N. d'ordre : ...

Ecole Doctorale SPI de Lille | Université d'Artois

THESE DE DOCTORAT DE
L'UNIVERSITE D'ARTOIS
Spécialité : Informatique et Automatique

Ecole doctorale SPI Lille Nord de France

Présentée par

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Pour obtenir le grade de
DOCTEUR de l'UNIVERSITÉ D'ARTOIS

Sujet de la thèse :

Conception des chaînes logistiques multicirtères avec prise en compte des incertitudes

soutenue le 09/12/2011 devant le jury composé de :

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Multi-criteria Supply Chain Network Design under Uncertainty

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12 2011

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Abstract

This thesis contributes to the debate on how uncertainty and concepts of sustainable development can be put into modern supply chain network and focuses on issues associated with the design of multi-criteria supply chain network under uncertainty.

First, we study the literature review , which is a review of the current state of the art of Supply Chain Network Design approaches and resolution methods.

Second, we propose a new methodology for multi-criteria Supply Chain Network Design (SCND) as well as its application to real Supply Chain Network (SCN), in order to satisfy the customers demand and respect the environmental, social, legislative, and economical requirements. The methodology consists of two different steps. In the first step, we use Geographic Information System (GIS) and Analytic Hierarchy Process (AHP) to build the model. Then, in the second step, we establish the optimal supply chain network using Mixed Integer Linear Programming model (MILP).

Third, we extend the MILP to a multi-objective optimization model that captures a compromise between the total cost and the environment influence. We use Goal Programming approach seeking to reach the goals placed by Decision Maker. After that, we develop a novel heuristic solution method based on decomposition technique, to solve large scale supply chain network design problems that we failed to solve using exact methods. The heuristic method is tested on real case instances and numerical comparisons show that our heuristic yield high quality solutions in very limited CPU time.

Finally, again, we extend the MILP model presented before where we assume that the costumer demands are uncertain. We use two-stage stochastic programming approach to model the supply chain network under demand uncertainty. Then, we address uncertainty in all SC parameters: opening costs, production costs, storage costs and customers demands. We use possibilistic linear programming approach to model the problem and we validate both approaches in a large application case.

Chapter 1

Introduction

In 1915, Arch Shaw (1915) pointed out that: *" The relations between the activities of demand creation and physical supply...illustrated the existence of the two principles of interdependence and balance. Failure to co-ordinate any one of these activities with its group-fellows and also with those in the other group, or undue emphasis or outlay put on any one of these activities, is certain to set the equilibrium of forces which means efficient distribution... The physical distribution of the goods is a problem distinct from the creation of demand...Not a few worthy failures in distribution campaigns have been due to such a lack of co-ordination between demand creation and physical supply."*

It has taken more than 70 years the principals of Supply Chain Management (SCM) to be clearly defined in literature : according to Jones and Riley (1985), supply chain management is an integrative approach to dealing with the planning and control of the materials flow from suppliers to end-users. In Berry et al (1994), the SCM aims at building trust, exchanging information on market needs, developing new products, and reducing the supplier base to a particular original equipment manufacturer so as to release management resources for developing meaningful, long term relationship.

Tan et al. (1998) integrated the recycling step in the definition of SCM, it encompasses materials/supply management from the supply of basic raw materials to final product (and possible recycling and re-use). Supply chain management focuses on how firms utilize their suppliers' processes, technology and capability to enhance competitive advantage. It is a management philosophy that extends traditional intra enterprise activities by bringing trading partners together with the common goal of optimization and efficiency.

Recently Simchi-Levi et al. (2000) defined SCM as the set of approaches utilized to efficiently integrate suppliers, manufacturers, warehouses and stores so that merchandise is produced and distributed at the right quantity, to the right locations, and at the right time, in order to minimize system wide costs while satisfying service level requirements. The objectives of supply chain management concern satisfying the customer effectively. This means to fulfil costumer requests with maximum profit or minimum cost.

Part of the design processes in SCM aim to find the best possible supply chain configuration so that all operations can be performed in an efficient way.

- *What is Supply Chain Network Design (SCND)?*

It is clear from above definitions that, the supply chain is a network of suppliers, factories, warehouses, and distribution centers through which raw materials are procured, transformed, and delivered to the customer.

According to Diaby and Martel (1993), SCND problems deal with strategic decisions related to the number, size, and location of warehouses, as well as the assignment of customers and products to warehouses. These decisions involve trade-offs between investment costs, including inventory carrying and transportation costs, but at a very aggregate level.

Cornuejols et al. (1990) defined supply chain network design as follows: Given a set of potential sites, a set of clients, and relevant profit and cost data, the goal is to find a maximum profit plan giving the number of facilities to open, their locations and an allocation of each client to an open facility.

In Pomper (1976) paper, SCND decisions focus on the development of a worldwide manufacturing policy. These decisions are those which normally result from the capital-planning, budgeting process within the firm, i.e. location, technology, capacity, and time-phasing of new facilities.

For Shulman (1991), SCND is to select the time schedule for installing facilities at different locations to optimize the total discounted costs for meeting customer demands specified over the time-period referred to as the planning horizon.

According to Chopra and Meindl (2004), a supply chain design problem comprises the decisions regarding the number and location of production facilities, the amount of capacity at each facility, the assignment of each market region to one or more locations, and supplier selection for sub-assemblies, components and materials.

Many researchers have attempted to extend these classical definitions by incorporating various themes such as: sustainability of supply chains has emerged since the impacts of climate change have effected producers and consumers decision-making and how their decisions effect the environment, transportation modes, tax issue and risk management, etc.

As the competitive context of business continues to change, bringing with it new complexities and concerns for management generally, it also has to be recognized that the impact of these changes on logistics can be considerable. Indeed, perhaps the most challenging strategic issues that confront the business organization today are in the area of Supply Chain (SC), which are: (i) the customer service, (ii) time compression, (iii) globalization and (iv) organization.

- *The customer service:*

Nowadays, the customer is more demanding, not just of product price and product quality, but also of service. As more and more the technical difference between offers decrease, products don't have value until they are in the hands of the customer at the time and place required. In other words, customer needs for the creation of added value through customer service (Christopher (2001)). To achieve this, a company may be able to save millions of Euro in logistic costs and simultaneously improve service levels by redesigning or designing its supply chain network.

- *Time compression:*

In recent years, time has become a critical issue in supply chain management. Logistic actors require just-in-time deliveries, products life cycle and order cycles are shorter than ever and customers accept a competitor product if their first choice is not instantly available. To overcome these problems and ensure timely response to volatile and uncertain demand, new approaches to the management of lead times are required (Christopher (2001)). Neglecting uncertainty in supply chain network design may cause more than high costs on the long term objectives of a company Santoso et al. (2005), Klibi et al. (2010), Sabri and Beamon (2000). Building a sustainable supply chain nowadays has become the ultimate objective of intelligent organisations.

- *Globalization:*

In the global business materials and components are sourced worldwide, manufactured offshore in many different countries perhaps with local customization. However, experts maintain that global supply chains are more difficult to manage than domestic supply chains (Wood et al. (2002), MacCarthy and Atthirawong (2003)). Geographical distances in these global situations not only increase transportation costs, but also inventory costs and lead-time in the supply chain. Different local cultures, languages, and practices reduce the effectiveness of demand forecasting and material planning. Deficiencies in transportation and telecommunication infrastructures, as well as inadequate worker skills, supplier quality, equipment and technology provide challenges normally not experienced in developed countries.

For global companies, the management of supply chain has become an issue of central concern. They seek to achieve competitive advantage by identifying world markets for their products then developing a supply chain strategy to support their marketing strategy (Christopher (2001)).

Indeed, the ultimate objective in supply chain network design should be not only to minimize common costs, but also to integrate multi-criteria in the SCND and to reduce vulnerability due to uncertainty , by reducing possible sources of lose due to uncertainty.

- *Organisation:*

The classical business organization is based on strict functional divisions and hierarchies, where each manager manages each own function independently from others. In today's environment, the company organisation needs broad-based integrators which are oriented to achieve marketplace success based on managing processes and people that deliver service. Generalist and specialist managers are required to integrate materials management with operational management and delivery. They will focus on customer service to achieve the integration of functions (Christopher (2001)).

To achieve this, an ideal network must have the optimum number, size, and location of warehouses to support the inventory replenishment activities of its retailers. This statement calls for sophisticated facility location models to determine the best supply chain configuration.

1.1 Problem statement

The main concepts that we focus on this thesis are the considerations of multi-criteria Supply Chain Network Design (SCND), the uncertain environment in SCD and heuristic algorithm to solve large size SCND problems.

We consider a multi-criteria, multi-level, single product, single period and multi-modal (roads, railways, waterways) supply chain network problem. The network has four levels: suppliers, storage depots or warehouses, production plants or distribution centers and customers.

In this context, this research deals with the design of a sustainable supply chain network under uncertain environment in order to satisfy the customers demand and to respect the environmental, social, legislative, and economical requirements. The strategic supply chain network we intend to establish, should answer the following questions under uncertain environment: (i) how many facilities (manufacturing plants, warehouses or/and distribution centers) should be installed? (ii) where the new sites should be located? (iii) how much goods should each warehouse and/or distribution center handle? (iv) which sellers should be served by each distribution centers? (v) products quantities to transport throughout the supply chain network? (vi) which transportation mode should be used?

1.2 Research Contribution

According to what is presented previously, the main contributions of this research can be summarized under five headings:

(1) A review of approaches and resolutions methods taking into account multi-criteria and uncertainty in supply chain network design problems.

(2) A new methodology to design multi-criteria supply chain networks and applying the model to a real-world treatment sediment supply chain. Geographic Information System (GIS), Analytic Hierarchy Process (AHP) and Mixed Integer Linear Programming approaches are combined together to design the SCN.

(3) A new heuristic algorithm to solve large scale supply chain network problems and applying the heuristic to a real-word textile supply chain (European Textile Company. The heuristic is based on a decomposition technique.

(4) A two-stage stochastic programming approach for supply chain network design under demand uncertainty. This proposal is tested by using data from a real Textile supply chain.
(5) A possibilistic linear programming based approach for supply chain network design in an uncertain environment. This model is validated by using data from a real-world supply chain. The detail of these headings is outlined in the following.

1.3 Outline of Dissertation

This thesis is organised into 7 chapters and is presented according to the following diagram (Figure 1.1).

This introductory Chapter is followed by the literature review in Chapter 2, which

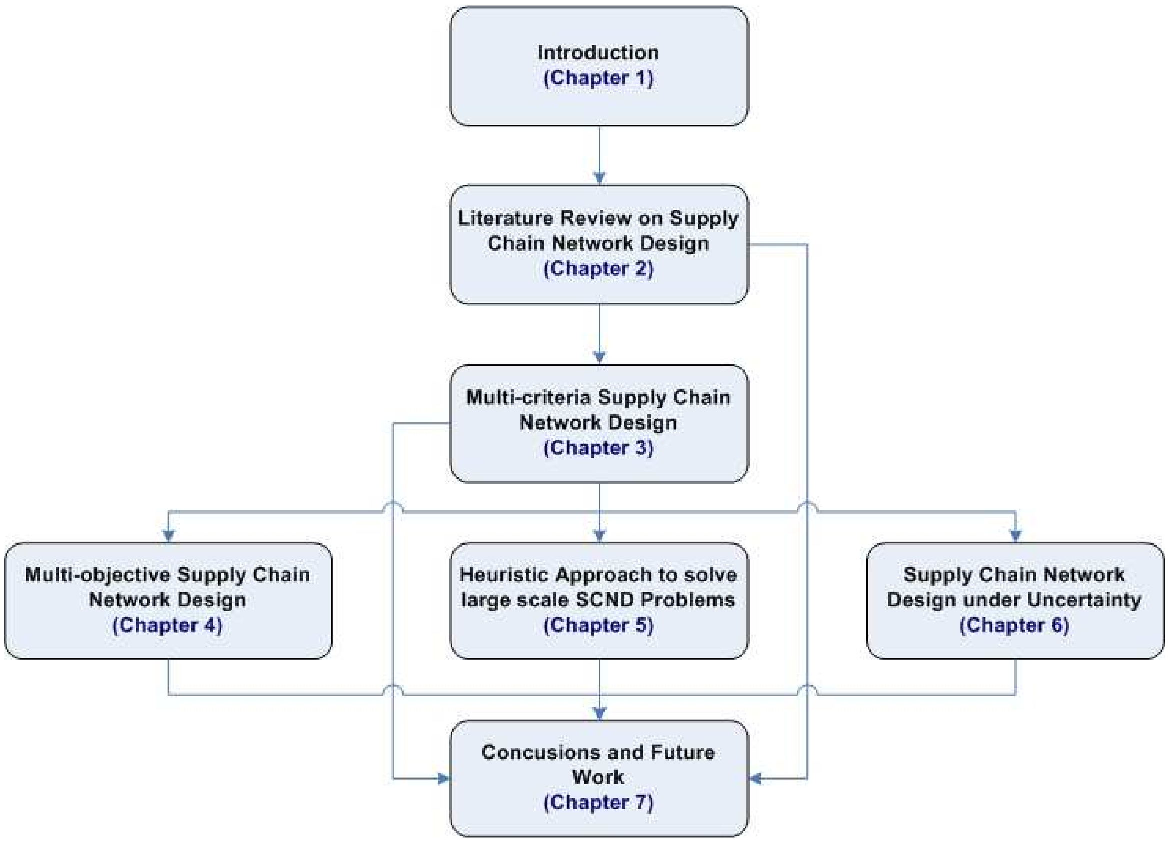

Figure 1.1: Thesis structure diagram

is a review of the current state of the art of Supply Chain Network Design approaches and resolution methods. Among other things, we recall the different decision levels in Supply Chain (strategic, tactical and operational level), the supply chain network structure (single/multiple layer(s), single/multiple product(s), single/multiple period(s), single/multiple objective (s), single/multiple modality, deterministic/stochastic parameters) and existing deterministic SCND models and SCND models under uncertainty. We end the chapter with some concluding remarks.

In order to satisfy the customers demand and to respect the environmental, social, legislative, and economical requirements, a novel framework for multi-criteria Supply Chain Network Design (SCND) and its application to real Supply Chain Network (SCN) are presented in Chapter 3. The methodology consists of two different steps. The first step looks for the best potential facility locations to open in order to satisfy the different criteria: environmental, social, and legislation aspects, using the Geographic Information System (GIS) and Analytic Hierarchy Process (AHP). The second step looks for the optimal supply chain design to satisfy customer demands and economic criteria using mixed integer linear programming model. The objective in this step is to determine location of treatment facilities and their capacities minimizing the sum of : opening facilities cost, products storage cost, production cost, transportation cost, and CO_2 emissions taxes. We apply our methodology to a real application case concerning the recycling of sediment waterways, which was presented in Bouzembrak et al. (2010). We end the Chapter with some concluding remarks.

In Chapter 4, we extend the second step of our methodology that we developed in Chapter 3. We study a supply chain network design problem with environmental concerns. We are interested in the environmental investments decisions in the design phase and propose a multi-objective optimization model that captures a compromise between the total cost and the environment influence. We use Goal Programming approach seeking to reach the four goals placed by Decision Maker: (i) total costs goal, (ii) energy consumption costs goal, (iii) waste treatment costs goal and (iv) CO_2 emissions goal.
The strategic decisions considered in the model are facilities location, building technology selection and flow of materials throughout the SC. We present numerical results illustrating and comparing the performance of the GP model, the instances elaborated from the real application case presented in Chapter 3. We conclude the chapter with some

conclusions from our study.

In Chapter 5, a novel heuristic solution method is developed based on a decomposition technique, to solve large scale supply chain network design problems that we failed to solve using exact methods. The heuristic method is tested on real case instances, European Textile Company, and it is compared to an exact method in solving small instances. Computational tests with up to 1 500 customers, 220 potential warehouses, 220 potential distribution centers and 220 suppliers are reported.
For the general model, a numerical comparison of the heuristic solutions to the exact method solutions shows that the heuristics yield high quality solutions in very limited time. We conclude the chapter with some conclusions from our study.

The deterministic model discussed in the previous chapter provides a base for Supply Chain Network Design (SCND). Nevertheless, any network design obtained based on this model, which represents the optimal deterministic configuration, has no assurance of performance for any other future parameter fluctuation. However, we extended the deterministic model presented in chapter 3. We first assume that we got the statistical data of the customer demands, so, we use two-stage stochastic programming approach to model the supply chain network under demand uncertainty. After that, we address uncertainty in all SC parameters: opening costs, production costs, storage costs and customers demands. In the case where the statistical data of all these parameters are not available, we use possibilistic linear programming approach to model the problem and we validate the approach in a large real case textile supply chain network.

Finally, Chapter 7 concludes the research findings and the activities undertaken throughout the thesis.

Chapter 2

Literature Review on Supply Chain Network Design

In this chapter existing Supply Chain Network (SCN) modelling approaches and resolution methods in literature will be discussed. In section 2.2, we show the different decision levels in Supply Chain (SC) : strategic, tactical and operational level. Then, in section 2.3, we recapitulate the supply chain network structure. In section 2.4, we introduce the most important approaches used in Supply Chain Network Design (SCND). We end the chapter in section 2.5 with some concluding remarks.

2.1 Introduction

Most articles on supply chain management include different form of categorization for logistic decisions (Ballou (2004), Bowersox et al. (2002), Chopra and Meindl (2004), Coyle et al. (2003), Johnson et al (1999), Simchi-Levi et al. (2003)). These works generally enumerate the logistic functions, indicate that many of decisions are interdependent and present in detail models for solving various problems. Huang et al. (2003) considered four classification criteria: supply chain structure, decision level, modelling approach and shared information.

In this chapter we propose three classification criteria: decision level, supply chain network structure and modelling approaches used on SCND. All of them are briefly described below:

- *Decision level:* three decision levels may be distinguished in term of the decision to be made; strategic, tactical and operational.

- *Supply chain network structure:* it defines the features that may be included in a SCN model : single/multiple layer(s), single/multiple product(s), single/multiple period(s), single/multiple objective (s), single/multiple modality, deterministic/stochastic parameters.

- *Supply chain network modelling approach:* it consists in the type of representation, mathematical relationship, and the aspects to be considered in the supply chain. Also, it resumes the resolution methods that may be used in solving supply chain network models. These categories will be detailed in the following sections.

2.2 Decision Levels

The decision making process in supply chain networks is highly complex. It can be decomposed according to the time horizons considered (Gupta and Maranas, 1999). This process results in the following temporal classification of the models: strategic, tactical and operational. Figure 2.1 describes the different decision levels in supply chain management.

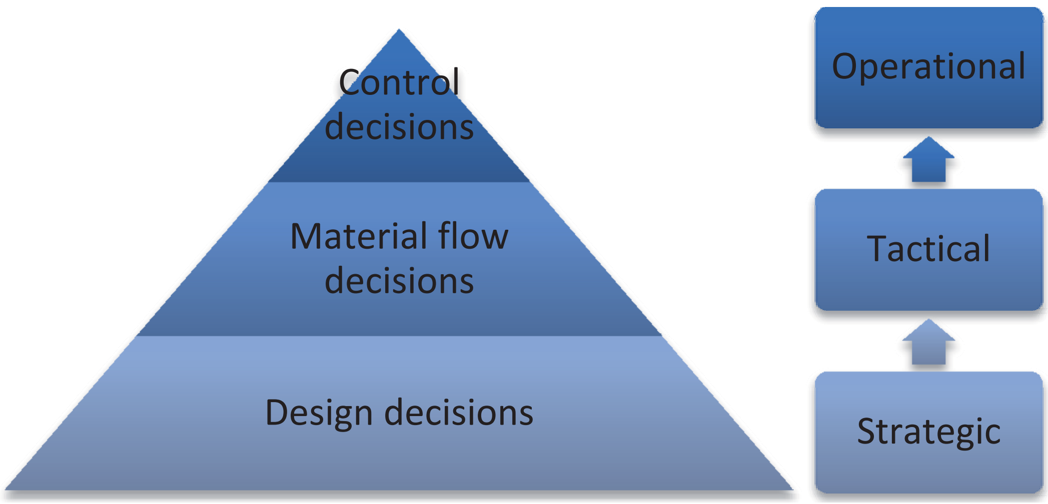

Figure 2.1: Supply Chain Levels

As we can see, strategic level decisions determine the configuration of the supply chain, tactical level decisions prescribe material flow management and operational level decisions present control decisions. The following paragraphs give the definitions of these levels.

2.2.1 Strategic level

This section addresses strategic level decisions, which determine the configuration of the supply chain by prescribing supplier selection, facility location (plants, warehouses, distribution centers and costumers zones), production technologies, plant capacities and transportation modes. Simchi-Levi et al. (2004) state that the strategic level deals with decisions that have a long-lasting effect on the firm. These include decisions regarding the number, location and capacities of warehouses and manufacturing plants, or the flow of material through the logistic network. The main strategic questions addressed in SCND approach are presented in the following Table 2.1:

In strategic phase, generally, the planners are not constrained by existing resources. The

Table 2.1: Strategic level decisions

Strategic Decisions	***Strategic Questions***
Type and number of facilities	How many production and Distribution Centers (DC) should be implemented? Which activities should be externalized? Which products should be produced/stocked in each location?
Size of facilities	What production, storage and handling technologies should we adopt and how much capacity should we have?
Facility location	Where should they be located?
Supplier selection	Which supplier should be selected?
Activities from each facility	Which factory/DC/demand zones should be supplied by each supplier/factory/DC? What delivery time should we provide in different product markets and at what price?
Utilisation of facilities	Which factory/DC/Warehouse should be opened or closed?
Transportation Modes	What means of transportation should be used (road, train, waterways,...etc.)?

data used in this phase are often imprecise. Moreover, an operating plan must be constructed to assess various scenarios depending on the forecasts. Many factors contribute to the complexity of SCN decision models. The first one is the long-term impact of the design decisions. It may be reasonable to use one year model when the decisions are limited to the selection of warehouses or distribution centers, as most of the literature suggests.

A second complexity factor is uncertainty. Most models proposed in the literature are deterministic. The interested reader can find these strategic questions in some important works on supply chain network design: ReVelle and Eiselt (2005), Daskin et al. (2005), Vila et al. (2006), Martel (2005), Klose and Drexl (2005), Arntzen et al. (1995), Cordeau et al. (2006), Amiri (2005), Amrani et al. (2005), Ghiani et al. (2004). In stochastic strategic supply chain design, you can find Santoso et al. (2005) and Shapiro (2001). Furthermore, many references considered aspects related to the strategical and tactical levels simultaneously (Dogan and Goetschalckx (1999), Jayaraman and Pirkul (2001), Goetschalckx et al. (2002), Jang et al. (2002)).

2.2.2 Tactical Level

On the tactical level, medium term decisions are made. They are related to the flow of materials between the supply chain actors, such as materials requirement planning, production planning, inventory planning, transport capacities, inventories and managing safety inventories and distribution planning (Table 2.2).

At this level, the policies and decisions not only aim to an adequate allocation and utilization of existing resources, but also strive to achieve the best trade-off between benefits and service performance. Furthermore, they are commonly used to model and analyse different scenarios, such as determining the incremental operating costs or inventory quantities for a set of volume changes. They are somewhat sensitive only to broad variations in data. Midterm tactical models are intermediate in nature and incorporate some features from both the strategic and operational models (Gupta and Maranas (2003)).

The main tactical decisions related to the supply chain management are recapitulated in Table 2.2. Some works focus on the tactical decision level (Sabri and Beamon (2000), Timpe and Kallrath (2000), Kallrath (2002), Liang and Cheng (2008), Torabi and Hassini (2008) and Chen and Lee (2004)).

Table 2.2: Tactical decisions

Tactical Decisions	***Tactical Questions***
Material requirement planning	Which raw material supplier should be selected?
	Which raw material should be selected?
	How much raw materiel should be supplied from each supplier?
Production planning	Which products should be produced?
	How much goods should they be produced?
	When should they be produced? On which machine?
	Where should they be produced?
Inventory planning	How much products should be stored?
	Where should they be stored?
	When should they be stored?
	How should the cost of storing inventory be reduced?
Distribution planning	Which plant to supply which distribution centers?

