadi. A simplex-based simulated annealing algorithm for node-arc capacitated multicommodity network design. *Applied Soft Computing*, 12(9):2997 – 3003, 2012. 21

W. Yeh. An efficient memetic algorithm for the multi-stage supply chain network problem. *International Journal of Advanced Manufacturing Technology*, 29(7-8):803–813, 2006. 81

F. You and B. Wang. Life cycle optimization of biomass-to-liquid supply chains with distributed centralized processing networks. *Industrial and Engineering Chemistry Research*, 50:10102–10127, 2011. 20, 28, 29, 30, 31, 41, 45, 48, 50, 55

F. You, L. Tao, D. Graziano, and S. Snyder. Optimal design of sustainable cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle assessment and input-output analysis. *AIChE Journal*, 58(4):1157–1180, 2012. 29, 30, 31, 37, 41, 45, 48, 50, 51

D. Yue, M. A. Kim, and F. You. Design of sustainable product systems and supply chains with life cycle optimization based on functional unit: General modeling framework, mixed-integer nonlinear programming algorithms and case study on hydrocarbon biofuels. *ACS Sustainable Chemistry & Engineering*, 1 (8):1003–1014, 2013. 30, 31, 42, 45, 47, 48, 50

D. Yue, M. Slivinsky, J. Sumpter, and F. You. Sustainable design and operation of cellulosic bioelectricity supply chain networks with life cycle economic, environmental, and social optimization. *Industrial & Engineering Chemistry Research*, 53(10):4008–4029, 2014a. 30, 31, 37, 42, 45, 47, 48, 50

D. Yue, F. You, and S. W. Snyder. Biomass-to-bioenergy and biofuel supply chain optimization: Overview, key issues and challenges. *Computers & Chemical Engineering*, 66(0):36–56, 2014b. Selected papers from ESCAPE-23 (European Symposium on Computer Aided Process Engineering - 23), 9-12 June 2013, Lappeenranta, Finland. 25, 26

Y. Y. Yusuf, A. Gunasekaran, A. Musa, N. M. El-Berishy, T. Abubakar, and H. M. Ambursa. The UK oil and gas supply chains: An empirical analysis of adoption of sustainable measures and performance outcomes. *International Journal of Production Economics*, 146(2):501–514, 2013. 25

L. Zadeh. Fuzzy sets as a basis for a theory of possibility. *Fuzzy Sets and Systems*, 1:3–28, 1978. 43

S. Zailani, K. Jeyaraman, G. Vengadasan, and R. Premkumar. Sustainable supply chain management (SSCM) in Malaysia: A survey. *International Journal of Production Economics*, 140(1):330–340, 2012. 25

A. Zamboni, F. Bezzo, and N. Shah. Spatially explicit static model for the strategic design of future bioethanol production systems. 2. multi-objective environmental optimization. *Energy & Fuels*, 23(10): 5134–5143, 2009. 30, 31, 41, 45, 47, 48, 50

A. Zamboni, R. Murphy, J. Woods, F. Bezzo, and N. Shah. Biofuels carbon footprints: Whole-systems optimisation for ghg emissions reduction. *Bioresource Technology*, 102(16):7457–7465, 2011. 30, 31, 41, 48, 50, 51

R. Zanjirani Farahani, M. SteadieSeifi, and N. Asgari. Multiple criteria facility location problems: A survey. *Applied Mathematical Modelling*, 34(7):1689 – 1709, 2010. 14, 115, 117

R. Zanjirani Farahani, S. Rezapour, T. Drezner, and S. Fallah. Competitive supply chain network design: An overview of classifications, models, solution techniques and applications. *Omega*, 45(0):92 – 118, 2014. 19, 25, 26

M. Zhang, B. Wiegmans, and L. Tavasszy. Optimization of multimodal networks including environmental costs: A model and findings for transport policy. *Computers in Industry*, 64(2):136–145, 2013. 33, 35, 42, 45, 46, 50, 53

E. Zitzler, L. Thiele, M. Laumanns, C. Fonseca, and V. da Fonseca. Performance assessment of multiobjective optimizers: an analysis and review. *IEEE Transactions on Evolutionary Computation*, 7(2):117 – 132, 2003. 14, 132, 134

E. Zitzler, M. Laumanns, and S. Bleuler. A tutorial on evolutionary multiobjective optimization. In X. Gandibleux, M. Sevaux, K. Sörensen, and V. T'kindt, editors, *Metaheuristics for Multiobjective Optimisation*, volume 535 of *Lecture Notes in Economics and Mathematical Systems*, pages 3–37. Springer Berlin Heidelberg, 2004. 116

l'université nantes angers le mans
COMMUNAUTÉ D'UNIVERSITÉS ET ÉTABLISSEMENTS

MINES Nantes
Institut Mines-Télécom

Thèse de Doctorat

Majid ESKANDARPOUR

Modèles génériques et algorithmes d'optimisation pour la conception des chaînes logistiques durables

Generic models and optimization algorithms for sustainable supply chain network design

Résumé
Cette thèse porte sur le développement de modèles mathématiques et d'algorithmes d'optimisation pour la conception de chaînes logistiques durables. Nous proposons des modèles mono-périodiques, multi-produits et multi-modes de transport à quatre niveaux (fournisseurs, unités de production, entrepôts et clients) couvrant les piliers économique et environnemental du développement durable. Les variables de décision concernent la localisation des sites logistiques intermédiaires (unités de production et entrepôts), les choix de technologie et de mode de transport, et la détermination des flux de produits. Un premier modèle est basé uniquement sur la minimisation des coûts totaux. Ce modèle est étendu au cas bi-objectif en considérant la minimisation des émissions de CO_2.
Nous proposons une procédure d'optimisation basée sur la recherche à voisinage large (LNS : Large Neighborhood Search). L'application de cette méthode à un problème à variables mixtes tel que la conception de chaîne logistique est inédite. Notre extension au cas bi-objectif fait intervenir l'algorithme récent de recherche locale multi-directionnelle. Les expérimentations numériques permettent d'évaluer la pertinence de nos modèles et de comparer les performances de nos algorithmes à celles d'un solveur du marché.

Abstract
This thesis focuses on the development of mathematical models and optimization algorithms for the design of sustainable supply chains. We propose single-period, multi-commodity, multi-mode, four level models (suppliers, production facilities, warehouses and customers) covering economic and environmental pillars of sustainable development. The decision variables are related to the location of the intermediate logistics sites (production units and warehouses), the choice of technology and mode of transport, and the determination of product flow. A first model is based solely on minimizing total costs. This model is extended to bi-objective minimization by considering CO_2 emissions.
We propose an optimization procedure based on the Large Neighborhood Search (LNS) metaheuristic, which had almost never been applied to problems with mixed variables such as design supply chain. Our extension to the bi-objective case involves the use of the multi-directional local search (MDLS). Extensive numerical experiments assess the relevance of our model and compare the performance of our algorithms to those of a state-of-the-art solver.

Mots clés
Recherche opérationnelle, réseaux logistiques, localisation, recherche à voisinage large, optimisation bi-objectif, développement durable.

Key Words
Operations research, network design, facility location, large neighborhood search, bi-objective optimization, sustainable development.