2.2.3 Operational Level

Operational level decisions involve shorter term horizon, generally one or several days, and smaller area than the tactical level and strategic level decisions. They include a wide variety of operational problems such as: demand forecasting, production, warehousing, inventory management, transportation, product packaging, procurement and supply management, etc. Particularly, real-time control problems are solved in real time during operations and aim to minimize customer inconvenience.

In this level, the time factor plays a highly dynamic role. Notably, sometimes emergency management is regarded as real-time level in the operation process. Table 2.3 classifies the most important questions reviewed in terms of the operational decisions level.

Rizk et al. (2006, 2008) cover the operational decision level exclusively. The interested reader can find operational models in some important works: the vehicle routing problem (Eksioglu et al. (2009)), inventory management (Andersson et al. (2010)) and production scheduling (Eren Akyol and Bayhan (2007)).

In the context of this thesis, we focus on the strategic supply chain network design. The strategic SCN we intend to elaborate should answer the following strategic questions: (i)

Table 2.3: Operational level

Operational Decisions	***Operational Questions***
Demand forecasting	Quantities of future demand?
	When should the future demand be received?
	Where should be the future demand?
Production	Where the product should be completed?
	Who should produce the product?
	Which layout of production facilities should be selected?
	Which master production schedule should be selected?
Warehousing	Which warehouse layout should be selected?
	Where in the warehouse should each item stored?
	What should be the storage policy of each item?
Inventory management	Which methods should be used for controlling inventories?
	Which should be the inventory levels?
	The safety stock?
Transportation	Which carrier type should be selected?
	Vehicle routing and scheduling?
	Assignment of customers to vehicles?
Product packaging	Which type of packaging should be selected?
	Which information should be provided with the product?

what type and how many facilities should be installed? (ii) where the new sites should be established? (iii) how much goods should each plant handle? (iv) which transportation mode should be used?

2.3 Supply Chain Network Structure

In supply chains, many basic features are included in strategic supply chain configuration: single/multiple layer(s), single/multiple product(s), single/multiple period(s), single/multiple objective (s), single/multiple modality, deterministic/stochastic parameters. We conducted a detailed literature survey for the last decade period to reveal the current state of art in SCND literature. The main review used to elaborate this work are (Melo et al. (2009), Klibi et al. (2010), Kabak and Ulengin (2010), Meixell and Gargeya (2005), Vidal and Goetschalckx (1997), Goetschalckx et al. (2002), Farahani et al. (2010) and Strivastava (2007)). Table 2.7 classifies the surveyed literature according to these aspects. It can be seen from Table 2.7 that the single product literature in SCND is approximately equal to the multiple products one. Around 52% of papers presented include the single product aspect. (Aghezzaf (2005), Barros et al. (1998), Daskin et al. (2002), Shu et al. (2005), Tushaus and Wittmann (1998)).

The most of papers in SCND deal with single-period problem. Approximately 83% of the surveyed papers present single-period model. (Vidal and Goetschalckx (2001), Yan et al. (2003), Pirkul and Jayaraman (1998), Sabri and Beamon (2000), Santoso et al. (2005)). Further, the number of multi-layer models are scarce compared with the one or two layers models. Approximately 66% of the surveyed papers refer to two layers problem. (Melo et al. (2006), Pati et al. (2008), Santoso et al. (2005), Wilhelm et al. (2005)).

Another important conclusion that can be drawn from Table 2.7 refers to the large number of deterministic models when compared with stochastic ones. Approximately 79% of the literature in SCND refers to deterministic models. As pointed out by Sabri and Beamon (2000), uncertainty is one of the most challenging problems in SCND. However, the literature integrating uncertainty with location decisions in an SCND context is still scarce (Van Ommeren et al. (2006), Sabri and Beamon (2000), Santoso et al. (2005), Hwang (2002), Listes and Dekker (2005)).

The surveyed literature can also be divided into those papers that consider single-objective problem and those that propose multiple-objective problem. The small number of papers in this Table refers to models with multiple objective (approximately 10% against 90%). (Melachrinoudis et al. (2005), Sabri and Beamon (2000), Altiparmak et al. (2006), Farahani and Asgari (2007)). The last and smallest group of articles integrating decisions regarding transportation modes, in strategic planning level, show that the existing literature is still far from combining many aspects relevant to SCND (approximately 7% against 93%). In fact, this integration leads to much more complex models due to the large size of problems that may results. (Carlsson and Ronnqvist (2005), Cordeau et al. (2006), Eskigun et al. (2005)).

Table 2.4: Supply chain structure

	Product		Period		Layer		Model		Objective		Transportation Mode	
Authors	Single	Multiple	Single	Multiple	Two	Multiple	Deterministic	Stochastic	Single	Multiple	Single	Multiple
Aghezzaf (2005)	X			X	X			X	X		X	
Altiparmak et al. (2006)	X		X			X	X			X	X	
Ambrosino and Scutell (2005)	X			X		X	X		X		X	
Amiri et al. (2006)		X	X		X		X		X		X	
Barros et al. (1998)	X		X			X	X		X		X	
Carlsson and Ronnqvist (2005)	X		X		X		X		X			X
Cordeau et al. (2006)		X	X			X	X		X			X
Daskin et al. (2002)	X		X		X			X	X		X	
Dogan and Goetschalckx (1999)		X	X			X	X		X		X	
Erlebacher and Meller (2000)	X		X		X		X		X		X	
Eskigun et al. (2005)	X		X		X		X		X			X
Guillen et al. (2005)		X	X		X			X		X	X	
Gunnarsson et al. (2004)	X		X		X		X		X		X	
Hinojosa et al. (2000)		X		X	X		X		X		X	

Table 2.5: Supply chain structure (suite 1)

	Product		Period		Layer		Model		Objective		Transportation Mode	
Authors	Single	Multiple	Single	Multiple	Two	Multiple	Deterministic	Stochastic	Single	Multiple	Single	Multiple
Hinojosa et al. (2008)		X		X	X		X		X		X	
Hwang (2002)	X		X		X			X	X		X	
Jang et al. (2002)		X	X			X	X		X		X	
Jayaraman and Pirkul (2001)		X	X		X		X		X		X	
Jayaraman and Ross (2003)		X	X		X		X		X		X	
Jayaraman et al. (1999)		X	X		X		X		X		X	
Jayaraman et al. (2003)	X		X		X		X		X		X	
Karabakal et al. (2000)		X	X		X		X		X		X	
Keskin and Ulster (2007)		X	X		X		X		X		X	
Ko and Evans (2007)		X		X		X	X		X		X	
Kouvelis and Rosenblatt (2002)		X	X		X		X		X		X	
Lee and Dong (2008)	X		X		X		X		X		X	
Lieckens and Vandaele (2007)	X		X		X			X	X		X	
Lin et al. (2006)		X	X			X	X		X		X	
Listes and Dekker (2005)		X	X			X		X	X		X	

Table 2.6: Supply chain structure (suite 2)

	Product		Period		Layer		Model		Objective		Transportation Mode	
Authors	Single	Multiple	Single	Multiple	Two	Multiple	Deterministic	Stochastic	Single	Multiple	Single	Multiple
Lu and Bostel(2007)	X		X		X		X		X		X	
Ma and Davidrajuh (2005)	X		X			X	X		X		X	
Melachrinoudis and Min (2007)	X		X		X		X		X		X	
Melachrinoudis et al. (2005)	X		X		X		X			X	X	
Melo et al. (2006)		X		X		X	X		X		X	
Min et al. (2006)	X		X		X		X		X		X	
Miranda and Garrido (2004)	X		X		X			X	X		X	
Pati et al. (2008)		X	X			X	X			X	X	
Pirkul and Jayaraman (1998)		X	X		X		X		X		X	
Romeijn et al. (2007)	X		X		X		X		X		X	
Sabri and Beamon (2000)		X	X			X		X		X	X	
Salema et al. (2006)		X	X			X	X		X		X	
Salema et al. (2007)		X	X			X		X	X		X	
Santoso et al. (2005)		X	X			X		X	X		X	
Schultmann et al. (2003)	X		X		X		X		X		X	

Table 2.7: Supply chain structure (suite 3)

	Product		Period		Layer		Model		Objective		Transportation Mode	
Authors	Single	Multiple	Single	Multiple	Two	Multiple	Deterministic	Stochastic	Single	Multiple	Single	Multiple
Srivastava (2008)		X		X	X		X		X		X	
Troncoso and Garrido (2005)	X			X		X	X		X		X	
Tushaus and Wittmann (1998)	X		X			X	X		X		X	
Vidal and Goetschalckx (2001)		X	X		X		X		X		X	
Vila et al. (2006)		X		X	X		X		X		X	
Wilhelm et al. (2005)		X	X			X	X		X			X
Wouda et al. (2002)		X	X		X		X		X		X	
Yan et al. (2003)		X	X			X	X		X		X	
Nb of papers	28	30	48	10	38	20	46	12	52	6	54	4
%	48%	52%	83%	17%	66%	34%	79%	21%	90%	10%	93%	7%

2.4 Supply Chain Network Modelling Approaches

In this section, we aim to present in detail the most important modelling approaches used in SCND. First, we present a review of deterministic SCN models such as: Mixed Integer Linear Programming (MILP), Non-Linear Programming (NLP) and Multi-Criteria Problems (MCP). Then, we enumerate the SCN models under uncertainty like: Stochastic Programming (SP), Robust Optimization (RO), Fuzzy Linear Programming (FLP), Possibilistic Linear Programming (PLP) and Catastrophe Models (CM).

2.4.1 Deterministic SCND Models

Methods discussed in this subsection are deterministic approaches. Most of them are used to design SCN problems.

Mixed Integer Linear Programming

The Mixed Integer Linear Programming (MILP) problems or Integer Linear Programming (ILP) are special cases of the Linear Programming (LP) problems with integer decision variables.

Linear programming problems involve a linear objective function and linear constraints. The classical model of linear programming can be written as follows:

$$Optimize \qquad \psi(x) \tag{2.1}$$

$$s.t \qquad Ax \leq b \tag{2.2}$$

$$x \geq 0 \tag{2.3}$$

Where the goal of the problem, is to determine the decision variables x that optimize the objective function $\psi(x)$, while ensuring that the model operates within established limits enforced by equality and/or inequality constraints. As a general rule, linear programming computational effort depends on the number of constraints rather than the number of variables.

In SCND literature most authors have used MILP approach to formulate their supply chain network. Wilhelm et al. (2005) presented a MILP model that represents the strategic design of an assembly system in international business environment. Amiri (2004) developed a mixed integer programming model to formulate a supply chain system problem. He designed a distribution network problem in a supply chain system that involves locating production plants and distribution warehouses, and tried to determine the best strategy for distributing products from plants to warehouses and from warehouses to customers. Keskin and Ulster (2007) considered a multi-product production/distribution system design problem. They used a mixed-integer programming approach to formulate their problem.

Pirkul and Jayaraman (1997) proposed a mixed integer programming formulation for multi-commodity, multi-plant, distribution system design problems. The objective is minimize the total operating costs of the distribution network, such that all customer demands are satisfied. Authors presented an efficient heuristic based on Lagrangian relaxation method, to solve the problem.

Canel and Khumawala (1997) proposed an efficient branch and bound procedure for solving the uncapacitated multi-period international facility location problem. A heuristic approach based on simulated annealing and Lagrangean relaxation was developed by Syam (2002) for a multi-source, multi-product, multi-location framework. Jayaraman and Ross (2003) proposed a heuristic approach based on simulated annealing for the designing of distribution network and management in supply chain environment. Jayaraman and Ross (2001) used simulated annealing methodology to solve a model of distribution supply chain. Brown et al. (1987) presented a MIP multi commodity model that determines the opening/closing of plants, the commodities produced at each plant and delivered to each customer, and the assignment of equipment to plants. Variable production and shipping costs, fixed costs of equipment assignment and fixed costs of plant operations were included in the objective function.

Eskigun et al. (2005) presented a large-scale network design model for the outbound supply chain of an automotive company. The most important characteristics mentioned in the paper are considering lead times and choice of transportation mode. To solve this large-scale design model, a Lagrangian heuristic is presented. The algorithm gives excellent solution quality in modest computational time. Amiri (2006), Eskigun et al. (2005), Hinojosa et al. (2008), Santoso et al. (2005), Pirkul and Jayaraman (1998), Miranda and Garrido (2004), Sourirajan (2007), Lu and Bostel (2007) used explicitly this method to solve their models. The interested reader is referred to some important reviews where MILP are deployed in SCND problems: Tushaus and Wittmann (1998), Shu et al. (2005), Melachrinoudis and Min (2007), Melo et al. (2006).

Non-Linear Programming

Non-linear programming problems involve either the objective function or constraints, or both the objective function and constraints are non-linear.

Lababidi et al. (2004) developed a deterministic mixed integer non-linear programming model to optimize the supply chain of a petrochemical company. Non-linear MIP model presented by Cohen et al. (1989) considered the operation of a network of suppliers, producers and markets. Min et al. (2005) presented a non-linear integer program for solving the multi-echelon, multi commodity closed loop network design problem involving product returns. Also, Chen and Lee (2004) proposed a multi-objective mixed integer non-linear programming model which considers uncertainty for demands and prices, and models according to the production, transport, sales and inventory planning stages.

Cohen et al. (1989) presented the main features that differentiate an international supply chain model from a single-country model. The most important characteristics mentioned in the paper are the necessity of treating multinational firms as global systems to obtain economies of scale in order to reduce costs. A heuristic method that initially fixes the transfer prices and allocated overhead variables, was presented.

To solve this NLP, two most popular methods, reduced gradient methods and successive quadratic programming methods, were applied.

Multi-Criteria Problems

In real-world SCND problems, companies like to pursue more than one target or consider more than one factor or measure. Such a desire transforms the decision making problem to a multi-objective decision making (MODM) problem or a multi-attribute decision making (MADM) problem. These groups of problems all come together in one category, named multi-criteria decision making (MCDM) problems (see Figure 2.2). Furthermore, as the *bi-objective* problems have become of particular consideration, they investigated them separately from other *k-objective* ones. Figure 2.2 illustrates Farahani et al. (2010) classification of multi-criteria problems and some important papers of each problems group. The optimization focuses in traditional SCM problems are maximizing profit or mini-

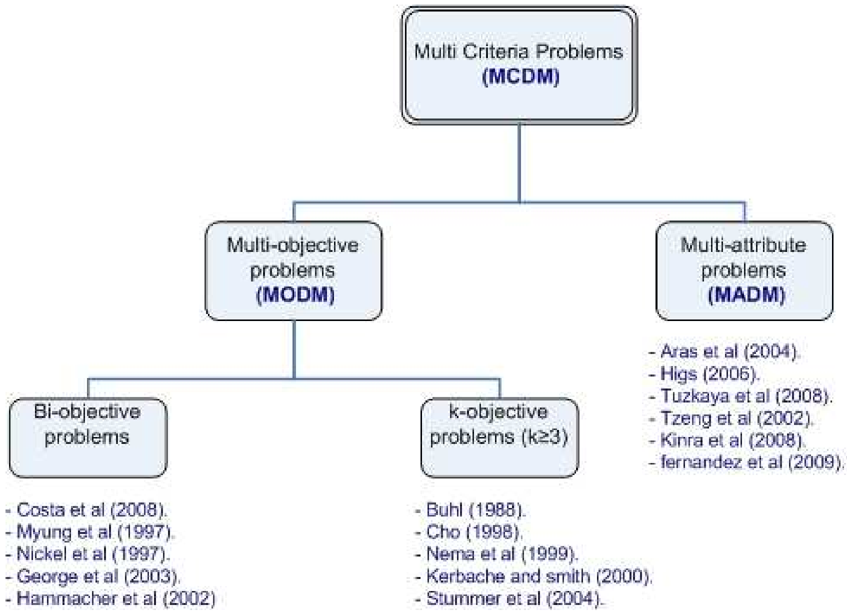

Figure 2.2: Multi-criteria problems

mizing costs as a single objective (Tsiakis et al. (2001), Santoso et al. (2005), Elhedhli and Gzara (2008)). Nevertheless, other important criteria such as environmental criteria, customer response time, social criteria, economic criteria should be taken into account.

- Multi-objective programming models:

In this subsection, we evaluate that part of SCND literature in which there are more than two objectives. We call them multi-objective integer programming problems with k-objectives (Ozlen and Azizoglu (2009)). The k-objective problem is defined as:

$$Optimize \quad \psi_1(x) \tag{2.4}$$

$$Optimize \quad \psi_2(x) \tag{2.5}$$

$$\vdots \tag{2.6}$$

$$Optimize \quad \psi_k(x) \tag{2.7}$$

$$s.t \quad x \in X \tag{2.8}$$

where the objectives are defined as $\psi_1(x) = \sum_{j=1}^{n} c_j^1 x_j$, $\psi_2(x) = \sum_{j=1}^{n} c_j^2 x_j$ and $\psi_k(x) = \sum_{j=1}^{n} c_j^k x_j$; c_j^i is integer for all $i \in \{1, 2, \cdots, k\}$ and $j \in \{1, 2, \cdots, n\}$. X is the set of feasible solutions in which $x_j \geq 0$ and integer for all $j \in \{1, 2, \cdots, n\}$.

Several criteria for SCND have been appeared in literature. Alcada-Almeida et al. (2009) proposed a multi-objective programming approach to identify locations and capacities of hazardous material incineration facilities and balance the society, economic, and environmental impacts. Customer response time was integrated in the distribution network design by (Erol and Ferrell (2004), De Toni and Tonchia (2001)). Azaron et al. (2008) used the goal attainment technique to optimize total cost, total cost variance, and financial risk cost of a three echelon supply chain. Mincirardi et al. (2002) proposed a multi-objective programming model to analyse solid waste management.

Paksoy et al. (2010) considered the green impact on a close-looped supply chain network and tried to prevent more CO_2 gas emissions and encourage customers to use recyclable products via giving a small profit. They presented different transportation choices between echelons according to CO_2 emissions. They also considered recyclable ratio of raw material. Many network facility location problems utilize multi-objective optimization concepts. Cantarella and Vitetta (2006) introduced an urban network layout and link capacity through a multi-objective Road Network Design Problem. Pati et al. (2008) proposed a multi-objective model for a paper recycling network system in determining the facility location, route and flow of different varieties of recyclable waste paper in a multi-item, multi-echelon and multi-facility environment. Selim and Ozkarahan (2006) presented a supply chain distribution network design model that utilizes maximal covering approach in the reporting of the service level and with multiple capacity levels, through a fuzzy multi-objective model.

Altiparmak et al. (2006) proposed a Genetic Algorithm , for designing a four-echelon supply chain (suppliers, plants, warehouses and customers). It has three objectives to be minimised. The first one is the cost that includes the fixed costs of operating and opening plants and warehouses plus the cost of supplying raw materials and delivering products. The second one is the total customer demand that can be delivered within the orders due date. The third one is capacity utilisation for plants and warehouses.

Papers involving an integrated design of supply chain networks under uncertainty and considering several objectives is significantly smaller in number (Sabri and Beamon (2000), Chen et al. (2008), Guillen et al. (2005). The Bi-objective integer programming problem is a special case of the multi-objective integer programming problem with only two objectives Ozlen and Azizoglu (2009). Fernandez et al. (2007) presented a bi-objective supply chain design and facility location problem of supermarkets on the plane in which the main objective was to maximize the profit obtained by the chain, and the secondary objective was to minimize the difference between market shares before and after entering a new facility.

For SCND, the main criteria used were costs, price, operating service, quality, distance, ease of access, etc. Nowadays, with changing supply chain network these criteria are not sufficient. The set of criteria should be expanded to take into account new dimensions and represent the ability to deal with social, environmental and economic criteria in sustainable context.

- Multi-attribute problems:

There are many techniques which are used to tackle the MADM problems. The most used ones are as follows: Analytic Network Process (ANP) (Tuzkaya et al. (2008), Analytic Hierarchical Process (AHP) (Saaty (1980)), elimination and choice expressing reality (ELECTRE) (Barda et al. (1990)), Multi-Attribute Utility Theory (MAUT) (Canbolat et al (2007)), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon (1981)), Stochastic Multi-criteria Acceptability Analysis (SMAA) (Lahdelma et al. (2002)) are utilized for solving location problems (Farahani et al. (2010)).

One analytical approach often suggested for solving such a complex multi-criteria problem is the Analytic Hierarchy Process. The Analytic Hierarchy Process (AHP) provides a framework to cope with multiple criteria situations, involving intuitive, rational, qualitative, and quantitative aspects (Khurrum et al. (2002)). We present some of the literature where AHP multi-attribute decision making method is used to solve location problems. Higgs (2006) presented a waste management problem where Geographical Information Systems (GIS) have been combined with multi-criteria evaluation techniques to take into account the role of public in the decision making process. Tuzkaya et al. (2008) included qualitative and quantitative criteria (benefits, opportunities, costs and risks), to assess and select undesirable facility locations. Aras et al. (2004) employed Analytic Hierarchical Process in wind observation station location problem, and a considerable number of criteria were taken into consideration.

In all these works, existing AHP approaches were applied for a very small number of location alternatives and logistic actors are not considered in the selection criteria. To the best of our knowledge, no comprehensive supply chain design approach, dealing with all sustainable criteria, using GIS, has been proposed yet.

Models discussed above have several drawbacks, the most important being their deterministic nature. However, in SCD problems, there are several uncertainties that should be taken into account. Generally, in SCND problems we are not dealing only with numbers and mathematical findings but many decisions are based on human judgement. In addition, existing multi-attribute approaches are applied for facility location problems and logistic actors are not considered in the selection criteria. However, integrating multi-criteria approaches with MILP problem can be an important development in supply chain network design.

2.4.2 SCND Models Under Uncertainty

In this section, we present the most used uncertainty approaches to model SCND problems under uncertainty, such as: stochastic approach, possibilistic approach, fuzzy approach and the robust approach (Figure 2.3).
The future business environment where a supply chain network operates is generally unknown and critical parameters such as customer demands, prices, and capacities are uncertain.
Uncertainty implies that, in certain situations, a person does not dispose about information which qualitatively is appropriate to describe, prescribe or predict deterministically and numerically a system, its behaviour or other characteristic (Zimmermann (2001)).
However, informations are indispensable in supply chain design, in order to make appropriate strategic decisions. Decision support systems provide decision makers with useful informations to guide their thoughts and actions. Sufficient informations enable the decision-makers to achieve the supply chain objectives through better and effective decisions and actions. However, for many reasons these informations may be incomplete due to many causes of uncertainty: lack of information, abundance of information, approximation, ambiguity, conflicting evidence and belief.

To model these uncertainties, we can find in literature numerous uncertainty approaches, such as: probability theories (Shapiro (2003)), evidence theory (Shafer (1990)), possibility theory (Zadeh (1965)), fuzzy set theory (Zadeh (1965)), rough set theory (Pawlak (1985)), convex modelling (Ben-Haim and Elishakoff (1990)), etc. The most used to model supply chain network under uncertainty is stochastic approach, where parameters are considered as random variables with known probability distributions. The joint-events associated to the possible values of the random variables can be considered as plausible future scenarios, and each of these scenarios has a probability of occurrence. (Shapiro (2008), Santoso et al. (2005), Vila et al. (2007)). A review of recent robust supply chain networks design is found in Klibi et al. (2010). Several authors have discussed robustness in a supply chain context (Rosenblatt and Lee (1987)), Gutierrez et al. (1996), Dong (2006), Snyder and Daskin (2006)).

Figure 2.3 shows the most popular mathematical approaches considered by the researchers

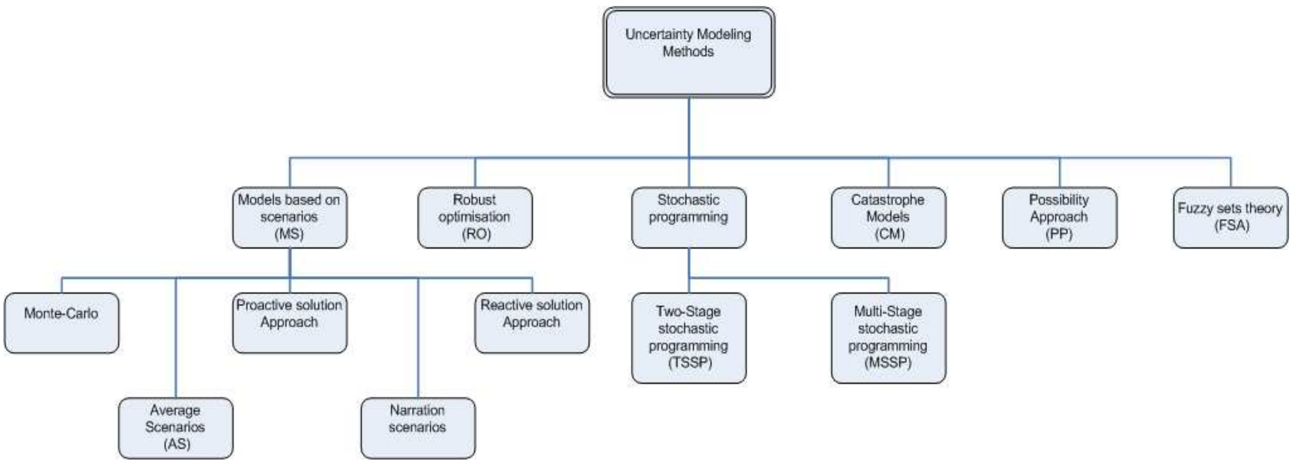

Figure 2.3: Uncertainty Modelling Methods

for designing SCN. many papers are proposed and they are summarized in Table 2.8 and Table 2.9. Notations used in Table 2.8 and Table 2.9 are: Average Scenario (AS), Models based on Scenarios (MS), Two Stage Stochastic Programs (TSSP), Multi Stage Stochastic Programs (MSSP), Catastroph Models (CM), Robust Optimisation (RO), Fuzzy Sets Theory (FST), Possibilistic Programming (PP).

Stochastic Programming

We begin by abstracting the statement of a LP model with random parameters. Problem (2.1)-(2.3) can be presented as follows:

$$Optimize \qquad \psi(x) \tag{2.9}$$

$$s.t \qquad A(\xi)x \leq b(\xi) \tag{2.10}$$

$$x \geq 0 \tag{2.11}$$

Where $A(\xi)$ and $b(\xi)$ denote, respectively, the random coefficients matrix and right-hand-side vector, and decision x corresponds to a setting of all the decision variables. ξ denotes a random vector varying over a set $\Phi \in \Re^k$. If we model the random parameters as discrete scenarios, the model (2.9)-(2.11) can be transformed into deterministic equivalent which is an ordinary linear programming. The deterministic equivalent of the model (2.9)-(2.11) can be introduced in various ways. Depending on how the random parameters are modelled and whether a risk measure is included in the objective function, the resulting deterministic equivalent model will be the two-stage stochastic programming, multi-stage stochastic programming, and robust optimization.

In order to transform the SCN models with random parameters (2.9)-(2.11) into a deterministic equivalent model, the random data should be modelled as discrete scenarios. In SCND problems, random data can be modelled as a random variable with a stationary distribution, or as a non-stationary and dynamic data process. In stationary distribution, the random data are represented as a number of scenarios with known probabilities. The origin of scenarios can come from known discrete distributions, can be obtained from the discretization of a continuous known distribution, or they can result from a preliminary analysis of the problem with probabilities of their occurrence that may reflect an *ad hoc* belief of the problem or a subjective opinion of an expert (Dupacova (1996), Miller and Rice (1983)). This approach for random data representation in stochastic models is illustrated in Figure 2.4.

In two-stage stochastic programs, the structure of the tree encloses the first and second stage phases, as shown in Figure 2.4. The beginning of the tree is represented by a single node of the first stage since states of the world during the first stage are known with certainty. The second stage is represented by many nodes. This means that the scenario tree is a set of individual scenarios s which occur with probabilities p_s. In dynamic data

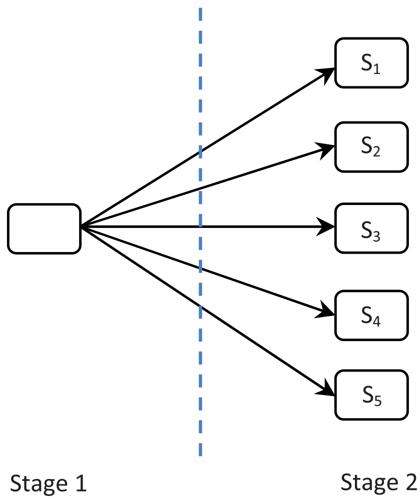

Figure 2.4: A scenario tree in two stage stochastic programming models

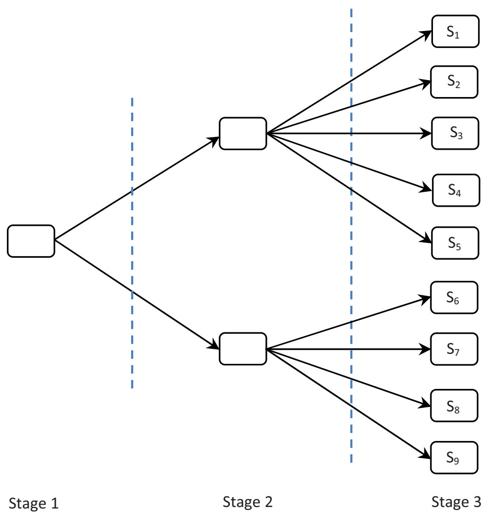

Figure 2.5: A scenario tree in multi-stage stochastic programming models

process, the random data are characterized by cycles or temporal patterns, they should be modelled as dynamic stochastic data. A representative scenario tree corresponding to the multi-stage stochastic programming formulation (Figure 2.5) can be visualised as a tree starting similarly with the previous case with a single node at first stage and branches into a finite number of nodes at second stage. This branching continues for all stages of the problem until last stage.

- Multi-stage stochastic programming:

The stochastic programming models that we have discussed so far, are static in the sense that we make a decision at one point in time, while accounting for possible recourse actions after all uncertainties have been resolved. There are many situations where one is faced with problems where decisions should be made sequentially at certain periods of time based on information available at each time period. Such multi-stage stochastic programming problems can be viewed as an extension of two-stage programming to a multi-stage setting. Guan and Philpott (2009) presented an application of multi-stage stochastic programming to a production planning problem for a leading company in the New Zealand dairy industry, taking into account uncertain milk supply, price demand curves and contracting. Goh et al. (2007) constructed a stochastic model of the multi-stage global supply chain network problem, incorporating a set of related risks, namely, supply, demand, exchange, and disruption (Shapiro and Philpott (2007)).

The equivalent deterministic models of the Multi-stage stochastic programming models are very large in scale due to the problem structure and the size of the problem increase as a quadratic function of the number of scenarios. To solve these models, many algorithms have been presented such as the augmented Lagrangian decomposition method (Ruszczynski (1989)) and the decomposition methods (Liu and Sun (2004)).

- Two-stage stochastic programming:

In two-stage stochastic programming, we assume that the random data has a stationary probability distribution during the time. The decision variables are explicitly classified according to whether they are implemented, before or after a scenario of the random data is observed. In other words, we have a set of decisions to be taken without full information on the random parameters. These decisions are called first-stage decisions. Later, full information is received on scenarios of the random vector. Then, second-stage actions are taken under the full insight on the random data. These second-stage decisions allow us to model a response to each of the observed scenarios of the random variable. In general, this response will also depend upon the first-stage decisions. The objective of the two-stage stochastic model would be to minimize the first-stage cost in addition to the expected second-stage cost for all scenarios of random parameters.

We define the two-stage stochastic linear programming corresponding to model (2.9)-(2.11), (Shapiro (2008), Santoso et al. (2007)) as follows:

$$\begin{aligned} Optimize \quad & \psi(x) + \sum_{s=1}^{N} p^s q^{sT} y^s && && (2.12) \\ s.t \quad & A^s x + W y^s = b^{sT} && s = 1, ..., N. && (2.13) \\ & x, y^s \geq 0 && s = 1, ..., N. && (2.14) \end{aligned}$$

Where, q^{sT} denotes the vector of second stage costs, A^s denotes coefficients matrix, b^{sT} is the right-hand-side vector and y^s second-stage vector under scenario s. W denotes the recourse matrix. N presents the number of scenarios, s is the scenario index and T denotes the transpose matrix notation.

Dyer and Stougie (2006) proved that under the assumption that the stochastic parameters are independently distributed, two-stage linear stochastic programming problems are NP-hard.

MirHassani et al. (2000) presented a two-stage stochastic programming model for multi-period supply chain networks with uncertain demand scenarios. The first stage decisions, concern the opening and closing of plants and distribution centers and setting their capacity levels. In the second stage decisions, based on the particular demand scenario realized, the production and distribution decisions are to be decided optimally.

Tsiakis et al. (2001) also considered a two-stage stochastic programming model for supply chain network design under demand uncertainty. The authors developed a mixed-integer linear programming model for a European supply chain network involving three demand scenarios. Two-stage stochastic supply chain network design models were proposed by Santoso et al. (2005), Vila et al. (2007), Alonso Ayuso et al. (2003), Vila et al. (2008) and Azaron et al. (2008).

The difficulty with this approach is that the model can become very large in scale if a huge number of scenarios for the random parameters are taken into account. It could be impossible to be solved by the existing commercial solvers. In order to solve two stage stochastic programs with a huge number of scenarios, approximate methods based on Monte Carlo sampling were proposed by (Higle an Sen (1996), Shapiro (2005), and sample average approximation (SAA) scheme was presented by (Mak et al. (1999), Shapiro and Hommen-de-Mello (1998), Santoso et al. (2004)) and decomposition methods and approximation methods were used (Kall and Mayer (2005), Higle and Sen (1996), Shapiro et al. (2005)).

Robust Optimization

The robust optimization method developed by (Mulvey et al. (1995)) is a special class of two-stage stochastic programming. It extends stochastic programming with the introduction of higher moments of the objective function. In other words, traditional expected cost minimization objective is replaced by one that explicitly addresses cost variability and a serie of solutions are generated that are progressively less sensitive to scenarios and random data.

The robust optimization approach introduced by (Mulvey et al. (1995)) is to modify the objective function in two-stage stochastic linear programming as follows:

$$Optimize \quad \psi(x) + \sum_{s=1}^{N} p^s d^{sT} y^s + \lambda\sigma\left(y^1, \cdots, y^N\right) + \omega\rho\left(\delta^1, \cdots, \delta^N\right) \tag{2.15}$$

$$s.t \quad A^s x + W y^s + \delta^s = b^{sT} \qquad s = 1, ..., N. \tag{2.16}$$

$$x, y^s \geq 0 \qquad s = 1, ..., N. \tag{2.17}$$

Where, $\lambda \geq 0$ is a goal programming weight and $\sigma\left(y^1, \cdots, y^N\right)$ denotes the recourse cost variability measure. By changing λ, the relative importance of the recourse cost in the objective function can be controlled. $\rho\left(\delta^1, \cdots, \delta^N\right)$ is the model robustness measure. It is a feasibility penalty function, which is used to penalize the violation of constraint (2.16) under some scenarios. $\omega \geq 0$ is a goal programming weight which measures the relative importance of solution robustness and model robustness.

Wu (2006) applied the robust optimization approach to uncertain production problem under the global supply chain management environment. Leung et al. (2007) developed a robust optimization model to address a multi-site aggregate production planning problem with uncertain data. Stochastic parameters are modelled by introducing different scenarios which are defined for different economical growth scenarios. Gutierrez et al. (1996) proposed a robust optimization framework for network design under uncertainty. This approach seeks network configurations that are nearly optimal for a variety of scenarios (11 scenarios) of the design parameters at the expense of being suboptimal for any one scenario.

This method can be used to find adequate SCN designs (Mulvey et al. (1995), Kouvelis and Yu (1997)). It can be used with min-max regret criterion (Mulvey et al. (1995)), or the minimization of the maximum cost and mean-variance. Mean-variance measure has been presented in many works, namely stochastic aggregate production planning (Leung and Wu (2004), Leung et al. (2007)), stochastic logistic problems (Yu and Li (2000)). Robust optimization has been applied to different versions of the facility location problem under uncertainty (Snyder and Daskin (2006), Yu and Li (2000), Gutierrez et al. (1996), Takriti and Ahmed (2004)).

A major difficulty with this approach is the same one as two-stage stochastic programming that the model can become very large in scale if a huge number of scenarios for the random parameters are taken into account, making it impossible to be solved by the existing commercial solvers.

The small size robust optimization models can be solved by the Cplex quadratic programming solver. In order to solve the large size ones with large number of scenarios, decomposition methods and approximations methods can be used (Takriti and Ahmed (2004)).

Fuzzy Linear Programming

In SCND problems, the conventional approaches tend to be less effective in dealing with the imprecision or uncertainty nature of the data. There has been an increasing interest for fuzzy sets to be used for the SCDN in the recent years. The fuzzy mathematical programming in the first category was initially developed by Bellman and Zadeh (1970). It treats decision-making problem under fuzzy goals and constraints. The fuzzy goals and constraints represent the flexibility of the target values of objective functions and the elasticity of constraints.

We assume that the decision maker can establish an aspiration level, z, for the value of the objective function he or she wants to achieve and that each of constraints is modelled as a fuzzy set. The equivalent fuzzy linear programming of the LP (2.1)-(2.3) is (Bellman and Zadeh (1970)):

Find x such that

$$z = \psi(x) \tag{2.18}$$

$$s.t \qquad \tilde{A}x \leq \tilde{b} \tag{2.19}$$

$$x \geq 0 \tag{2.20}$$

where x is the vector of decision variables; A and b are fuzzy quantities; operations of addition and multiplication by a real number of fuzzy quantities are defined by Zadeh's extension principle; the objective function z, is to be maximized in the sense of a given problem.

Linear programming problems with fuzzy parameters are formulated by fuzzy functions. The ambiguity considered here is not randomness, but fuzziness which is associated with the lack of a sharp transition from membership to non-membership. Parameters on constraint, relationship between constraints or objective functions and objective functions are given by fuzzy numbers.

Fuzzy linear programming problem with fuzzy numbers can be regarded as a model of decision problems where human estimation is influential. The model helps in determining the optimal number and site locations of fire stations at an international airport. Several distinct methods are frequently mentioned for representing uncertainty. For example, the fuzzy-based approach (Giannoccaro et al. (2003), Liu and Sahinidis (1997), Petrovic et al. (1998), (1999)), where in the forecast parameters are considered as fuzzy numbers with accompanied membership functions.

Possibilistic Linear Programming

Zadeh (1978) presented the theory of possibility, which is related to the theory of fuzzy sets by defining the concept of possibility distribution as a fuzzy restriction. After pioneering work of Zadeh, possibility theory has found gradual acceptance in the literature. Several research efforts have concentrated on possibilistic linear programming (Buckley (1988), Buckley (1989), Hsu and Wang (2001)). In this section, we consider the following possibilistic linear programming problem:

$$Optimize \qquad \psi(x) \tag{2.21}$$

$$s.t \qquad \tilde{A}x \leq \tilde{b} \tag{2.22}$$

$$x \geq 0 \tag{2.23}$$

Where, $\tilde{A}$ is a matrix represented by a possibility distribution and $\tilde{b}$ is a possibilistic variable restricted by a possibility distribution. Wang and Shu (2010) suggested a possibilistic decision model to determine the supply chain configuration and inventory policies for new products with unreliable or unavailable statistical data. Fuzzy sets were used to model uncertain and flexible supply chain parameters such as total supply chain cost, demand, service time, lead and response time. Authors presented a case study of computer assembly company to evaluate the performance of the entire supply chain.

Wang and Liang (2005) presented a possibilistic linear programming (PLP) approach for solving the multi-product aggregate production planning problem with imprecise parameters : customer demands, operating costs and capacities. They used LINDO computer software to solve the model. Peidro et al. (2009) proposed a fuzzy mathematical programming model for supply chain planning which considers supply, demand and process uncertainties. The model has been formulated as a fuzzy mixed integer linear programming model where data are unknown and modelled by triangular fuzzy numbers. They tested the proposed PLP on an automotive supply chain network involving: 44 suppliers, one seat manufacturer, one seat assembly plant and an Automobile Assembly Plant. To solve the MILP model they used the CPLEX 9.0 solver. Petrovic et al. (1999) considered a production supply chain with all facilities in a serial connection. The supply chain includes inventories and production facilities between them. Authors assumed customer demand and supply deliveries as uncertain parameters, and proposed small computational examples showing that uncertain customer demands and uncertain supply deliveries along the supply chain have great impact on supply chain behaviour.

Torabi and Hassini (2008) considered a supply chain master planning model consisting of multiple suppliers, one manufacturer and multiple distribution centers. They proposed a new multi-objective PLP model for integrating procurement, production and distribution planning with imprecise nature of many parameters such as demands, cost/time

coefficients and capacity levels. To validate their model they advised an industrial case involves 4 suppliers, one manufacturer and 3 distribution centers located in different customer zones. They solved the instances using OSL solver from IBM.
There are different approaches to solve probabilistic SCND problems. To convert the original model into an equivalent auxiliary crisp model, efficient possibilistic methods are proposed by Jimenez et al. (2007) and Parra et al. (2005). To find the final preferred compromise solution, the reader can refer to recently proposed fuzzy methods of Torabi and Hassini (2008) and Selim and Ozkarahan (2008). As evident from the above discussion, the existing possibilistic linear programming approaches for supply chain design under uncertainty are suited for very small size problems and a limited number of fuzzy parameters. In addition, the majority of these papers are theoretical (Kabak et al. (2011)).

Models Based on Scenarios

An other alternative is to solve the deterministic model for a set of representative scenarios, and to evaluate the solution obtained. The difficulty with this approach is to determine which among solutions found is the best. Many methods have been used to evaluate and select solutions obtained such as Monte-Carlo sensitivity analysis (Saltelli et al. (2004), Ridlehoover (2004)), screening procedure using many filtering criteria such as Pareto optimality and mean-variance. Good examples of how this approach works, are found in Vidal and Goetschalchx (2000), Mohamed (1999).
Average scenario is an approach often used to solve supply chain network problems under uncertainty, by elaborating an average scenario, and then solve the resulting deterministic model.
The solution obtained is not necessary optimal. Solutions may be very bad or even infeasible under specific scenarios (Sen and Higle (1999)).

Catastrophe Models

Catastrophe models used to estimate the location, severity and frequency of potential future natural disaster. They are usually based on catastrophe arrival process, and they provide a compromise between economic loss and the probability that certain level of loss will be exceeded on an annual basis (Haimes (2004), Grossi and Kunreuther (2005), Banks (2006)). Qualitative SC disruptions risk identification and assessment approaches were proposed by Kleindorfer and Saad (2005) and Manuj and Mentzer (2008).

To conclude this discussion of SCND models under uncertainty, note that the most used approach in SCND under uncertainty are stochastic linear programming approach and robust models. The most important problem with these approaches is that the model can become very large in scale for a small number of scenarios for the random parameters are taken into account. It could be impossible to be solved by the existing commercial solvers. Only few models based on the possibilty and fuzzy sets on SCND problems are proposed in literature (Sule (2001), Torabi and Hassini (2008), Wang and Shu (2007)). Other approaches such as evidence theory, rough set theory (Pawlak (1985)) and convex modelling (Ben-Haim and Elishakoff (1990)), etc. were used by authors to model uncertainty.

2.4.3 Resolution Methods

As we discussed before, various approaches such as Branch-and-Bound, Bender decomposition and Lagrangian relaxation were proposed for solving the SCND problem. However, not all of these methods are regarded as feasible when the size of the system increases. For small size network systems, exact methods can be used to solve the SCND problems. For larger systems, exact methods fail because the size of the solution space increases exponentially with the number of constraints and variables in the network. As a result, the computation time of exact methods becomes impractical. In these cases, heuristic or meta-heuristic methods can be used to produce near optimal solutions in a reasonable computation time. Table 2.10 and Table 2.11 classify the literature according to most important resolution methods used in solving SCND problems.

2.5 Concluding Remarks

In this chapter, we have described a review of mathematical programming models and resolution methods for SCND. We have proposed a classification based on the analysis of three aspects: supply chain network structure, decision level and supply chain modelling approaches.

Conclusions drawn from this chapter affirm that: (i) papers integrating multiple periods, multiple products, multiple criteria, multiple transportation modes, multiple objective and uncertainty in SCND context are still scarce, (ii) the most widely used modelling approach is mixed integer linear programming, where the use of heuristic algorithms and meta-heuristics to solve the approach stands out, (iii) more proposed models validated by small numerical examples are presented than case studies applied to real supply chains.

The design of a multi-criteria supply chain network to respect the environmental, social, legislative, and economical aspects and to satisfy customer demands, is presented in the next chapter.

Table 2.8: Supply chain design under uncertainty (Part 1)

Authors	AS	MS	TSSP	MSSP	CM	RO	FST	PP
Eppen et al. (1989)				**X**				
Mulvey et al. (1995)			**X**			**X**		
Gutierrez et al. (1996)						**X**		
Huchzermeier and Cohen (1996)				**X**				
Kouvelis and Yu (1997)						**X**		
Bok et al. (1998)						**X**		
Kurksalan and Sural (1999)		**X**						
Mohamed (1999)		**X**						
Sen and Higle (1999)	**X**							
Vidal and Goetschalckx (2000)		**X**						
Yu and Li (2000)						**X**		
Sule (2001)							**X**	
Tsiakis et al. (2001)			**X**					
Lowe et al. (2002)		**X**						
Ahmed and Sahinidis (2003)				**X**				
Ruszczynski and shapiro (2003)		**X**						
Shapiro (2003)				**X**				
Kahraman et al. (2003)							**X**	
Saltelli at al, (2004)		**X**						
Ridlehoover (2004)		**X**						
Haimes (2004)					**X**			
Christopher and lee (2004)					**X**			
Santoso et al. (2005)			**X**					
Grossi and Kunreuther (2005)					**X**			

Table 2.9: Supply chain design under uncertainty (Part 2)

Authors	AS	DMS	TSSP	MSSP	CM	RO	FST	PP
Kleindorfer and saad (2005)					**X**			
Sheffi (2005)					**X**			
Snyder and Daskin (2006)						**X**		
Chen and Lee (2006)							**X**	
Banks (2006)					**X**			
Shapiro (2007)		**X**	**X**					
Vila et al. (2007)			**X**					
Wang and Shu (2007)								**X**
Torabi and Hassini (2007)								**X**
Matos (2007)								**X**
Vila et al. (2008)			**X**					
Manuj and Mentzer (2008)					**X**			

Table 2.10: Resolution Methods

Authors	Heuristic	Meta-heuristic	Resolution Method
Aghezzaf (2005)	X		Lagrangean Relaxation
Lu and Bostel (2007)	X		Lagrangean Relaxation
Aliev et al. (2007)		X	Genetic algorithm
Amiri (2006)	X		Lagrangean Relaxation
Arntzen et al. (1995)	X		Factorization
Barahona and Jens (1998)	X		Decomposition techniques
Barros et al. (1998)	X		Relaxation heuristic
Brown and Olson (1994)	X		Factorization
Brown et al. (1987)	X		Decomposition
Canel and Khumawala (1997)	X		Branch and Bound
Canel and Khumawala (2001)	X		Branch and Bound
Cohen and Lee (1985)	X		A heuristic method
Cohen and Lee (1989)	X		Relaxation and Approximation
Cohen and Moon (1991)	X		Benders Decomposition
Cohen et al. (1989)	X		Relaxation and Approximation
Cole (1995)	X		Branch and Bound
Cordeau et al. (2006)	X		Benders Decomposition
Dogan and Goetschalckx (1999)	X		Valid inequalities
Eksioglu et al. (2006)	X		Relaxation and Approximation
Erlebacher and Meller (2000)	X		Relaxation and Approximation
Eskigun et al. (2005)	X		Lagrangean Relaxation
Geoffrion and Graves (1974)	X		Benders Decomposition
Geoffrion et al. (1978)	X		Decomposition techniques
Geoffrion et al. (1982)	X		Decomposition techniques
Goetschalckx et al. (2002)	X		Decomposition techniques
Goetschalckx et al. (1994, 1995)	X		Decomposition techniques

Table 2.11: Resolution Methods

Authors	Heuristic	Meta-heuristic	Resolution Method
Hinojosa et al. (2000)	X		Lagrangean Relaxation
Hinojosa et al. (2008)	X		Lagrangean Relaxation
Hodder and Dincer (1986)	X		Relaxation and Approximation
Hwang (2002)		X	Genetic Algorithm
Jang et al. (2002)		X	Genetic Algorithm
Jayaraman and Pirkul (2001)	X		Lagrangean Relaxation
Jayaraman and Pirkul(2001)	X		Lagrangian relaxation
Jayaraman and Ross (2003)	X		Simulated Annealing
Jayaraman et al. (2003)	X		Decomposition techniques
Keskin and Ulster (2007)		X	Tabu Search
Ko and Evans (2007)		X	Genetic Algorithm
Lee and Dong (2008)	X		Decomposition techniques
Lieckens and Vandaele (2007)		X	Genetic Algorithm
Listes (2006)	X		L-Shaped
Ma and Davidrajuh (2005)	X		Genetic Algorithm
Marin and Pelegrin (1999)	X		Lagrangean Relaxation
Min et al. (2006)		X	Genetic Algorithm
Miranda and Garrido (2004)	X		Lagrangean Relaxation
Paquet et al. (2004)	X		Valid inequalities
Pirkul and Jayaraman (1998)	X		Lagrangean Relaxation
Romeijn et al. (2007)		X	Column Generation
Santoso et al. (2005)	X		Lagrangean Relaxation
Shu (2004)		X	Column Generation
Sourirajan (2007)	X		Lagrangean Relaxation
Vidal and Goetschalckx (1996)	X		Branch and Bound

Chapter 3

Multi-criteria Supply Chain Network Design

3.1 Introduction

The main purpose of this chapter is to present a novel framework for multi-criteria Supply Chain Network Design (SCND) as well as its application to real Supply Chain Network (SCN).

This chapter deals with the design of a multi-criteria supply chain network in order to satisfy the customer demands and to respect the environmental, social, legislative, and economical requirements.

The methodology consists of two different steps. The first step looks for the best potential facility locations to open in order to satisfy the different criteria: environmental, social, and legislation aspects, using the overlay weighted and Analytic Hierarchy Process (AHP). The second step looks for the optimal supply chain design to fulfill customer demands and economic criteria using mixed integer linear programming model. The objective in this step is to determine location of treatment facilities and their capacities minimizing the sum of: opening facilities cost, products storage cost, production cost, transportation cost, and CO_2 emissions taxes. We apply our methodology to a real life application concerning the recycling of sediment waterways, which was presented in Bouzembrak et al. (2010).

The chapter is organized as follows. In Section 3.2, we describe the problem in more detail. In Section 3.3, we discuss our proposed methodology. In Section 3.4, we present the real case. The experimental study is discussed in Section 3.5. Finally, Section 3.6 contains some concluding remarks.

3.2 Problem description

Before presenting the methodology, we will briefly introduce a multi-criteria, multi-level, single product, single period and multi-modal supply chain network problem (see Table 3.1). Figure 3.1 depicts a supply chain network that includes different transportation modes: roads, railways and waterways. The network has four levels: suppliers, storage depots, production plants and customers. In addition to different types of transportation modes, the possible flows of material are shown in the Figure 3.1. Multi-criteria supply

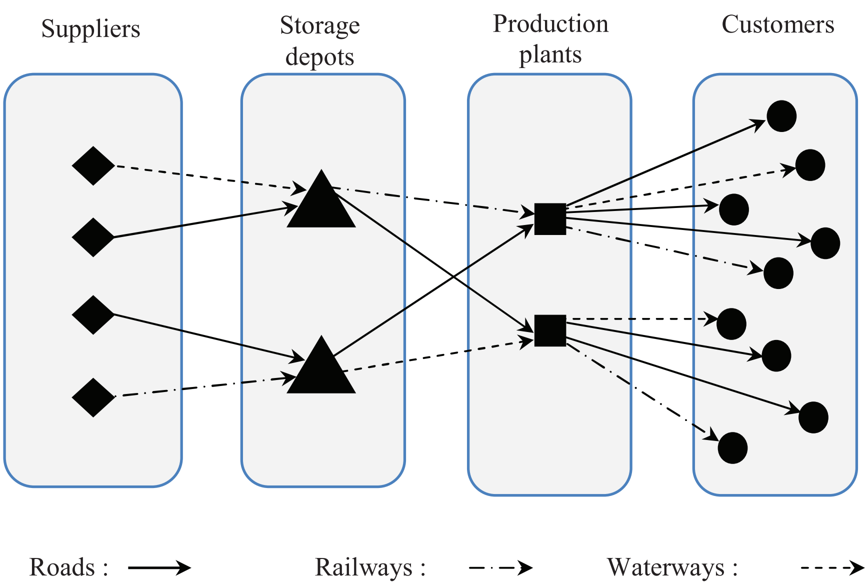

Figure 3.1: Supply chain network

Table 3.1: Problem description

	Criteria	Level	Product	Period	Modalily
Single			X	X	
Multiple	X	X			X

chain network design problems are complex and, like most real world problems depend on a multitude of criteria and uncertain parameters. Many factors contribute to the complexity of the model. The first one is the multi-criteria aspect. For example, problems involving many criteria decision are much more difficult than problems involving only one criterion decision. The second factor is the integration of multi-modality and CO_2 emissions taxes in the model. Indeed, the majority of papers consider only one transportation mode. The third factor is uncertainty which will be addressed in Chapter 6.

3.2.1 SCND evaluation criteria

In the section below, we aim to present in detail the most popular criteria in the literature used for design supply chain networks.

As we explained in Chapter 2, the majority of papers, in supply chain network design literature, propose a cost minimization objective and their aim is to determine the network configuration with the least total cost. These models do not gather several of the criteria depicted in Figure 3.2, simultaneously.

Thus, in this thesis, we will integrate, simultaneously, four different categories of aspects in the SCND, which are: environmental aspects, social aspects, regulation aspects and economic aspects.

In actual business world, thinking of criteria other than economic one (like profit, cost, revenue, etc) is becoming an important opportunity. Sustainability imposes on any development and design, like in supply chain network design, to consider social and environmental aspects (see Dehghanian and Mansour (2009)).

When a selection decision needs to be made, the company establishes a set of evaluation criteria that make it possible to compare potential performance features (Masella and Rangone (2000)). In single criterion SCND problems, the criterion has usually been cost. However, in multi-criteria SCND problems, there is at least one other criterion to consider which, for the nature of these problems, is in conflict with the first one. As the number of criteria used in such problems is important, we decided to present the main criteria that we will consider in this work, in some general categories (Figure 3.2) which are:

Environmental aspects

Environmental aspects are matters on health effects, sound and optical pollution, smells, air or water pollution, transportation risk, natural risk, waste disposal or treatment risk,

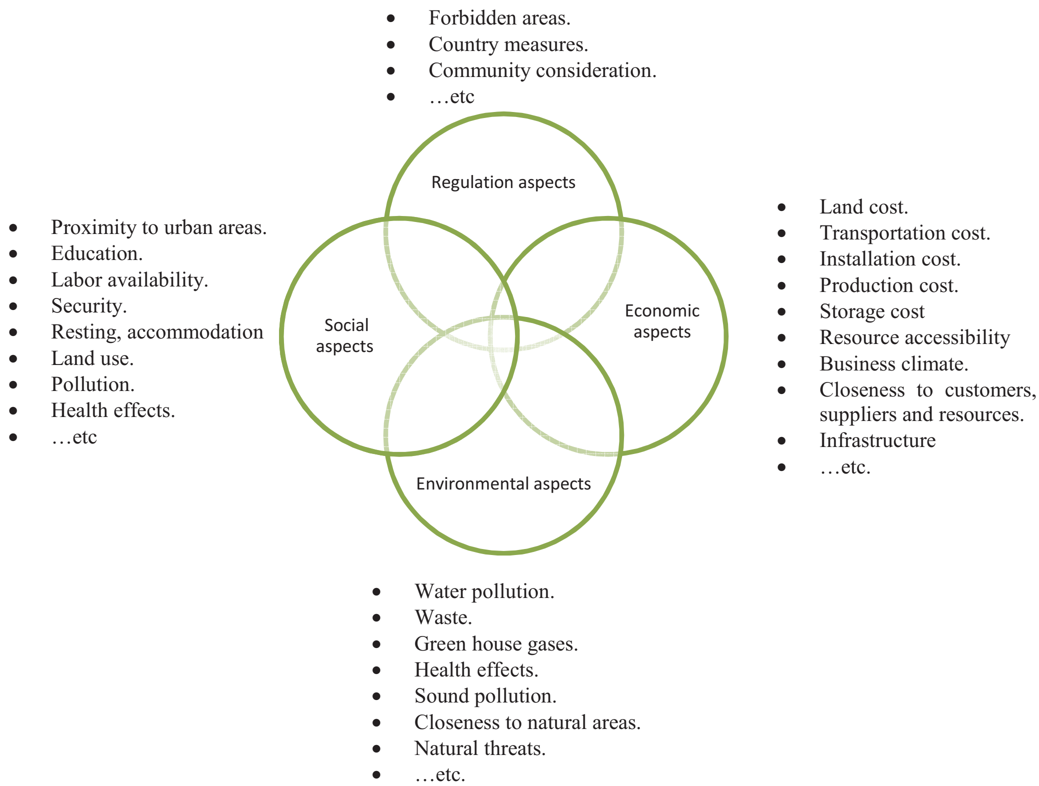

Figure 3.2: Sustainable supply chain network criteria

the protection of natural area , etc.).

Social aspects

In this category, we can find cultural and social aspects: education, labour availability, job opportunities, security, land use, natural threats, pollution, resting, accommodation, infrastructure and any other factors which represent this category.

Political and regulations aspects

Political matters and regulations include community consideration, country measures, and government regulations.

Economical criteria

- *Cost:* There are different types of cost. These types can be divided into fixed and variable. Fixed cost includes installation and opening cost, along with investment. Variable cost can be transportation, inventory, production, services, distribution, logistics, waste disposal, maintenance and environmental cost. Generally, transportation cost is the highest and installation cost is the second one. Several problems have used a total cost criterion which contains all costs under one objective. Other criteria like currency value, business climate, access to public facilities like airports, roads or railways infrastructure, could be taken into account.

- *Profit:* Some problems are interested in the net profit, difference between benefits and costs, or other outcomes of the capital they invested in their facility location decision making. We assembled these criteria under the profit category.

- *Coverage:* Most of location problems, are about coverage by distance, time, amount or even coverage deviation. Although many problems use distance and population coverage as their criteria, time is well considered in some problems.

For a deeper understanding of criteria cited above, the reader can refer to Farahani et al. (2010), Alcada-Almeida et al. (2009), De Toni and Tonchia (2001), Azaron et al. (2008), Chen et al. (2008).

3.2.2 Multi-modality in SCND

The main four transportation modes for freight are: rail, road, water, and air. Each of these modes has different characteristics, and any of them can be considered the best under different circumstances, depending on the location, distance, pollution, type of freight, and value of freight, among other things. The main criteria for transportation are the type and volume of freight and the distance to be covered. Other criteria may include speed, availability, reliability, capacity, security, and frequency of delivery (Tuzkaya and Onut (2008)).

According to Vidal and Goetschalckx (1997), several important SC features are ignored in the methodology for the strategic and tactical planning of global logistics systems. One of these factors is the integration of transportation modes in the SCND. Also, as we showed in chapter 2, the existing literature integrating transportation modes in supply chain network design, is still scarce. Only 7% of these papers included these aspects.

Arntzen et al. (1995) developed a mixed integer linear program to solve the global supply chain design problem at an Electronic manufacturer. They proposed supply chain problem that involves multiple products, production stages, time periods, and transportation modes. The objective function is to minimize fixed and variable production costs, inven-

tory costs, and distribution expenses, including transportation, taxes, and duties.
Cordeau et al. (2006) introduced a new formulation of logistics network design problem. Authors integrated location and capacity choices for plants and warehouses with supplier and transportation mode selection, product range assignment and product flows.
Carlsson and Ronnqvist (2005) integrated three transportation modes in the design of the larger Swedish forest company supply chain network. The international three possible modes of transportation are vessel, train and lorry. A detailed discussion regarding this aspect is provided in Carlsson and Ronnqvist (2005).

The strategic supply chain network we intend to elaborate should respect criteria elaborated above, problem constraints and answer the following questions: (i) how many production plants should be installed? (ii) where new sites should be located? (iii) how much goods should each production plant handle? (iv) which customers should be served by each production site? (v) products quantities to transport throughout the supply chain network? (vi) which transportation mode should be used?

3.3 Approach presentation

In this section, we detail the idea of the novel multi-criteria supply chain network design methodology by explaining each step with small examples. We start by providing the basic steps of our methodology design.
Our method, as illustrated in Figure 3.3, contains two steps. The first step is related to the identification of the potential facility locations set and to satisfy the different criteria: environmental, social, and legislation aspect, using Geographic Information System (GIS) overlay weighted and AHP method. The GIS model is implemented on a Arcview 9.2 GIS to locate elements of the potential facility set. The second step looks for the optimal supply chain design to satisfy customer demands and economic criteria using mixed integer linear programming model. These approaches will be presented in detail in the next chapters. Figure 3.3 presents two steps of our methodology. Now that you have seen the basic outline of two steps, lets delve into the methodology process in more detail.

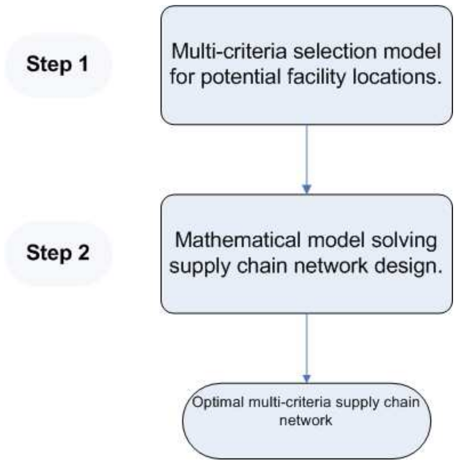

Figure 3.3: Multi-criteria supply chain network design steps

3.3.1 STEP 1: Multi-criteria selection model for potential facility locations

The multi-criteria selection process contains several steps, as it can be seen in this Figure 5.8. The first phase is related to the description of the problem. Evidently, better understanding of the problem provides better solutions to the decision makers. The second phase consists in the determination of criteria included in the supply chain network design. During this phase, GIS input parameters are elaborated. This should be followed by data collection. Then, the weight of each criterion should be calculated using AHP method. This notification is based on the data questionnaires collected by experts. Then, results are obtained via solving GIS model. Results of this phase are investigated and then if they are unsatisfactory, expert's corrections are done and lastly a set of sustainable potential locations are obtained. To establish the potential facilities set, this step can be applied to many levels in the supply chain network such as: suppliers level, distribution centers level, manufacturing plants level and customers level, etc.

The following subsection explains the basic steps of GIS Model.

GIS Model

This section introduces key components and concepts of a GIS model. To create the GIS Model, we used ModelBuilder, an application in GIS Arcview 9.2 in which user can create, edit, and manage models.

At the highest level, models contain only three components; elements, connectors, and

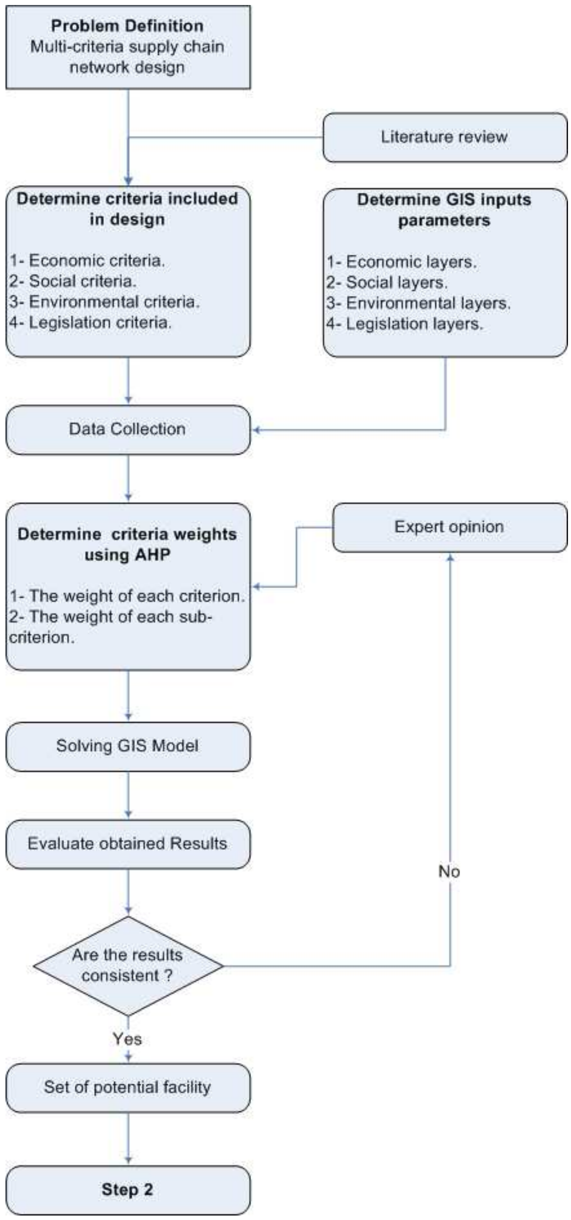

Figure 3.4: First step phases

text labels. Elements are the data and tools you work with. Connectors are lines that connect data to tools. Text labels can be associated with the entire model, individual elements, or individual connectors (Arcview (2010)).

As we can see on Figure 3.5, a process consists of a tool and all variables are connected to it. Connector lines indicate the sequence of processing. In this GIS Model several processes are chained together, C_1, C_2, $\cdots$, C_n; so that the derived data from one process becomes the input data for another process, as shown in the following diagram (Figure 3.6). A real case GIS model will be presented in section 3.4.

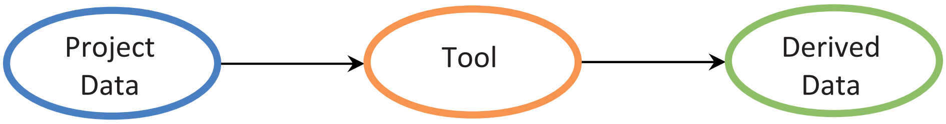

Figure 3.5: Structure of GIS process

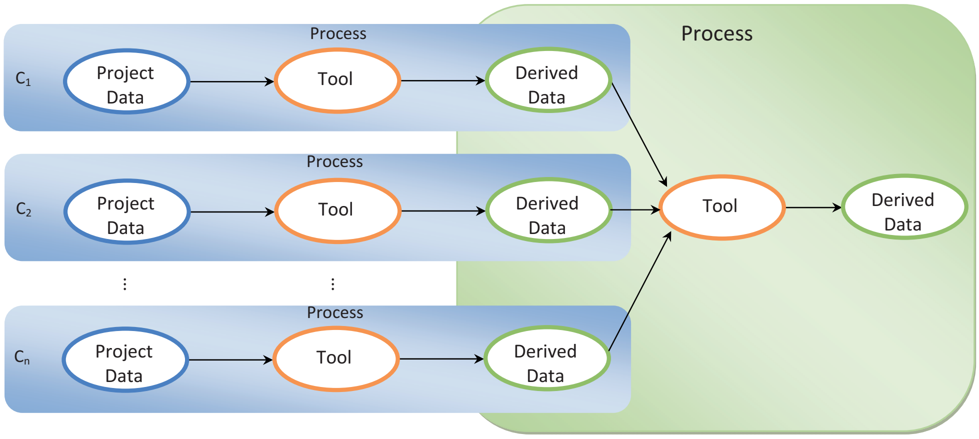

Figure 3.6: GIS Model

The weighted overlay process

The second method that we integrate in this step is the weighted overlay. In general, the weighted overlay function involves the combination of different data layers. Practically, this can involve a number of different processes depending on inputs to analyse (Arcview (2010)).

Supply chain network design problems often require analysis of many different factors. For instance, choosing the location of a new facility means assessing such things as land cost, proximity to existing services, environmental aspects, legislative aspects and social aspects. These information should be elaborated in different rasters with different value scales: Euro, distances, degrees, and so on.

The Weighted Overlay tool lets as to take all these criteria into consideration. It reclassifies values in the input rasters into a common evaluation scale of suitability or preference, risk, or some similarly unifying scale. The input rasters are weighted by importance and added together to produce an output raster. Steps are summarized as follows:

- A numeric evaluation scale is chosen. This may be 1 to 9, or any other scale. In this thesis we will use the Saaty scale (Table 3.2).

- The cell values for each input raster in the analysis are assigned values from the evaluation scale and reclassified to these values. This makes it possible to perform arithmetic operations on rasters that originally held dissimilar types of values.
- Each input raster is weighted, or assigned a percent influence, based on its importance to the model.
- The total influence for all rasters equals to 100 percent.
- The cell values of each input raster are multiplied by the raster's weight.
- The resulting cell values are added together to produce the output raster.

Example:

Below, we provide illustrative example composed of two layers. The two input rasters

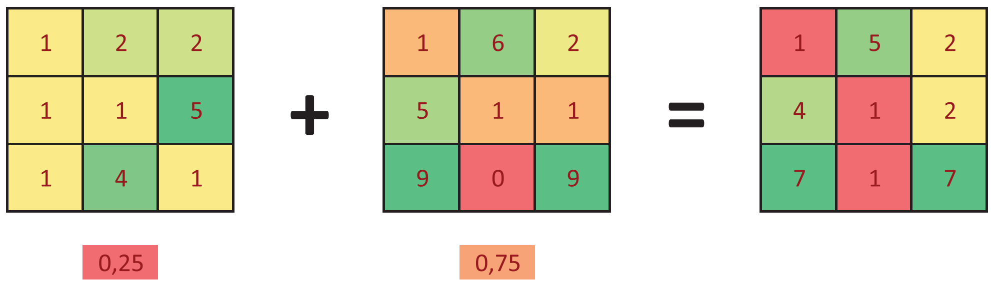

Figure 3.7: Raster Layers

above (Figure 3.7) have been reclassified to an evaluation scale of 1 to 9 (Table 3.2). Each raster is assigned a weight. The weight of the first raster is 25% and the weight of the second is 75%. The cell values are multiplied by their weights, then added together to create the output raster.

Take the top middle cell as an example $(2 \times 0.25) = 0.5$ and $(6 \times 0.75) = 4.5$. The sum of 0.5 and 4.5 is 5.

Determination of criteria weights using AHP

In this section, we provide a description of AHP method and give some examples in the next section.

The AHP is a relatively simple and systematic approach that can be used by decision makers, firstly introduced by Saaty (1980). In general, AHP consists of five main steps: hierarchy construction, pairwise comparison, relative weights estimation, consistency check and synthesizing (Saaty (1980)).

- *Hierarchy construction:* the hierarchy construction step consists of decomposing the problem into hierarchical structural with distinctive levels which are, generally, the goal level, criteria, and decision alternatives. The decomposition can be obtained using a graphical representation, as shown in Figure 3.8.

- *Pairwise comparison:* this step involves establishing priorities at each level by com-

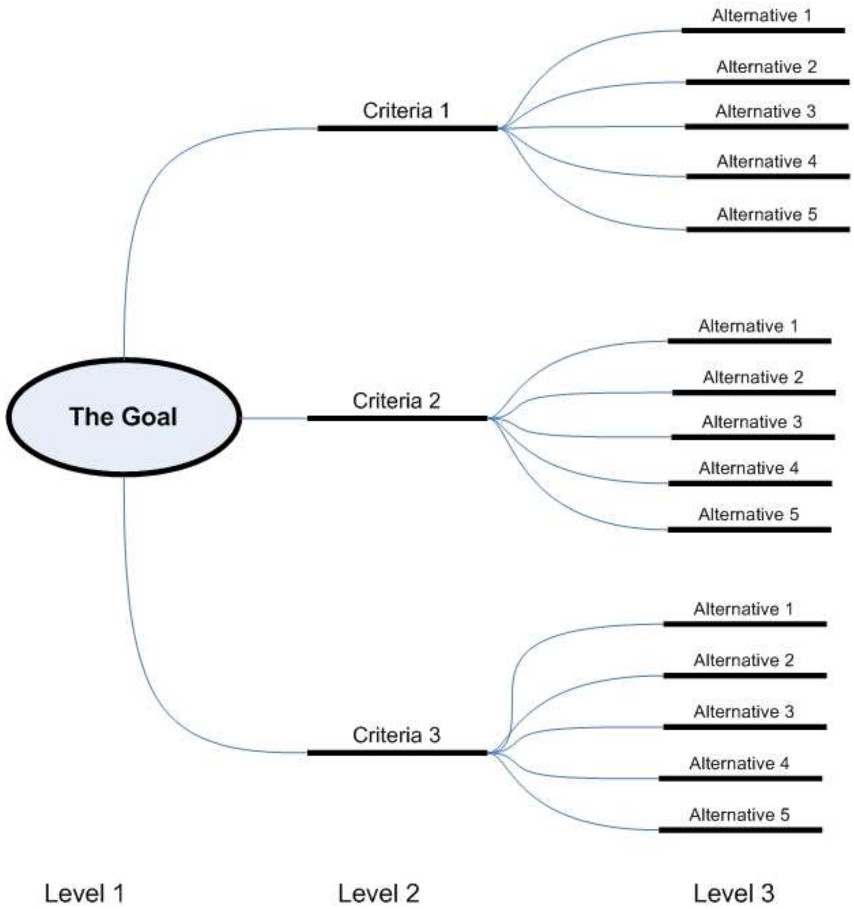

Figure 3.8: AHP graphical representation

paring pairwise each criteria and alternatives. Experts express the relative importance of one criterion versus another regarding the fixed objective, and express also the relative importance of one alternative versus another regarding each criterion. Since experts' judgements are used as a scale, the alternative ratios reflect the relative importance of the criteria in achieving the goal.

Experts' judgements are based on the scale of relative importance that assumes values between 0 and 9 (Kim et al. (1999), Saaty (1980)) as presented in Table 3.2. A Basic assumption is that if attribute A is absolutely more important than attribute B and is rated at 9, then B must be absolutely less important than A and is valued at $\frac{1}{9}$.

- *Relative weights estimation:* this step involves calculating the relative weights of crite-

Table 3.2: Saaty Rating Scale

Weight	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
2	Weak	Between equal and moderate
3	Moderate importance	Experience and judgement slightly favor one activity over another
4	Moderate plus	Between moderate and strong
5	Strong importance	Experience and judgement strongly favor one activity over another
6	Strong plus	Between strong and very strong
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	Between very strong and extreme
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation

ria; technically, this set is called an eigenvector. We prefer to use the right eigenvector method to show how the relative weights are calculated because of its simplicity.

- *Consistency check:* the final step is to calculate a Consistency Ratio (CR) to check how matrix judgements is consistent. It is checking at each level of the hierarchy. It is calculated by:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \qquad and \qquad CR = \frac{CI}{RI} \tag{3.1}$$

$$CR = \begin{cases} 0.05 & n = 3 \\ 0.08 & n = 4 \\ 0.10 & n > 4 \end{cases} \tag{3.2}$$

Where, CI is the Consistency Index, n is the number of criteria, λ_{max} is the largest eigenvalue of judgements matrix, RI is the Random Index which depends on the number of criteria n. We can find in Saaty (1980) matrix the RI value for each n. It is noted in Saaty (2008), if CR is less than or equal to the given upper bound (3.2), matrix is of sufficient consistency and the judgement is acceptable.

- *Synthesizing:* this step consists of determining overall rating and normalized priorities of alternatives by aggregating the relative weights of criteria.

In Appendix A, we provide an example of AHP method, where we calculate weights, CI, λ_{max} and RI, so that a reader can further study the technique.

3.3.2 STEP 2: Mathematical model solving supply chain network design

There is a wealth of literature and research on modelling of strategic supply chain, but with an apparent lack of consideration of transportation mode and CO_2 taxes. Hence, in this part, we formulate a strategic supply chain network design model which includes explicitly the carbon taxes and multi-modality.

Figure 5.9 shows the second step phases. The set of potential facilities is defined in the first step. Expert arguments are taken to determine costs and inputs parameters. Then, variables, costs, constraints and all input parameters are determined and then the model is solved. In results evaluation phase, results are investigated and they are unsatisfactory, expert corrections are done. Last, optimal multi criteria supply chain design is represented.

Mathematical Model

Notation used for the formulation of the model is:

The objective function (3.3) minimizes the sum of the fixed facility location costs, the transportation, storage, and CO_2 emissions costs from supply points to storage depots. The shipment, the processing, and CO_2 emissions costs from storage depots to production facilities. The transportation and CO_2 emissions costs from production facilities to customers.

Minimize ψ

$$\psi = OC + \omega_1 \cdot [TC + SC + RC] + \omega_2 \cdot EC \tag{3.3}$$

Where

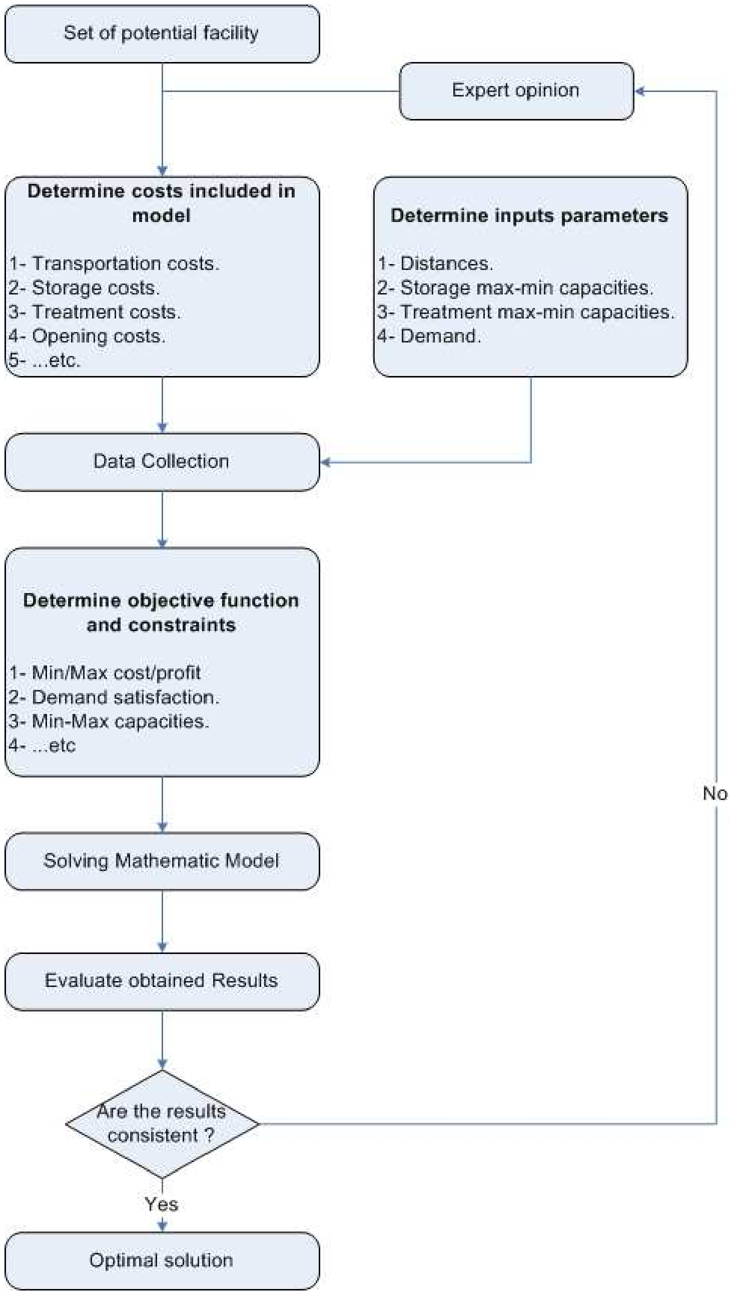

Figure 3.9: Second step phases

-	Sets size:
I	number of suppliers.
J	number of storage depots.
K	number of potential production plants locations.
L	number of customers.
M	number of transportation modes.
-	Sets and indexes:
S	set of suppliers, indexed by i.
D	set of storage depots, indexed by j.
K	set of potential production plants locations, indexed by k.
C	set of customers indexed by l.
T	set of transportation modes, indexed by m.
-	Inputs are:
CO_k	The fixed cost of opening production facility j (€).
C_{ijm}	The unit transportation costs of goods between supplier i and storage depot k using transportation mode m (€/Ton).
C_{jkm}	The unit transportation costs of product between storage depot j and production site k using transportation mode m (€/Ton).
C_{klm}	The unit transportation costs of product between production facility k and customer l using transportation mode m (€/Ton).
ϑ_{ijm}	The distance between supplier i and storage depot k using transportation mode m (Km).
ϑ_{jkm}	The distance between storage depot j and production facility k using transportation mode m (Km).
ϑ_{klm}	The distance between production facility k and customer l using transportation mode m (Km).
CT_k	The processing costs at production facility k (€/Ton).
CS_j	The storage costs at storage depot j (€/Ton).
Q_k	The maximum processing quantity of production facility k (Tons/Year).

Q_j The storage capacity of storage depot j (Tons/Year).

β_m The unit CO_2 emission using transportation mode m (Tons/Ton.Km).

ω_1 Weight of economic dimension (%).

ω_2 Weight of environmental dimension (%).

γ Carbon taxes (€/Ton).

Q_{ijm} The transportation capacity between supplier i and storage depot k using transportation mode m (Tons).

Q_{jkm} The transportation capacity between storage depot j and production facility k using transportation mode m (Tons).

Q_{klm} The transportation capacity between production facility j and customer l using transportation mode m (Tons).

D_l The demand of costumer l (Tons).

- Decision variables:

X_k =1 if production facility k is opened =0 otherwise

q_{ijm} The amount of goods shipped from the supplier i to the storage depot j using transportation mode m.

q_{jkm} The amount of goods shipped from the storage depot j to the production site k using transportation mode m.

q_{klm} The amount of goods shipped from the production site k to the customer l using transportation mode m.

- Opening costs denoted by OC:

$$OC = \sum_k (CO_k \cdot X_j) \tag{3.4}$$

- Transportation costs denoted by TC:

$$TC = \left[\sum_{i,j,m} C_{ijm} \cdot q_{ijm} + \sum_{j,k,m} C_{jkm} \cdot q_{jkm} + \sum_{k,l,m} C_{klm} \cdot q_{klm} \right] \tag{3.5}$$

- Storage costs denoted by SC:

$$SC = \sum_{i,j,m} CS_j \cdot q_{ijm} \tag{3.6}$$

- Treatment costs denoted by RC:

$$RC = \sum_{j,k,m} CT_k \cdot q_{jkm} \tag{3.7}$$

- Environmental costs denoted by EC:

The greenhouse gases include carbon dioxide CO_2, nitrous oxide NO_x, and carbon monoxide CO. Modes of transport are considered to be only the source of CO_2 in our case. The CO_2 emissions of each mean of transport in the way back are integrated. The environmental costs function is formulated as:

$$EC = \gamma \cdot \left[\sum_{i,j,m} \vartheta_{ijm} \cdot \beta_m \cdot (q_{ijm} + 1) + \sum_{j,k,m} \vartheta_{jkm} \cdot \beta_m \cdot (q_{jkm} + 1) + \sum_{k,l,m} \vartheta_{klm} \cdot \beta_m \cdot (q_{klm} + 1) \right] \tag{3.8}$$

Subject to

Constraint (3.9) guarantees that the demand of the customers will be satisfied.

$$\sum_{k,m} q_{klm} = D_l \qquad \forall l \in C \tag{3.9}$$

Constraint (3.10) imposes a capacity restriction for each storage depot.

$$\sum_{i,m} q_{ijm} \leq Q_j \qquad \forall j \in D \tag{3.10}$$

Constraint (3.11) limits the capacity of the production facilities.

$$\sum_{j,m} q_{jkm} \leq Q_k \cdot X_k \qquad \forall K \in K \tag{3.11}$$

Constraints (3.12), (3.13) enforce the flow conservation of the product.

$$\sum_{k,m} q_{jkm} = \sum_{i,m} q_{ijm} \qquad \forall j \in D \tag{3.12}$$

$$\sum_{j,m} q_{jkm} = \sum_{l,m} q_{klm} \qquad \forall k \in K \tag{3.13}$$

Constraints (3.14), (3.15), (3.16) impose a capacity restriction of each mode of transport throughout the network.

$$q_{ijm} \leq Q_{ijm} \qquad \forall i \in S, \forall j \in D, \forall m \in M \tag{3.14}$$

$$q_{jkm} \leq Q_{jkm} \qquad \forall k \in K, \forall j \in D, \forall m \in M \tag{3.15}$$

$$q_{klm} \leq Q_{klm} \qquad \forall k \in K, \forall l \in C, \forall m \in M \tag{3.16}$$

Constraint (3.17) enforces the binary nature of the configuration decisions for the facilities.

$$X_k \in \{0,1\} \qquad \forall k \in K \tag{3.17}$$

Constraints (3.18), (3.19), (3.20) are standard integrality and non-negativity constraints.

$$q_{ijm} \geq 0 \qquad \forall i \in S, \forall j \in D, \forall m \in M \tag{3.18}$$

$$q_{jkm} \geq 0 \qquad \forall k \in K, \forall j \in D, \forall m \in M \tag{3.19}$$

$$q_{klm} \geq 0 \qquad \forall k \in K, \forall l \in C, \forall m \in M \tag{3.20}$$

It is important to remark that our multi-criteria supply chain network design method is such that two steps cooperate in designing the network. Each step may execute an appropriate task. The first one is to determine the set of sustainable potential facilities. The second one is to give the optimal design of the SCN.

3.4 Case study

To illustrate the concept of the two-step multi-criteria methodology that we have seen above, we would like to present an application case to validate our methodology steps. This study focuses on inland waterways sediments recycling in NPDC (Nord-Pas De Calais) region in France (Bouzembrak et al. (2010)). These sediments have been stored along waterways or in some agriculture lands, used as depots, bought by French waterways VNF (Voies Navigable de France). However, these sediments could be polluted with zinc, plumb, cadmium and mercury. VNF management plans to recycle waterways sediments because of new European directive exists.

3.4.1 Supply Chain Network

Treatment process steps are as follows: sediments which come for treatment are sent to phosphating where heavy metals are stabilized by capturing them in calcium phosphate matrix and then the organic compounds are destroyed by calcination to get clean sediments that can be used by customers (Novosol (2009)). In France, treated waterways sediments can be used in the following areas: (i) brickworks, (ii) concrete facilities, (iii) concrete stations, (iv) roads projects.

A schematic representation of the multi-modal network is shown in Figure 3.10. The

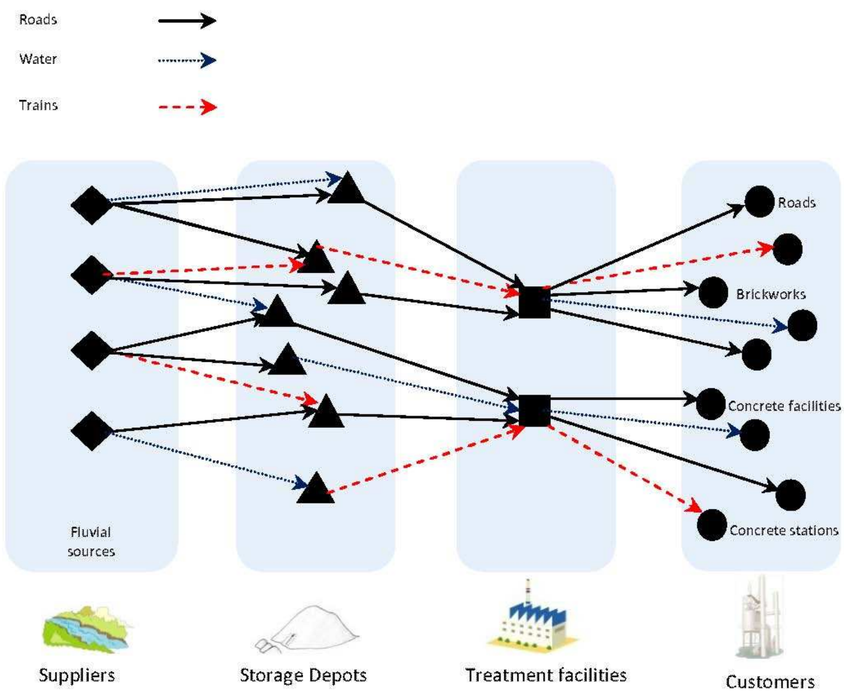

Figure 3.10: Supply chain network in NPDC region

network has four layers. The first level corresponds to suppliers of polluted sediments or waterways in our case study. The second one represents storage depots where sediments must be stored before treatment, and the third one corresponds to the treatment process where sediments should be treated then transported to customers. Finally, the fourth level is composed of customers: roads projects, brickworks, concrete facilities, and concrete stations. The transportation of the sand throughout the network yields transportation assets. In NPDC region, goods can be transported by roads, railways and inland waterways. Some assumptions are considered :

- There are fixed costs of opening treatment facility. For this reason the number of facilities to open, depends on the amount of recycled sediments that will be ordered by customers. This amount should be fixed by the decision maker.

- Capacities of recycling, storage and transportation are fixed.

- Amount of sediments dragged from inland waterways is certain.

- The problem dimensions are presented in Table 3.3.

- Demands of customers are assumed to be known.

- Sediments must be stored before treatment.

- All treated sediments must be transported to customers. Before presenting results, it is important to explain how we elaborated the data used in this model.

Table 3.3: Characteristics of the case study network

Description	Value
Number of waterways sources	50
Number of storage depots	30
Number of potential facility locations	5
Number of customers	60

3.5 Application of the Approach

3.5.1 STEP 1: Multi-criteria selection model for potential facility location

Criteria included in SCND

We started by the elaboration of the most important criteria that we used in the design of the SCN. In order to identify the appropriate criteria, citizens had been consulted. We have asked citizens of this region to complete a questionnaire and to describe and justify their most desirable criteria. After expressing their different points of view, Experts turned to study questionnaires collected. Finally, the most important criteria were formed based on the obtained information while taking into consideration all different points of view of each citizen (see SEDIBET (2010)).

Inhabitants considered that the most important effects were the possible changes in the value of real estate, effects on nature, landscape, and ground and surface waters. Possible smells, noise, and pest animals were also reasons for concern, as well as a possible negative influence on population growth. They fear that the value of their land and property may decrease. Similarly, the closeness of a waste treatment area may prevent further settlement in the region thereby slowing the development of the community structure.

We decided to summarize the main criteria in the following general categories:

- *Environmental aspects:* several criteria are used to measure the global environmental consequences of treatment facility locations. These criteria take into account water pollution, CO_2 emissions, wastes, sound pollution, health effects, natural threats and the green house gases.

- *Economic aspects:* concern facilities establishment costs, production costs, storage costs, transportation costs, infrastructure closeness to customers and to suppliers, etc. All these costs will be integrated in the second step of our methodology which is mathematical model.

- *Social aspects:* in social category, many aspects were considered concerning the local population quality life. The impacts on quality of life for each strategy were valued through the nuisances due to sediments treatment, pollution, security, health effects and also natural areas destruction in order to deposit sediments. However, sites should be located far from urban area and natural zones.

- *Regulation aspects:* treatment facilities could not be built in forbidden area of NPDC region.

Finally, the multi-criteria analysis, taking into consideration all the aspects described above, must rank the different strategies in relation to the sustainable development objectives.

Using GIS spacial analyst, we want to locate potential facilities set. We need to obtain related map information and perform a GIS overlay analysis for this task. The following criteria must be used to guide the potential location set (Table 3.5):

1. The land use must be close or adjacent to the urban area.

2. Sites must be located close to the roads, railways and waterways.

3. Sites will need 20 000 m^2 in a compact shape.

4. Sites must be far from natural zones.

5. The land use must be close or in the brown-fields.

6. Sites must not be located in forbidden area such as: urban area, airports, extraction of materials, urban green spaces, sports and entertainment, irrigated continuously, rice

fields, vineyards, orchards and berry, olive trees, hardwood forests, coniferous forests, mixed forests, forest and shrub, burned areas, inland marshes, marshes, courses and waterways, seas and oceans.

7. The site can be in, close or adjacent to area such as: port areas, industrial and commercial areas, landfills, crop-land out of irrigation schemes, grasslands, annual crops, moors and heathland, rocks area, sparse vegetation. Based on these criteria, we will need the following data for this analysis (Table 3.4):

Table 3.4: Criteria layers

Layers	
1- The land use	5- Natural zones
2- Roads network	6- VNF landfills
3- Railways network	7- Brownfield
4- Waterways network	

GIS input Layers

To elaborate all the GIS input layers, we used the Euclidean distance output raster tool in Spatial Analyst toolbox. This function contains the measured distance from every cell to the nearest source. Distances are measured as Euclidean distance in the projection units of the raster. The Euclidean distance function is used frequently for applications, such as finding the nearest hospital for an emergency helicopter flight. Alternatively, this function can be used when creating a suitability map, when data representing the distance from a certain object is needed. Figure 3.11 shows an example of the euclidean distance output raster that we developed (see Arcview (2010)).

- *Land use layer:*

We now consider the land use layer, the most important raster in our GIS model. The raster contains more than forty different areas in NPDC region, as you can see on Table 3.5. We used the scale presented in Table 3.2 in order to attribute weights to each area. As shown in Table 3.5, DM attributes zero to all forbidden zones like airports, continuous area and 9 to landfills.

Table 3.5: Land cover

Criteria	**Weights**	**Criteria**	**Weights**	**Criteria**	**Weights**
Continuous urban area	0	Hardwood forests	0	Rocks area	2
Discontinuous urban area	0	Coniferous forests	0	Sparse vegetation	5
Industrial and commercial areas	5	Mixed forests	0	Burned areas	0
Road and rail networks	0	Lawns and natural pastures	2	Glaciers and perpetual snow	0
Port areas	9	Moors and heathland	5	Inland marshes	0
Airports	0	Sclerophyllous vegetation	0	Bogs	0
Extraction of materials	0	Forest and shrub	0	Marshes	0
Landfills	9	Beaches, dunes and sand	0	Salt marshes	0
Workspaces	0	Olive trees	0	Intertidal	0
Urban green spaces	0	Grasslands	5	Courses and waterways	0
Sports and entertainment	0	Permanent crops	2	Water bodies	0
Crop-land	5	Crops complex and fragmented	1	Coastal lagoons	0
Irrigated continuously	0	Predominantly agricultural areas	2	Estuaries	0
Rice fields	0	Territories forestry	2	Seas and Oceans	0
Vineyards	0	Orchards and berry	0		

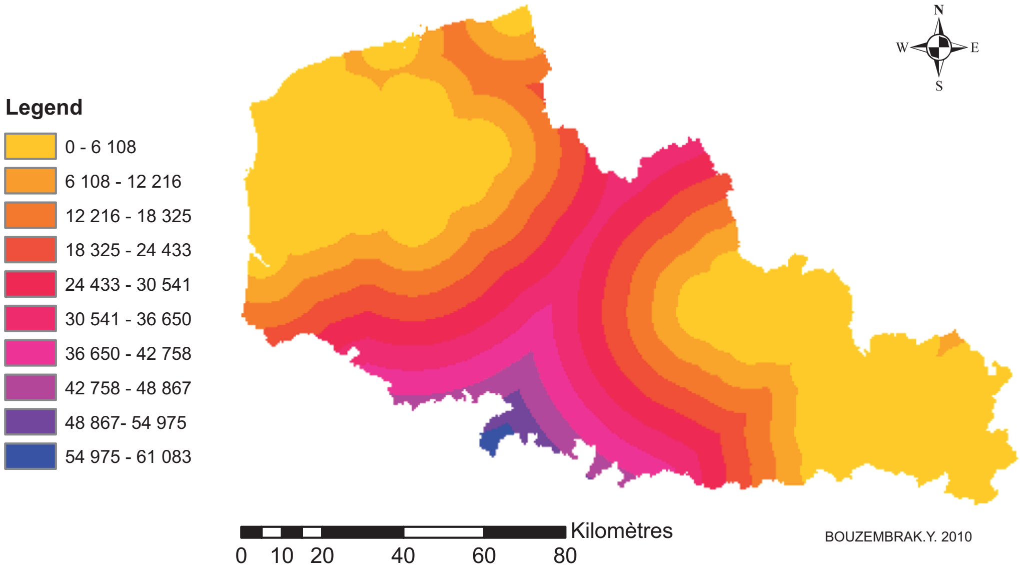

Figure 3.11: Nature area classes in NPDC region

- *Natural zones layer:*

Figure 3.11 presents the nature area network classes in NPDC region. As shown in this Figure, we have 10 different distance classes, for example, the first class (0 - 6 108 m) includes nature zones and area near these zones. The maximum distance between the nearest nature area cell and the near zones is equal to 6 108 m. Table 3.6 summarizes weights attributed by experts to each class.

In Appendix A, we provide all rasters used in this case study as well as Tables of weights.

Table 3.6: Natural area classes and weights

Classes	**Weights**	**Classes**	**Weights**
0 - 6 108	Exclu	30 541 - 36 650	9
6 108 - 12 216	1	36 650 - 42 758	9
12 216 - 18 325	5	42 758 - 48 867	9
18 325 - 24 433	9	48 867 - 54 975	9
24 433 - 30 541	9	54 975 - 61 083	9

- *Roads network layer:*

Figure A.2 shows the different classes of the roads network in NPDC region. To got this classification, we use ArcMap and we specify the number of intervals while the GIS determines where breaks should be. Table A.3 recapitulates weights attributed by experts to each class.

- *Railways network:*

Figure A.3 depicts classes of railways network in NPDC region. In Table A.4, we summarise weights attributed by experts to each class.

- *Waterways network layer:*

In Figure A.4, we depict classes of the inland waterways network in NPDC region. As we can see on Table A.5, we present weights attributed by experts to each class.

- *VNF landfills layer:*

In Figure A.5, we propose landfills classes in NPDC region and we summarize weights attributed by experts to each class in Table A.6.

- *Brownfield layer:*

Figure A.6 depicts the brownfield classes in NPDC region. In Table A.7, we summarise weights attributed by experts to each class.

AHP weights

In this section we apply principles and concepts from the AHP method to measure the importance of each criterion. The Expert's pairwise comparison matrix is presented in Table 3.7. Then the corresponding normalised matrix and the average of each line are

Table 3.7: Pairwise comparison matrix

Codes	Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	Proximity to railways	1	4	0.20	2	0.17	0.33	0.14
C_2	Proximity to roads	0.25	1	0.14	0.13	0.11	0.20	0.11
C_3	Proximity to natural area	5	7	1	5	4	8	2
C_4	Proximity to waterways	0.50	8	0.20	1	3	7	2
C_5	Proximity to brown field	6	9	0.25	0.33	1	4	2
C_6	Proximity to landfills	3	5	0.13	0.14	0.25	1	2
C_7	Proximity to landcover	7	9	0.50	0.50	0.50	0.50	1
Total		22.75	43	2.42	9.10	9.03	21.03	9.25

given in (Table 3.8). Weights of each layer can be observed in Figure 3.12 and Table 3.8.

Table 3.8: Relative importance ratios

Codes	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Average
C_1	0.04	0.09	0.08	0.22	0.02	0.02	0.02	0.07
C_2	0.01	0.02	0.06	0.01	0.01	0.01	0.01	0.02
C_3	0.22	0.16	0.41	0.55	0.44	0.38	0.22	0.34
C_4	0.02	0.19	0.08	0.11	0.33	0.33	0.22	0.18
C_5	0.26	0.21	0.10	0.04	0.11	0.19	0.22	0.16
C_6	0.13	0.12	0.05	0.02	0.03	0.05	0.22	0.09
C_7	0.31	0.21	0.21	0.05	0.06	0.02	0.11	0.14
Total	1	1	1	1	1	1	1	1

For example, the weight of proximity to protected natural areas criterion is equal to 0.34, while such weight decreases to 0.02 for proximity to roads.

GIS Model

In this section, we create our GIS model using ModelBuilder. We used all the data prepared before: GIS input layers, AHP weights and Experts weights. The created model are presented in detail in Appendix (Figure A.7).

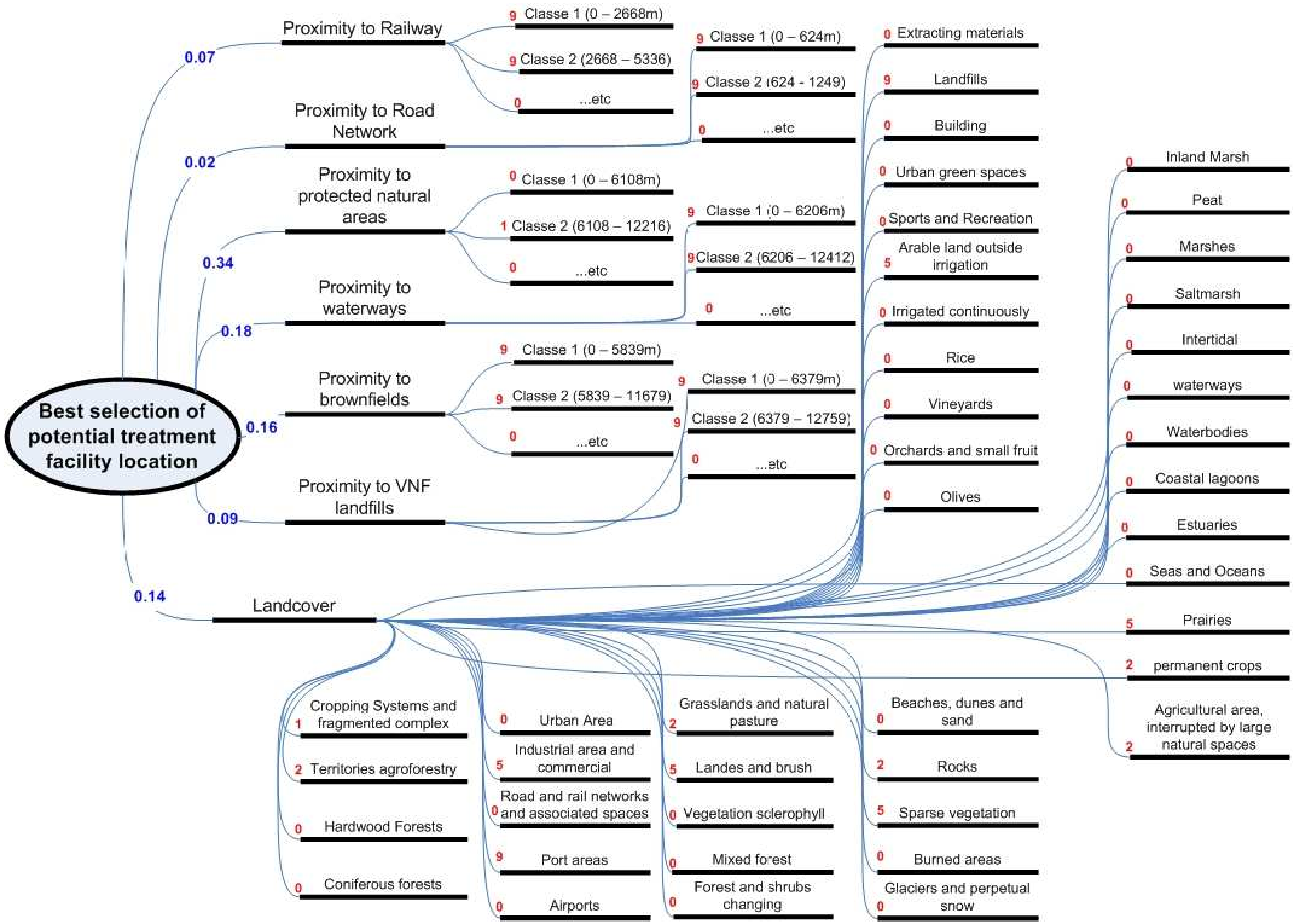

Figure 3.12: Hierarchical structure to the best selection of potential treatment facility location in NPDC region

The following two sections show results for each step. Tables of results include the objective function values, as well as the configuration of the supply chain network.

Computational results

In this section, we present results of solving the GIS model, the set of possible treatment facility locations in NPDC region which will be used in the next step. The GIS model was implemented on Windows XP 3 GHz Xeon processors and 4 GB of memory and solved by commercial GIS software Arcview 9.2. The Figure 3.13 shows results of the GIS model.

Only five sites are located in the best sustainable zones, these potential locations are

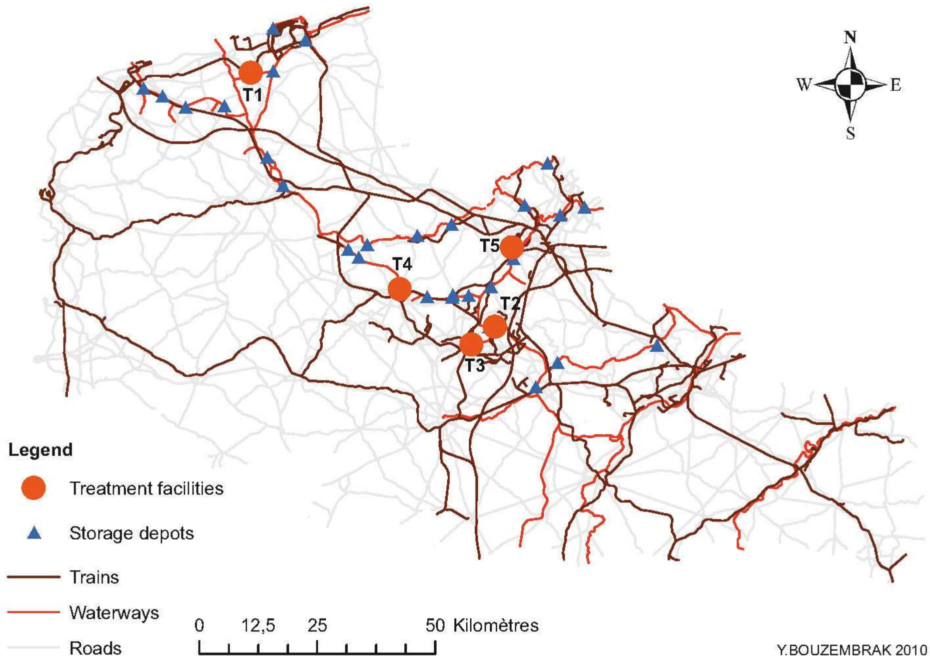

Figure 3.13: Potential treatment facility locations in NPDC region

denoted by $\{T_1,T_2,T_3,T_4,T_5\}$. One site is located in North West of the NPDC region and four sites are positioned in the North Center. Proximity of these treatment centers to road network, train network, waterway network, and storage depots reduces transport costs and CO_2 emissions and ensures a viable market destination for the recycled sediments. In Figure 3.13 majorities of the sustainable sites are located closeness to Urban and developed areas where we can find a high market demand for treated sediments as infrastructure development, landfills, and industrial and commercial areas. With GIS model we succeeded to reduce the potential set of locations from the entire NPDC region to five sustainable locations. This will speed up the process of finding the optimal supply chain configuration in the next step.

3.5.2 STEP 2: Mathematical model solving supply chain network design

Transportation costs

We start by determining distances between logistic actors in order to calculate the transportation costs from suppliers to storage depots, from depots storage to treatment facilities and from treatment facilities to customers. All these distances using railways, waterways and roads as transportation mode are calculated using GIS Arcview.9.2 tools like Spatial Analyst and Network Analyst (Figure 3.14). Transportation costs are calculated per weight and distance. They depend on the distance, and the quantity to be transported. The unit transportation cost for goods can be broken down to its main components: capital, fuel, lubricants, driver and maintenance costs. All expenses along the lifetime of a vehicle are calculated.

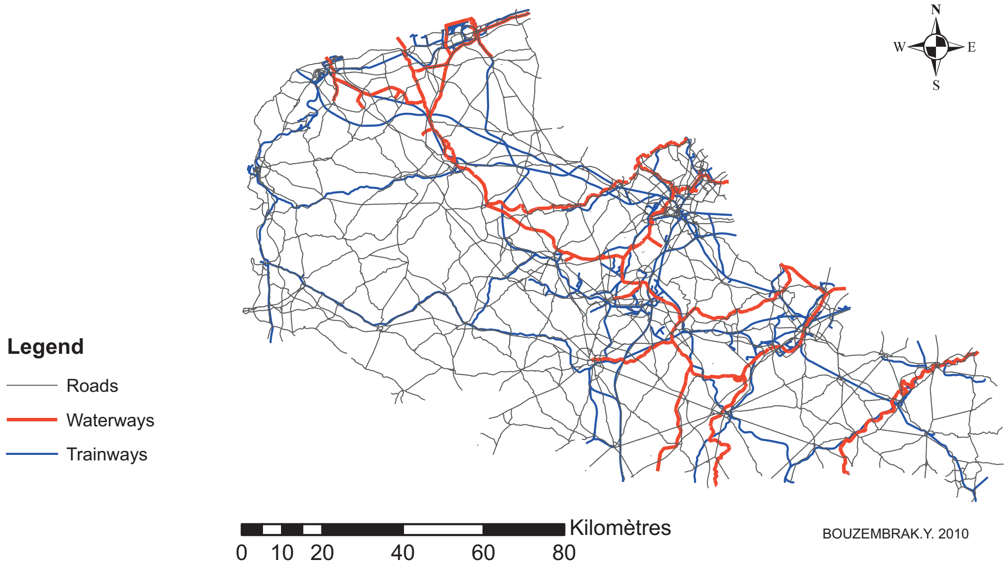

Figure 3.14: Transportation modes in Nord Pas De Calais (NPDC) region

Opening, treatment and storage costs

- *Opening costs:* The facility opening cost implies establishing a treatment facility. Therefore, it will change according to the place where it will be built. This cost variation is due to the variation of ground and workforce costs; similarly production and storage costs vary according to the location.
- *Treatment costs:* The treatment costs are composed of: equipment capital, energy consumption, workforce, operational and maintenance costs. Only these costs have to be taken into account. An average unit cost is assumed.
- *Storage costs:* The storage costs are composed of: storage equipment capital, energy consumption, workforce, operational and maintenance costs.

CO_2 Emissions

Air pollution generated by freight trains, barge and trucks affects negatively the environment and the health of people. We estimate the external costs associated with two general categories of emissions: air pollution and greenhouse gases. Assigning Euro values to emissions generated per ton-km of freight transportation is inherently difficult.
Decision Makers choose the green technology of treatment facility. So, we assume that only transportation means are sources of air pollution.
For CO_2 emissions in France, we found in some ADEME (Agency of Environment and Energy Management in France) reports, the CO_2 emissions factors of three transportation modes (Table 3.9).

Table 3.9: CO_2 Emissions factors

Transportation Mode	Roads	Waterways	Railways
CO_2 Emissions (g/ton.km)	133.11	37.68	5.75

Computational results

In this section, we analyse the computational results obtained from the resolution of the proposed mathematical model considering economic and environmental aspect. The integration of CO_2 emission taxes in the objective function represents the environmental aspect in model (3.3)-(3.20). This model is applied to a real case of VNF company in

NPDC region. To illustrate the validity and the usefulness of the proposed model, several numerical experiments are implemented and results are reported in this section. The mathematical model was solved on a Windows Vista 2 GHz Core 2 Due PC with 3 Go of memory by commercial software solver ILOG OPL 6.3/CPLEX 12.1.0.

- Environmental vs Economic supply chain:

In this section, we introduce the effect of varying ω_1 and ω_2 on the supply chain network configuration. For this problem size, the computation time was negligible and the mixed integer programming model contains 11 408 constraints and 4 876 decision variables.

Table 3.10 shows the impact of ω_1 and ω_2 on the supply chain network configuration decisions and on the transportation mode used.

In Table 3.10, Weight represents values of the ω_1 and ω_2 used on the objective function. Potential facilities column contains the set of the potential sites. % of transportation mode column presents the mode of transport used en percentage. Finally the value of the objective function expressed in (€).

Table 3.10: SCN Configuration varying ω_1 and ω_2

N°	**Weight**		**Potential facilities**					**% of transportation mode**			**Values(€)**
	ω_1	ω_2	T_1	T_2	T_3	T_4	T_5	Roads	Waters	Rails	Objective Value (€)
1	0	1	X			X		3%	24%	73%	30 039 950
2	0.1	0.9	X			X		3%	26%	71%	31 895 690
3	0.2	0.8	X			X		1%	26%	73%	33 750 860
4	0.3	0.7	X				X	1%	37%	63%	35 598 230
5	0.4	0.6	X				X	1%	36%	63%	37 445 080
6	0.5	0.5	X				X	0%	37%	63%	39 290 250
7	0.6	0.4				X	X	0%	37%	63%	41 134 900
8	0.7	0.3				X	X	0%	50%	50%	42 979 440
9	0.8	0.2				X	X	0%	53%	47%	44 823 850
10	0.9	0.1				X	X	0%	53%	47%	46 667 200
11	1	0				X	X	13%	73%	14%	48 509 520

As we can see on Table 3.10 , we have 4 types of supply chain configuration solutions, which are:

1. Environmental location solution: we find this solution $\{T_1,T_4\}$ when ω_1 is between 0 and 0.2. This solution presents the location of two treatment facilities from five potential facilities. The first site is located in the center north of the region, where we find the highest number of customers and the most important quantity of sediments to clean. The second treatment site is located in the center of the region, in order to serve the customer demands of this region and the north west of the NPDC region, and to reduce the transportation costs. Most of the treated sand are transported using trains with an average of 72.3%, 25.3% using waterways, and only 2.4% of the sand are transported using roads (Figure 3.15).

2. Economic-Environmental location solution: solution $\{T_1,T_5\}$ presents the opening of two treatment plants from five potential facilities when ω_1 is between 0.3 and 0.5. The first treatment facility is located in the center of the region, in order to serve customer demands of this region and the north west of the NPDC region. The second site is located in the center north of the region, where we find the highest number of customers and the most important quantity of sediments to clean. Analysis of the mode of transport used shows that 63% of the treated sand are transported using trains, 37% using waterways and only 0% of the sand are transported using roads (Figure 3.15).

3. Economic location solution: solution $\{T_4,T_5\}$ is obtained when ω_1 is between 0.6 and 0.9. This solution presents the location of two treatment facilities from five potential facilities. The first site is located in the center north of the region, the second one is located in the north west of the region, in order to serve the demand of the customers of each region, and to reduce the transportation costs. Analysis of the mode of transport used shows that 48% of the treated sand are transported using railways, 52% using waterways and only 0% of the sand are transported using roads (Figure 3.15).

4. Extremely Economic location solution: solution $\{T_4,T_5\}$ is obtained when ω_1 is equal to 1. Most of the treated sand is transported using waterways 73%, 14% using railways, and only 13% of the sand are transported using roads. Results obtained point out, first, the impact of the integration of CO_2 emissions taxes in the design of sediments recycling network; it changes decisions of location. It depends on the environmental policy of the

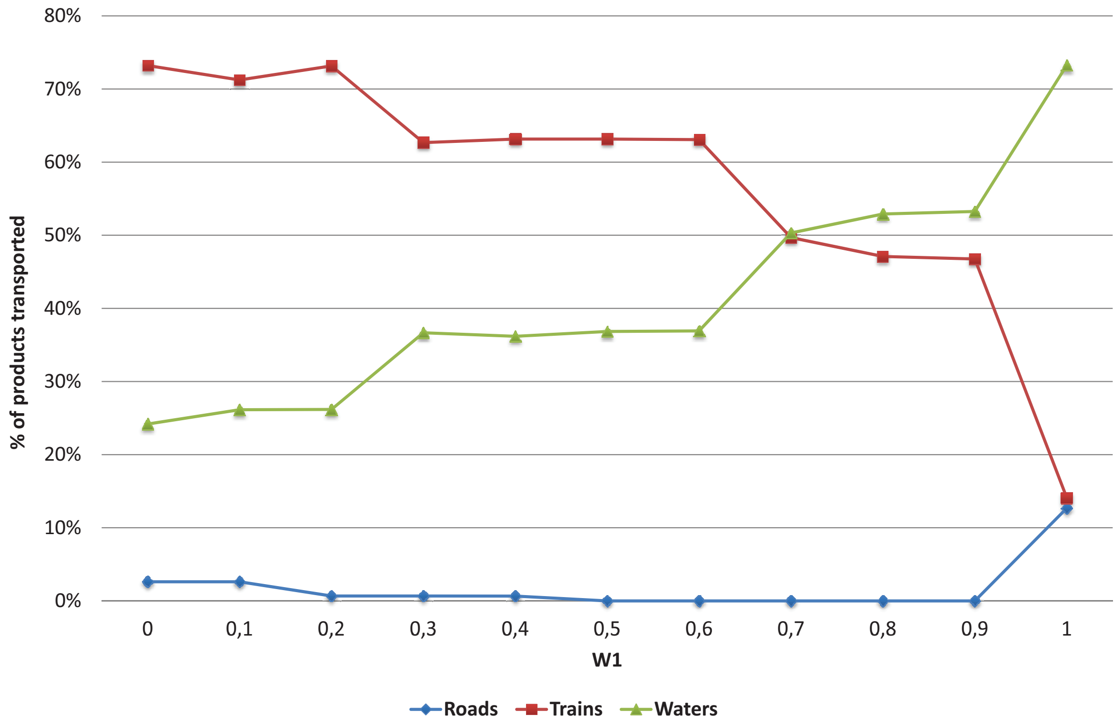

Figure 3.15: The transportation mode used varying ω_1

company, if managers are environmental they will take the first solution, if they are looking for the environmental and economic solution they should choose the second solution, and if they want the economic scenario they should adopt the forth solution. This means that using the model, supply chain managers are now able to see the impact of integration of the CO_2 taxes and multi-modality in the strategic decisions. That will help them to decide the best strategic design of the supply chain.

CO_2 taxes variation:

As in last subsection we varied ω_1 and ω_2 to see their effect on the SCN configuration. In this paragraph, we extend the analysis to CO_2 taxes γ. We fix the ω_i ($\omega_1 = 1$ and $\omega_2 = 1$) and we increase the value of γ from 0 to 200 000 (€/ton).

The following Table 3.11 shows the impact of γ on the supply chain design decisions and on the transportation mode used.

Supply chain configurations:

We present the optimal supply chain configurations obtained varying γ and a comparison between values of objective function of two cases (γ=0) and ($\gamma \neq 0$).

For instance, in Table 3.11, for γ=0 the SC structure is { T_4,T_5 } and the objective function

Table 3.11: Supply chain configuration varying CO_2 taxes

N°	γ (€/ton)	Configuration	Objective function(€)	Difference (%)*
1	0	T_4, T_5	48 509 520	0.0%
2	10	T_4, T_5	48 509 822	0.0%
6	200	T_4, T_5	48 515 341	0.0%
7	300	T_4, T_5	48 518 166	0.0%
22	3000	T_4, T_5	48 583 363	0.2%
23	4000	T_1, T_5	48 606 223	0.2%
32	13000	T_1, T_5	48 792 915	0.6%
33	14000	T_1, T_4	48 809 384	0.6%

value is equal to 48 509 520. For γ=4 000 the configuration is { T_1,T_5 } and the objective value is 48 606 223. As we can see on the Table 3.11, we have 3 different solutions, { T_4,T_5 }, { T_1,T_5 } ,and { T_1,T_4 }. The first configuration is obtained when γ is between 0 and 3 000. The second network is obtained when γ is between 4 000 and 13 000. The last one is fond when γ is higher than 14 000.
It can be observed, the optimal solution { T_4,T_5 } is approximately 0.2% cheaper than the second configuration { T_1,T_5 } and approximately 0.6% cheaper than the third solution.

CO_2 ***Emissions:***

In this section, we present a comparison of CO_2 emissions quantities obtained for ($\gamma = 0$) and ($\gamma \neq 0$). To get the quantity of CO_2 emissions of the supply chain, we used the equation (6.29). As we can observe on Table 3.12, the integration of environmental taxes reduces the quantity of CO_2 emissions to at least 70%. For $\gamma = 10$, the quantity of CO_2 emission decreases to approximately 70% less than the case with $\gamma = 0$.

Analysis of Figure 3.16 shows that the most polluted configuration is the first one, without carbon taxes, in this case the quantity of CO_2 gazes is 980 (tons). This quantity goes down to approximately 300 (tons) increasing γ to 10. As we can see also, we have four levels of CO_2 emissions: the fist level is obtained for γ between 10 and 600, the average of CO_2 emissions is equal to 285 (tons). The average of CO_2 emissions drops to an average of 238 (tons) in the second level when γ is between 600 and 4 000. In the third

Table 3.12: CO_2 Emissions varying CO_2 taxes γ

N°	γ (€/ton)	CO_2 Emissions (Tons)	Difference (%)
1	0	980	0.0%
2	10	302	69.2%
6	200	286	70.8%
7	300	280	71.4%
22	3000	233	76.2%
23	4000	226	76.9%
32	13000	205	79.1%
33	14000	164	83.3%

level for γ between 4 000 and 13 000, the average of CO_2 emissions is 205 (tons). Finally, above 13 000, we obtained the fourth level where the average of CO_2 is about 156 (tons).

Transportation Modes:

In this section, we show the effect of γ variation on the transportation modes used in shipment of the sediment throughout the supply chain network.

As we can see on Table 3.13 , we have 5 types of supply chain configurations, which are:

Table 3.13: Transportation modes used varying CO_2 taxes

		Transportation Modes		
N°	γ (€/ton)	% Roads	% Waters	% Trains
1	0	9.3%	80.7%	10%
2	10	0.0%	78%	22%
6	200	0%	74.7%	25.3%
7	300	0%	54.7%	45.3%
22	3000	0%	52.0%	48.0%
23	4000	0%	36.7%	63.3%
32	13000	0.7%	36.7%	62.7%
33	14000	1.3%	25.3%	73.3%

1. *Extremely Economic configuration:* solution { T_4,T_5 } is obtained when γ is equal to

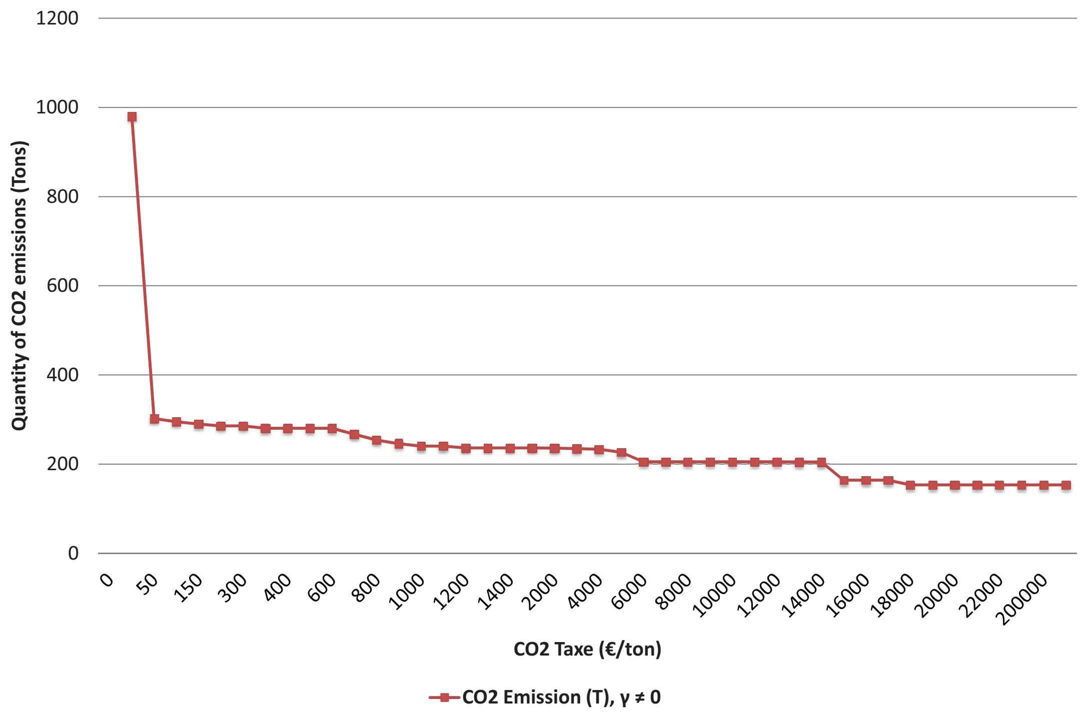

Figure 3.16: Quantity of CO_2 emission varying γ.

zero. Most of the treated sand are transported using waterways 80.7%, 10% using railways, and only 9.7% of the sand are transported using roads (Bouzembrak et al. (2010)).

2. Economic configuration: solution { T_4,T_5 } is obtained when γ is between 10 and 200. Analysis of the transportation mode used show that 24.3% of the treated sand are transported using railways, 75.7% using waterways and 0% of the sand are transported using roads.

3. Economic-Environmental configuration: solution { T_4,T_5 } is obtained when γ is between 300 and 3 000. We find that approximately 46.2% of the treated sand are transported using railways, 53.8% using waterways and 0% of the sand are carried using roads.

4. Environmental configuration: solution { T_1,T_5 } presents the location of two treatment facilities from five potential facilities when γ is between 4 000 and 13 000. As we can see, the majority of sediments 62.7% are transported using railways, 36.6% using waterways and only 0.7% of sediments are shipped using roads.

5. Extremely Environmental configuration: we find this solution { T_1,T_4 } when γ is above the value of 14 000. Most of the treated sand are transported using railways with an average of 73%, 25% using waterways, and only 2% of the sand are transported using roads.

Figure 3.17 shows that an increment in the value of γ implies a significant increase in the

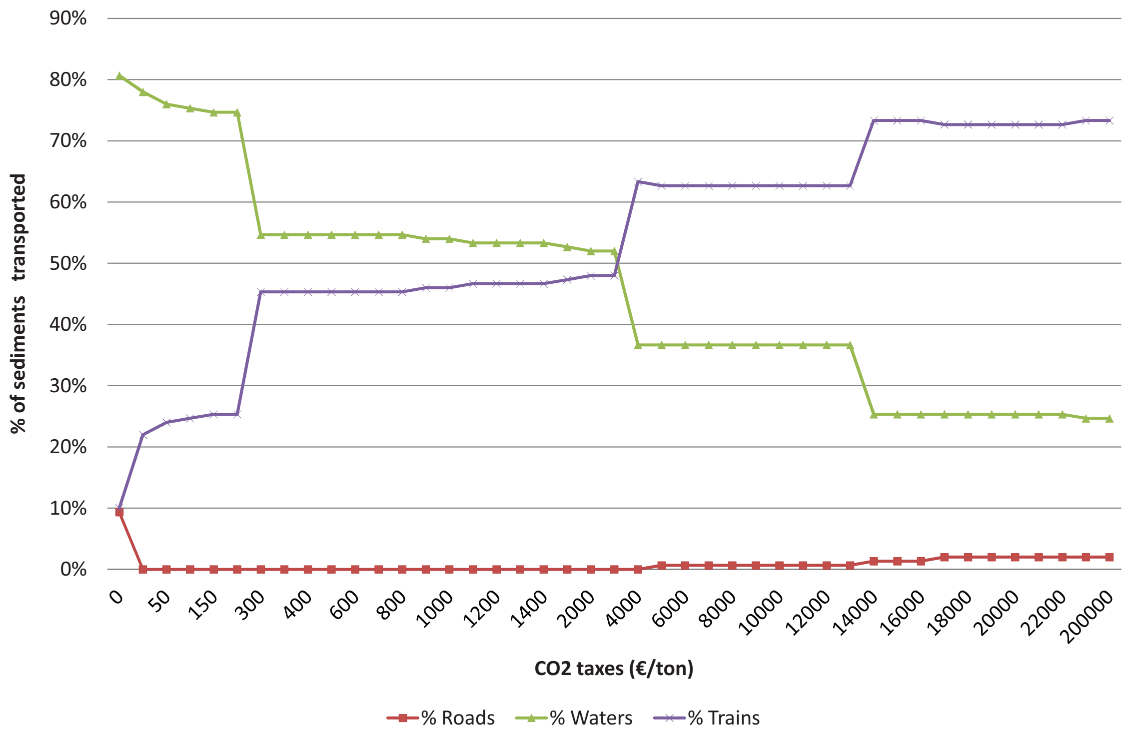

Figure 3.17: The transportation mode choose varying γ

amount of sediments transported using railways as transportation mode, when γ is equal to zero the percentage of sediments transported using train is approximately 10% and rising γ to 14 000 the percentage grows up to approximately 72%. Or, when we increase the value of γ, the percentage of sand transported using waterways decreases. When γ rises from 10 to 200 000 the % of using waterways goes down from 78% to 25%. The % of sediments transported using roads fluctuates between 0% to 10%.

From these results, it is clear that the integration of carbon taxes in the model is an efficient approach to reduce CO_2 emissions by choosing the best facility location and combination of the transportation mode. To achieve the objective of reducing CO_2 emissions, we should take into account the multi-modality in the design of the supply chain especially the railways and the waterways transportation modes.

- Demand variation:

In this section, we study the configuration of the supply chain, analysed via demand variation. Throughout, we will use the term Low demand case to denote demand cases with 100 500 tons as annual customers average, the term Medium demand case to refer to demand cases with annual customers average equal to 250 000 tons and the term High demand case to mention to the increase in the annual costumers average to 402 000 tons.

- *Low demand case*

In this section, the average of annual customer demands is equal to 100 500 tons per year. We generated 24 demand scenarios and the demand of each customer is assumed to be fitted to normal distribution with 2 000 tons as the mean value and 40% of mean value as the standard deviation. Clearly in this situation only one cleaning facility is necessary, which has to work at full capacity. Table 3.14 presents only four scenarios from 24 ones generated, for more detail see Table A.11. The optimal configurations of each demand scenario are illustrated in Table 3.14.

In Table 3.14 optimal solution contains the objective function value of each experience,

Table 3.14: Low demand case

		Treatment facility				
Scenarios	Objective function value (€)	T_1	T_2	T_3	T_4	T_5
S_1	21 499 647	0	0	0	0	1
S_6	22 557 098	1	0	0	0	0
S_{12}	21 497 861	0	0	0	0	1
S_{20}	22 511 297	0	0	0	0	1

expressed in Euro. Finally the treatment facility contains the set of location solution. For instance, the deterministic design exhibits two different location solutions (T_1) or (T_5). It is also interesting to point out that the configuration depends on demands scenario (Table 3.14).

- *Medium demand case*

For medium demand case, the demand rises to 250 000 tons per year. We generated 24 demand scenarios (Table A.12) and the demand of each customer is supposed to be fitted to normal distribution with an average of 5 000 tons and a standard deviation equals to 2 000 tons. Given the treatment capacity of 150 000 tons per year, it turns that at least two facilities have to be opened.

As it can be observed on Table 3.15, the deterministic design exhibits three different loca-

Table 3.15: Medium demand case

		treatment facilities				
Scenarios	Objective function value (€)	T_1	T_2	T_3	T_4	T_5
S_{25}	51 537 458	0	0	0	1	1
S_{33}	48 471 592	1	0	0	0	1
S_{40}	48 368 435	1	0	0	0	1
S_{45}	47 581 870	0	0	0	1	1
S_{49}	67 421 795	1	0	0	1	1

tion solutions $\{T_1, T_5\}$, $\{T_4, T_5\}$ or $\{ T_1, T_4, T_5\}$. The facility T_5 is frequent in all scenarios; others are reproduced by many scenarios.

- *High demand case*

We increase the average of annual demand of customers to 402 000 tons per year. The mean value of the normal distribution is 8 000 tons and the standard deviation is equal to 40% of mean value. The configurations of individual scenarios are illustrated in Table 3.16. As it can be observed, the optimal configuration is kept constant. It is clear that the

Table 3.16: High demand case

		Treatment facility				
Scenarios	Objective function value (€)	T_1	T_2	T_3	T_4	T_5
S_{50}	74 846 906	1	0	0	1	1
S_{58}	74 372 451	1	0	0	1	1
S_{66}	75 289 961	1	0	0	1	1
S_{74}	75 981 418	1	0	0	1	1

higher the quantity of sediments, the more stable the supply chain network configuration. The reader can find all scenarios results in Table A.13.

From these results, it is clear that the customer demands have a great influence on the configuration of the future SCN. So, we think that to establish a robust supply chain network, we should take into account the uncertainty of critical supply chain network parameters such as: demand and costs.

3.6 Concluding remarks

In this chapter, we have proposed a novel multi-criteria supply chain network design methodology. Under economical, social, environmental and legislative aspects, we have designed the optimal supply chain network.

Our methodology consists of two different steps. The first step looks for the best potential facility locations to open in order to satisfy the different criteria using the GIS model and the AHP method. The second step establishes the optimal supply chain design to achieve customer demands and economic criteria using mixed integer programming model.

The results obtained point out, first, using GIS model to location potential facilities in the design of sustainable supply chain network. In fact it provides a good way for integrating many criteria and constraints such as: location sites far from the urban areas; sites should be close to commercial zones, roads, railways and Landfills; plants should be far from natural area, airports and agriculture area, etc. With GIS model we succeeded to reduce the potential set of locations from the entire NPDC region to only five sustainable locations. This will speed up the process of finding the optimal supply chain configuration in the next step.

Studying the impact of CO_2 emissions in the SCND represents our second main contribution in this chapter. Indeed, it changes the structure of the supply chain network. It depends on the environmental policy of the company. This means that using the model, supply chain managers could be able to see the impact of integration of the CO_2 taxes and multi-modality in the strategic decisions of supply chain design. That will help them to select the best strategic supply chain network. From this chapter we have learned that integration of environmental taxes in the model can be an efficient way to achieve environmental goals, by choosing the best SCN and clean transportation modes. These results have also confirmed that to reduce CO_2 emissions, we should take into account multi-modal network, in the design of the supply chain.

In the next chapter, we will extend the mathematical model of our methodology to a multi-objective supply chain network model.

Chapter 4

Multi-objective Supply Chain Network Design

This chapter continues and extends a line of work that we started in Chapter 3. We study a supply chain network design problem with environmental concerns. We are interested in the environmental investments decisions of the supply chain design phase and we propose a multi-objective optimization model that captures a compromise between the total cost and the environment influence. We use Goal Programming approach seeking to reach the four goals placed by Decision Maker: (i) total costs goal, (ii) energy consumption costs goal, (iii) waste treatment costs goal and (iv) CO_2 emissions goal.

The strategic decisions considered in the model are treatment facilities location, building technology selection and flow of material throughout the SC network.

We first discuss the integration of environmental aspects in Supply Chain Network Design in Section 4.2. In Section 4.3, we present the Goal Programming (GP) method and the techniques used to improve it. Section 4.4 proposes the definition of the problem and the GP mathematical formulation. Section 4.5 presents numerical results illustrating and comparing the performance of the GP model. In Section 4.6, we discuss conclusions from our study and briefly summarize potential future research directions.

4.1 Introduction

Traditionally, the main objective of optimization models used in the design of supply chain networks focused on the economic aspect (Goetschalcks and Fleischmann (2008)). However, as environment concerns grow, environmental aspects are also emerging at academic and industry levels as decisive factors within the supply chain management context.
Nowadays, the investment towards logistics structures that considers both economic and environmental performances is an important and current research topic.
This growing importance is driven mainly by the deterioration of the environment and the new environmental regulations. However, companies must invest on the design and planning optimization of their logistic structures, while accounting for the trade-off between profit and environment impact (Grossmann (2004), Barbosa-Povoa (2009), Srivastava (2007), Guillen-Gosalbez and Grossmann (2009)).
Several authors have been working on the integration of CO_2 emissions in supply chain design. Recently Pan et al. (2009), showed that the logistical mutualisation is an efficient approach to reducing CO_2 emissions, at the same time they claimed that the rail transport is an aspect that should be taken into account in order to achieve the objective of reducing the CO_2 emissions. The disadvantage of this model is that the economic dimension is absent.
Paksoy et al. (2010), considered the green impact on a close-looped supply chain network and tried to prevent more CO_2 gas emissions and encourage the customers to use recyclable products via giving a small profit. They presented different transportation choices between echelons according to CO_2 emissions.
Wang et al. (2010) studied a supply chain network design problem with environmental aspects. They interested in the environmental investments decisions in the design phase and proposed a multi-objective optimization model that captures the trade-off between the total cost and the environment influence. Authors considered two objective functions. The first objective measures the sum of fixed set-up cost, environmental protection investment, total transportation cost and total handling cost. The second one measures the total CO_2 emission in all the supply chain. Wang et al showed that the model can be applied as an effective tool in the strategic planning for green supply chain.

Guillen-Gosalbez and Grossmann (2009) also addressed the design and planning of supply chains formulating a bi-objective stochastic mixed-integer non linear program that accounts simultaneously for the maximization of the net present value and the minimization of the environmental impact for a given probability level.

Another related study is conducted by Hugo et al. (2005), who developed a multi-objective optimisation approach for hydrogen SC networks, where they investigated trade-offs between investment and greenhouse gas emissions. Bojarski et al. (2009) addressed the optimization of the design and planning of supply chains considering economic and environmental issues.

The major drawbacks of these papers are the absence of incorporation of CO_2 emissions and multi-modality in supply chain network design. Also, only few studies have addressed the impact of integrating environmental regulations, green house gases emissions, energy consumption, green technology and carbon taxes Nagurney et al. (2006), emission trading (Stranlund (2007)) and carbon markets (Peace and Juliani, (2009)) on supply chain network design.

In this context, this chapter deals with the design of a multi-objective supply chain network in order to satisfy the customer demands and to respect the environmental requirements. We use Goal Programming approach seeking to reach the four goals placed by Decision Maker: (i) total costs goal, (ii) energy consumption costs goal, (iii) waste treatment costs goal and (iv) CO_2 emissions goal.

The strategic decisions considered in the model are treatment facilities location, building technology selection and flow of material quantities throughout the SC network. To solve the model, we apply a Goal Programming approach, which is a single model and easy to understand and to apply (Aouni and Kettani (2001)).

Finally, we conduct a comprehensive set of numerical studies and present the solutions and their sensitivities to various parameters.

4.2 Goal Programming

A goal refers to criterion and a numerical level known as a target level, which the decision maker desires to achieve on the criterion (Tamiz (2009)). There are three principal types of goal that can occur in a goal programming model: achieve at most the target level, achieve at least the target level and achieve the target level. A constraint is a restriction on the decision variables that must be satisfied in order to implement the solution in practice (Tamiz (2009)). This is different from the concept of a goal whose non-achievement does no automatically make the solution non implementable.

The first Goal Programming (GP) formulation was proposed by Charnes et al. (1955). At that period the term goal programming was not used as a model, but considered as an adaptation of the linear programming. After six years the theory of the GP was defined by Charnes and Cooper (1961), then by Ijiri (1965), Lee (1972) and Ignizio (1976), Romero (1991), Jones et al. (1995) and Tamiz (2009).

According to Field (1973), the formulation of goal programming is characterised by one or more goals which are directly incorporated in the objective function, through deviation variables, that is, the objectives are written in the form of goals restrictions, where each goal represents the value that intends to be reached. The goals can or not be reached completely and, to allow this flexibility, deviation variables are used δ^+ and δ^-, indicating how much the objective was surpassed or was lacked by that value respectively. Goal programming searches a form of reaching the goals as closest as possible; the objective of this technique is to minimize the sum of all the goal deviations.

There are several methods for specifying the corresponding weight values in GP, as detailed by Ringuest (1992). Gass (1986) explained how a link can be established between the Analytical Hierarchy Process (AHP) and GP. In fact, the weights derived from the pairwise comparison of AHP can be incorporated directly into a GP model. Gass (1986) also showed that in some cases the normalising weight is simply part of the whole weight that is absorbed by the AHP weight determination. To model a multi-objective decision making problem aiming at selecting the best warehouses, William (2007) combined the AHP and goal programming. The AHP is used to give weights or priorities to the warehouses based on two conflicting criteria; customer satisfaction level and operational cost. These weights are incorporated in a GP model that considers system and goal constraints.

4.2.1 Normalisation Techniques

Incommensurable in a GP model, occurs when deviation variables measured in different units are summed up directly. This simple summation will cause a deviation towards the objectives with a larger magnitude. This deviation may lead to erroneous or misleading results.

To overcome incommensurable in GP, researchers proposed the use of normalisation techniques. One suggestion to overcome this difficulty, is to divide each objective through by a normalising constant ($_i$) pertaining to that objective, as shown in model (4.5). This ensures that all objectives have roughly the same magnitude.

We are now able to show a simple achievement function of GP as follows:

$$Min \quad \sum_{i=1}^{n} \omega_i (\frac{\delta_i^+ + \delta_i^-}{k_i}) \tag{4.1}$$

$$s.t \quad f_i(X) + \delta_i^- - \delta_i^+ = g_i \qquad i = 1, 2, ..., n. \tag{4.2}$$

$$\delta_i^+, \delta_i^- \geq 0 \qquad i = 1, 2, ..., n. \tag{4.3}$$

$$x \in F \qquad . \tag{4.4}$$

$$\tag{4.5}$$

where ω_i is the weight of the i-th goal; $f_i(X)$ is the linear function of $\{x_i, x_2, \cdots, x_n\}$ for the ith goal, g_i is the aspiration level of the ith goal, δ_i^+ and δ_i^- are positive and negative deviations from the target value of the ith goal, respectively. $_i$ are normalising constants of the i-th goal; F is a feasible set.

We will next discuss an application case to which this approach applies.

4.3 Problem Formulation

We start by introducing the SC problem that we have studied in Chapter 3, which is : multi-level, multi-modal, multi-objective, single product and single period Supply Chain Network (SCN). As before, The SCN contains four layers: suppliers, storage depots, treatment facilities and customers. As illustrated in Figure 6.5, products are shipped

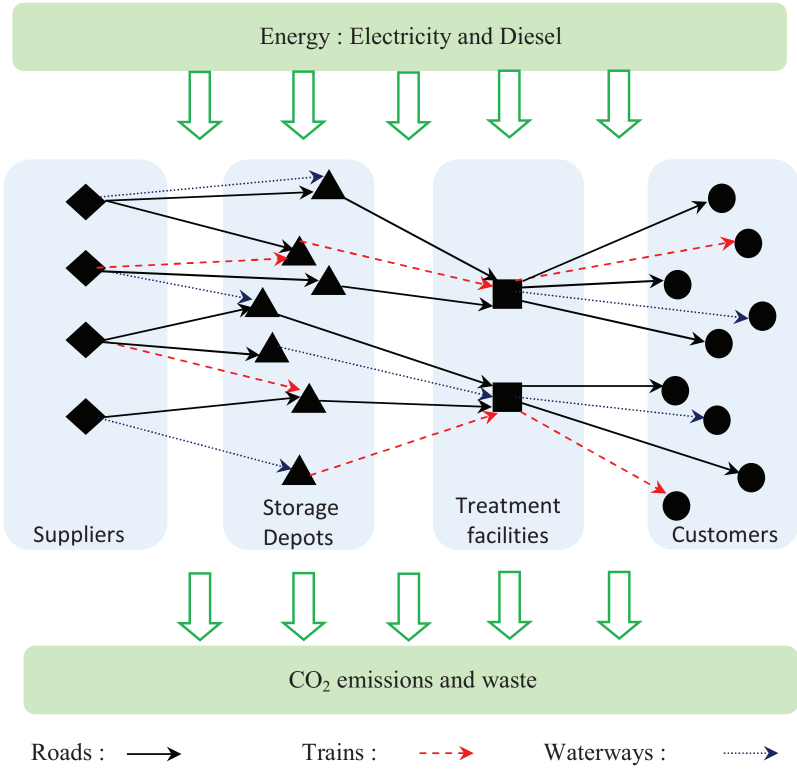

Figure 4.1: Supply Chain Network

from suppliers to storage depots, and after that, they are transported to treatment facility. The treatment facilities insure the treatment and the distribution of products to customers. Before formulating the model, some assumptions are accepted: Customers demand and suppliers quantity are assumed to be known. The wastes are generated only by the treatment facilities. The energy consumption depends on the transportation mode used and the technology of the treatment facility. The CO_2 emissions depends on the transportation modes and technology of treatment facility. For more details, see chapter 3.

The suppliers, storage depots, treatment facility, customers and transportation modes are defined through the following sets:

I supplier locations set, indexed by i.

J storage depot locations set, indexed by j.

K potential treatment facility locations set, indexed by k.

L customer locations set, indexed by l.

M transportation modes set, indexed by m.

N building technologies set, indexed by n.

P goal level set, indexed by p.

Each goal should be assigned a weight γ_i to represent its importance and a goal value g_i that required to be achieved. The deviation variables of the goals are δ_i^+ and δ_i^+. The unit transportation costs of goods between supplier i and storage depot j using transportation mode m is μ_{ijm}, the unit transportation costs of goods between storage depot j and treatment facility k using transportation mode m is μ_{jkm} and μ_{klm} represents the unit transportation costs of goods between treatment facility k and customer l using transportation mode m.

ϑ_{ijm} is the distance between supplier i and storage depot j using transportation mode m. ϑ_{jkm} represents distance between storage depot j and treatment facility k using transportation mode m. ϑ_{klm} represents distance between treatment facility k and customer l using transportation mode m.

β_m denotes the unit CO_2 emission using transportation mode m. The unit CO_2 emission in treatment facility k with building technology n is β_{kn}. Energy consumption parameters are ρ_m and γ_{kn}. The first one represents the unit energy consumption costs using transportation mode m and the second one denotes the unit energy consumption costs using treatment facility k with building technology n. η_{kn} denotes the unit waste treatment costs in treatment facility j with building technology n. γ is the environmental taxes. D_l denotes the demand of the customer l.

In our problem, we consider two types of decision variables: treatment facility location decisions will be taken based on the binary variables x_{kn} that indicate whether treatment facility k with building technology n is selected or not. Whereas, material flow related decisions will be taken according to the value of the variables q_{ijm} which is the quantity of products transported from node i to node j using transportation mode m.

4.3.1 Mathematical Model

In this section we will show the mathematical formulation of the inland waterways sediments treatment supply chain network.

We explicitly consider two objective functions: ϕ_1 measures the total cost (4.6) and ϕ_2

represents the total CO_2 emission in all the supply chain network (4.7).

$$\phi_1 : Min \quad OC + TC + LC + ECC + WTC \tag{4.6}$$

$$\phi_2 : Min \quad COE \tag{4.7}$$

Where

- Opening Costs (*denoted* OC):

$$OC = \sum_{k \in K} \sum_{n \in N} (CO_{kn} \cdot x_{kn}) \tag{4.8}$$

- Transportation Costs (*denoted* TC):

$$TC = \left[\sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \mu_{ijm} \cdot q_{ijm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \mu_{jkm} \cdot q_{jkm} + \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} \mu_{klm} \cdot q_{klm} \right] \tag{4.9}$$

- Logistic Costs (*denoted* LC):

$$LC = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} CS_j \cdot q_{ijm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} CT_k \cdot q_{jkm} \tag{4.10}$$

- Energy Consumption Costs (*denoted* ECC):

$$\begin{aligned} ECC = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \rho_m \cdot \vartheta_{ijm} \cdot q_{ijm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \rho_m \cdot \vartheta_{jkm} \cdot q_{jkm} + \\ \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} \rho_m \cdot \vartheta_{klm} \cdot q_{klm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \sum_{n \in N} \gamma_{kn} \cdot q_{jkm} \end{aligned} \tag{4.11}$$

- Waste Treatment Costs (*denoted* WTC):

$$WTC = \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \sum_{n \in N} \eta_{kn} \cdot q_{jkm} \tag{4.12}$$

- Total CO_2 emissions (*denoted* COE):

$$\begin{aligned} COE = \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \beta_m \cdot \vartheta_{ijm} \cdot q_{ijm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \beta_m \cdot \vartheta_{jkm} \cdot q_{jkm} + \\ \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} \beta_m \cdot \vartheta_{klm} \cdot q_{klm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \sum_{n \in N} \beta_{kn} \cdot q_{jkm} \end{aligned} \tag{4.13}$$

Subject to

Constraint (4.14) limits CO_2 emissions quantities.

$$\begin{aligned} \sum_{i \in I} \sum_{j \in J} \sum_{m \in M} \beta_m \cdot \vartheta_{ijm} \cdot q_{ijm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \beta_m \cdot \vartheta_{jkm} \cdot q_{jkm} + \\ \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} \beta_m \cdot \vartheta_{klm} \cdot q_{klm} + \sum_{j \in J} \sum_{k \in K} \sum_{m \in M} \sum_{n \in N} \beta_{kn} \cdot q_{jkm} \le COE^{max} \end{aligned} \tag{4.14}$$

Constraint (4.15) limits the energy consumption.

$$\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\rho_m\cdot\vartheta_{ijm}\cdot q_{ijm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\rho_m\cdot\vartheta_{jkm}\cdot q_{jkm}+$$
$$\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\rho_m\cdot\vartheta_{klm}\cdot q_{klm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\gamma_{kn}\cdot q_{jkm}\leq ECC^{max} \tag{4.15}$$

Constraint (4.16) guarantees that the demand of the customers will be satisfied.

$$\sum_{k\in K}\sum_{m\in M}q_{klm}=D_l \qquad \forall l\in C \tag{4.16}$$

Constraint (4.17) imposes a capacity restriction for each storage depot.

$$\sum_{i\in I}\sum_{m\in M}q_{ijm}\leq Q_j \qquad \forall j\in J \tag{4.17}$$

Constraint (4.18) limits the capacity of the treatment facilities.

$$\sum_{j\in J}\sum_{m\in M}q_{jkm}\leq Q_k\cdot x_{kn} \qquad \forall k\in K,\forall n\in N \tag{4.18}$$

Constraints (4.19), (4.20) enforce the flow conservation of the product.

$$\sum_{i\in I}\sum_{m\in M}q_{ijm}=\sum_{k\in K}\sum_{m\in M}q_{jkm} \qquad \forall j\in J \tag{4.19}$$

$$\sum_{j\in J}\sum_{m\in M}q_{jkm}=\sum_{l\in L}\sum_{m\in M}q_{klm} \qquad \forall k\in K \tag{4.20}$$

Constraints (4.21), (4.22), (4.23) impose a capacity restriction of each mode of transport throughout the network.

$$q_{ijm}\leq Q_{ijm} \qquad \forall i\in I,\forall j\in J,\forall m\in M \tag{4.21}$$

$$q_{jkm}\leq Q_{jkm} \qquad \forall j\in J,\forall k\in K,\forall m\in M \tag{4.22}$$

$$q_{klm}\leq Q_{klm} \qquad \forall k\in K,\forall l\in L,\forall m\in M \tag{4.23}$$

Constraint (4.24) enforces the binary nature of the configuration decisions for the facilities.

$$x_{kn}\in\{0,1\} \qquad \forall k\in K,\forall n\in N \tag{4.24}$$

Constraints (4.25), (4.26), (4.27) are standard integrality and non-negativity constraints.

$$q_{ijm}\geq 0 \qquad \forall i\in I,\forall j\in J,\forall m\in M \tag{4.25}$$

$$q_{jkm}\geq 0 \qquad \forall j\in J,\forall k\in K,\forall m\in M \tag{4.26}$$

$$q_{klm}\geq 0 \qquad \forall k\in K,\forall l\in L,\forall m\in M \tag{4.27}$$

4.3.2 Goal Programming Model

Among the different approaches available to solve the multi-objective supply chain network design, the GP method seems to be the most promising.

Goal Programming approach were used seeking to reach the following goals: g_1, g_2, g_3 and g_4 placed by the Decision Maker.

The first goal (4.30) seeks assigning as at most total costs target level g_1 (€). The second goal (4.31) aims to achieve at most the energy consumption target level g_2 (€). The third goal (4.31) aims to achieve at most the waste treatment cost target level g_3 (€). The fourth goal (4.32) seeks achieve at most the CO_2 emissions target level g_4 (T).

Objective function (4.28) aims at minimizing the deviations from the goals g_1, g_2, g_3 and g_4.

$$Min \quad \sum_{p\in P} \omega_p \left(\frac{\delta_p^+ + \delta_p^-}{k_p}\right) \tag{4.28}$$

where ω_p is the weight of the p-th goal and k_p is a constant ensures that all objectives have roughly the same magnitude.

Subject to

Total cost goal level (denoted by g_1).

$$\begin{aligned}
&\sum_{k\in K}\sum_{n\in N}(CO_{kn}\cdot x_{kn}) + \sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\mu_{ijm}\cdot q_{ijm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\mu_{jkm}\cdot q_{jkm} + \\
&\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\mu_{klm}\cdot q_{klm} + \sum_{i\in I}\sum_{j\in J}\sum_{m\in M} CS_j\cdot q_{ijm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M} CT_k\cdot q_{jkm} + \\
&\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\rho_m\cdot\vartheta_{ijm}\cdot q_{ijm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\rho_m\cdot\vartheta_{jkm}\cdot q_{jkm} + \\
&\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\rho_m\cdot\vartheta_{klm}\cdot q_{klm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\gamma_{kn}\cdot q_{jkm} + \\
&\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\eta_{kn}\cdot q_{jkm} + \delta_1^- - \delta_1^+ = g_1
\end{aligned} \tag{4.29}$$

Energy Consumption Costs goal (denoted by g_2).

$$\begin{aligned}
&\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\rho_m\cdot\vartheta_{ijm}\cdot q_{ijm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\rho_m\cdot\vartheta_{jkm}\cdot q_{jkm} + \\
&\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\rho_m\cdot\vartheta_{klm}\cdot q_{klm} + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\gamma_{kn}\cdot q_{jkm} + \delta_2^- - \delta_2^+ = g_2
\end{aligned} \tag{4.30}$$

Waste treatment Costs goal (denoted by g_3).

$$\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\eta_{kn}\cdot q_{jkm} + \delta_3^- - \delta_3^+ = g_3 \tag{4.31}$$

Total CO_2 emissions goal (denoted by g_4).

$$\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\beta_m\cdot\vartheta_{ijm}\cdot q_{ijm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\beta_m\cdot\vartheta_{jkm}\cdot q_{jkm}+ \tag{4.32}$$
$$\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\beta_m\cdot\vartheta_{klm}\cdot q_{klm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\beta_{kn}\cdot q_{jkm}+\delta_4^- - \delta_4^+ = g_4$$

Constraint (4.33) limits CO_2 emissions.

$$\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\beta_m\cdot\vartheta_{ijm}\cdot q_{ijm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\beta_m\cdot\vartheta_{jkm}\cdot q_{jkm}+ \tag{4.33}$$
$$\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\beta_m\cdot\vartheta_{klm}\cdot q_{klm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\beta_{kn}\cdot q_{jkm}\le COE^{max}$$

Constraint (4.35) limits Energy consumption.

$$\sum_{i\in I}\sum_{j\in J}\sum_{m\in M}\rho_m\cdot\vartheta_{ijm}\cdot q_{ijm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\rho_m\cdot\vartheta_{jkm}\cdot q_{jkm}+ \tag{4.34}$$
$$\sum_{k\in K}\sum_{l\in L}\sum_{m\in M}\rho_m\cdot\vartheta_{klm}\cdot q_{klm}+\sum_{j\in J}\sum_{k\in K}\sum_{m\in M}\sum_{n\in N}\gamma_{kn}\cdot q_{jkm}\le ECC^{max}$$

Constraint (4.35) guarantees that the demand of the customers will be satisfied.

$$\sum_{k\in K}\sum_{m\in M}q_{klm}=D_l \qquad \forall l\in C \tag{4.35}$$

Constraint (4.36) imposes a capacity restriction for each storage depot.

$$\sum_{i\in I}\sum_{m\in M}q_{ijm}\le Q_j \qquad \forall j\in J \tag{4.36}$$

Constraint (4.37) limits the capacity of the treatment facilities.

$$\sum_{j\in J}\sum_{m\in M}q_{jkm}\le Q_k\cdot x_{kn} \qquad \forall k\in K,\forall n\in N \tag{4.37}$$

Constraints (4.38), (4.39) enforce the flow conservation of the product.

$$\sum_{i\in I}\sum_{m\in M}q_{ijm}=\sum_{k\in K}\sum_{m\in M}q_{jkm} \qquad \forall j\in J \tag{4.38}$$

$$\sum_{j\in J}\sum_{m\in M}q_{jkm}=\sum_{l\in L}\sum_{m\in M}q_{klm} \qquad \forall k\in K \tag{4.39}$$

Constraints (4.40), (4.41), (4.42) impose a capacity restriction of each mode of transport throughout the network.

$$q_{ijm} \leq Q_{ijm} \qquad \forall i \in I, \forall j \in J, \forall m \in M \tag{4.40}$$

$$q_{jkm} \leq Q_{jkm} \qquad \forall j \in J, \forall k \in K, \forall m \in M \tag{4.41}$$

$$q_{klm} \leq Q_{klm} \qquad \forall k \in K, \forall l \in L, \forall m \in M \tag{4.42}$$

Constraint (4.43) enforces the binary nature of the configuration decisions for the facilities.

$$x_{kn} \in \{0, 1\} \qquad \forall k \in K, \forall n \in N \tag{4.43}$$

Constraints (4.44), (4.45), (4.46) are standard integrality and non-negativity constraints.

$$q_{ijm} \geq 0 \qquad \forall i \in I, \forall j \in J, \forall m \in M \tag{4.44}$$

$$q_{jkm} \geq 0 \qquad \forall j \in J, \forall k \in K, \forall m \in M \tag{4.45}$$

$$q_{klm} \geq 0 \qquad \forall k \in K, \forall l \in L, \forall m \in M \tag{4.46}$$

Constraint (4.47)Positive and negative deviational variable for i-th goal.

$$\delta_p^+, \delta_p^- \geq 0 \qquad \forall p \in P \tag{4.47}$$

In the next section, we will give computational results of this model, as well as the interpretation and analyse of the results.

4.4 Computational Results

In order to be able to analyse the behaviour of the optimal SC configuration, we will first derive a general multi-objective results.

Experiments were performed using a computer with 2 GHz Windows Vista 2 GHz Core 2 Due PC and 3 GB RAM. Both models are coded using ILOG OPL 6.3 and solved using CPLEX 12.1. The solver is set to solve integer problems using branch-and-bound algorithm .

Before we describe our results, we first briefly discuss how we determine the Goal Programming weights.

4.4.1 Goal Programming weights

To determine the corresponding weight values in GP, we used AHP method (see, section 3.3.1). The weights of each goal can be observed in Table 4.1. These values are fixed by the Decision Maker (DM).

As shown in Table 4.1, the number 1 indicates the equal importance of the goals. The

Table 4.1: The Goal Programming weights

	g_1	g_2	g_3	g_4	Weights
g_1	1	0.33	0.25	4	0.16
g_2	3	1	1	6	0.39
g_3	4	1	1	3	0.37
g_4	0.25	0.17	0.33	1	0.08
Total	8.25	2.50	2.58	14	1

number 3, indicates that g_2 is moderately important than g_1. The scale 4, indicates that g_3 is considerably more important than g_1. Finally, 6 indicates that g_2 is strongly more important than g_4. The weight of total cost criterion g_1 is equal to 0.16 and the weight of CO_2 emission g_3 is equal to 0.37. This means, ω_1 = 0.16, ω_2 = 0.39, ω_3 = 0.37 and ω_4 = 0.08.

We are now ready to start the resolution of our model.

4.4.2 Solutions

In this section, we will employ the classical approach to determine the optimal structure of the problem and to have an idea about the different goal level. It is well-known that there exist multiple non-dominated solutions for a multi-objective optimization problem. Those solutions are called *Pareto optimal* solutions.

First of all, the bi-objective model (4.6)-(4.27) has two objective functions, the objective value of these two functions are represented by ϕ_1 and ϕ_2, respectively. Then, we solve the Model (4.6)-(4.27) with each objective function separately and get the objective value ϕ_1^* and ϕ_2^* corresponding to objective one and two, respectively. Finally, we generate the corresponding Pareto point set.

As summarized in Table 4.2, we increase the CO_2 emissions value from 120 to 10 000. The first column shows the CO_2 emissions (CO_2), the second column shows the value of the objective function (Obj), then the potential facility locations (S_i), the eighth is the percentage of goods transported using waterways (W), the ninth is the percentage of products shipped using roads as transportation mode (R), and the last column is the percentage of goods transported using the train (T).

In Table 4.2, we generate the Pareto frontier which can provide the decision maker an idea about the alternative optimal solutions. It clearly demonstrates the trade-off between the total cost and the total CO_2 emission. It coincides with our logic that a lower CO_2 emission can only be reached by putting more investment. For example, the investment necessary to design the supply chain network with $g_3 = 120$ (T) is 94 859 779 (€). The table also shows that, in general, the number of facilities to open go up, decreasing the total CO_2 emission. This is due to reduction of transportation distances between logistic actors when we open more treatment facilities. Furthermore, in almost all cases the green treatment facilities (S_2 or S_4) are not selected. We should open two green treatment facilities for experiment with total CO_2 emission equal to 120 (T) and one green treatment facility for instances with total CO_2 emission between 130 and 150 (T). It's clear that if we don't integrate the CO_2 emission in the objective function, we will never choose to open green facilities because of the high investment cost comparing to the traditional ones.

According to these results, the DM fixed the goal levels as fellows: $g_1 = 60\,000\,000$ (€), $g_2 = 370\,000$ (€), $g_3 = 4\,500\,000$ (€), $g_4 = 250$ (T).

It can be noted in Figure 4.2 that the percentage of goods shipped using rails (T%) and roads (R%) decrease, as consequence of increasing the CO_2 emission value. While, the percentage of waterways (W%) used is incremented (from 25% to 93%) due to the CO_2 emission value rise.

4.4.3 Sensitivity Analysis

Since generally, decision makers cannot fix correctly the exact values of weights and goal levels, it is important to know the influence they have on the results when some changes occur in their values. More clearly, the robustness of the results must be demonstrated.

Table 4.2: Solutions

		Potential facilities					Transportation mode		
CO_2 (T)	Obj(€)	S_1	S_2	S_3	S_4	S_5	W (%)	R (%)	T (%)
120	94 859 779	1	1	1	1	0	25%	17%	58%
130	74 122 738	1	0	1	1	0	29%	17%	54%
140	59 143 025	1	1	0	0	0	37%	9%	55%
150	59 128 842	1	0	0	1	0	24%	13%	63%
160	56 132 771	1	0	1	0	0	21%	10%	69%
170	56 128 527	1	0	1	0	0	24%	6%	70%
180	56 127 934	1	0	1	0	0	25%	6%	69%
190	56 103 496	1	0	0	0	1	33%	12%	55%
200	56 083 323	1	0	0	0	1	33%	12%	55%
300	56 073 586	1	0	0	0	1	37%	17%	46%
400	56 083 612	1	0	0	0	1	44%	17%	39%
500	56 096 567	1	0	0	0	1	41%	25%	34%
600	56 110 390	1	0	0	0	1	39%	31%	30%
700	56 124 249	1	0	0	0	1	55%	6%	39%
800	56 138 139	1	0	0	0	1	55%	8%	38%
900	56 152 182	1	0	0	0	1	55%	9%	35%
1 000	56 166 444	1	0	0	0	1	58%	10%	32%
1 500	56 244 119	1	0	0	0	1	53%	19%	28%
2 000	56 323 797	1	0	0	0	1	55%	17%	28%
3 000	56 483 513	1	0	0	0	1	59%	13%	28%
4 000	56 643 206	1	0	0	0	1	64%	8%	28%
5 000	56 837 725	0	0	1	0	1	93%	7%	0%
6 000	57 070 118	1	0	0	0	1	93%	7%	0%
8 000	57 527 431	1	0	0	0	1	93%	7%	0%
9 000	57 757 436	0	0	1	0	1	93%	7%	0%
10 000	57 987 278	1	0	0	0	1	93%	7%	0%

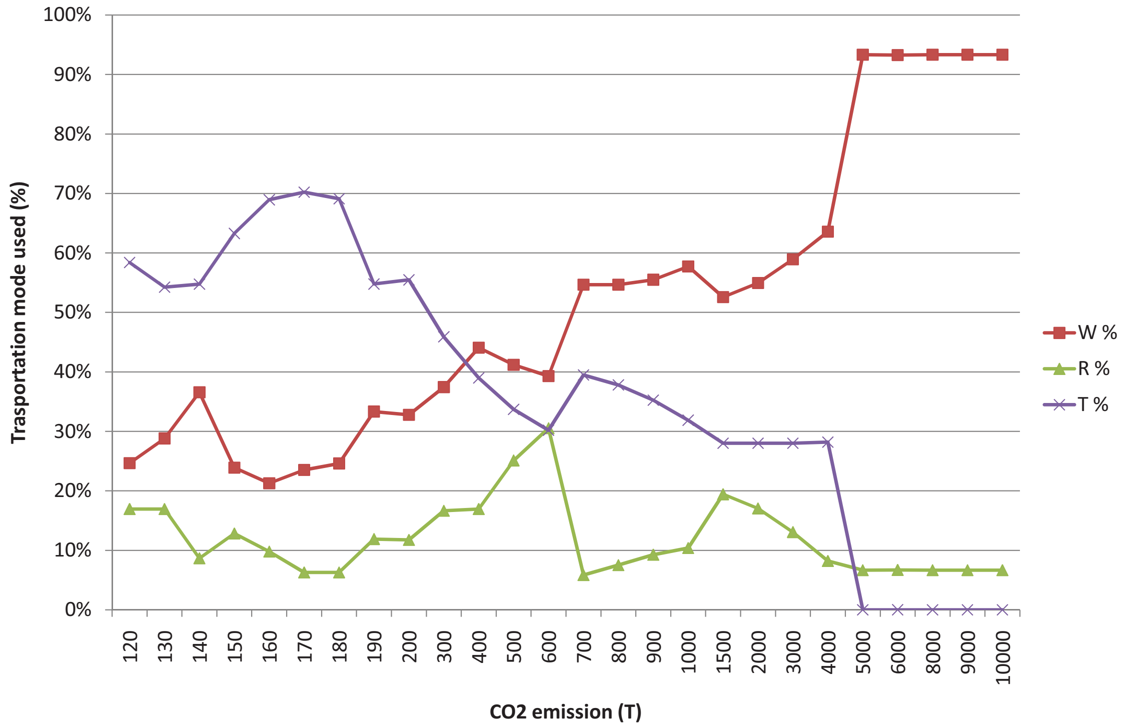

Figure 4.2: Transportation mode used (%)

Therefore, an important step in many applications of multi-objective decision making is to perform a sensitivity analysis on these parameters. Let's start with ω_i weights variation

ω_i variation

In order to show the sensitivity of the numerical solution with respect to the values of ω_i, we conduct experiments with ω_i variation. Table 4.3 focuses only on the results of 10 generated instances, where ω_i values are not far from the ones fixed previously by the Decision Maker (see Table 4.1). According to the obtained values of ω_i using AHP, ω_1 is varied from 0.1 to 0.5, ω_2 is varied from 0.1 to 0.7, ω_3 is increased from 0.1 to 0.6 and ω_4 is varied from 0.1 to 0.2. When ω_i are varied manually the others parameters are fixed : $g_1 = 60\,000\,000$ (€), $g_2 = 370\,000$ (€), $g_3 = 4\,500\,000$ (€), $g_4 = 250$ (T).

In all cases, we obtained the same supply chain structure composed of two treatment facilities $\{S_1, S_4\}$ a traditional treatment facility S_1 and a green facility S_4 (see, Table 4.3). In instance 4, we have the same SC configuration and a small variation in the percentages of the transportation modes used. The waterways use decrease from 55% to

Table 4.3: Sensitivity

ω_i variation				Potential facilities					Transportation mode		
ω_1	ω_2	ω_3	ω_4	S_1	S_2	S_3	S_4	S_5	W (%)	R(%)	T(%)
0,1	0.4	0.4	0.1	1	0	0	1	0	55%	17%	28%
0.1	0.3	0.5	0.1	1	0	0	1	0	55%	17%	28%
0.1	0.2	0.6	0.1	1	0	0	1	0	55%	17%	28%
0.2	0.1	0.6	0.1	1	0	0	1	0	49%	8%	43%
0.3	0.2	0.4	0.1	1	0	0	1	0	55%	17%	28%
0.4	0.2	0.3	0.1	1	0	0	1	0	55%	17%	28%
0.5	0.2	0.2	0.1	1	0	0	1	0	55%	17%	28%
0.1	0.5	0.2	0.2	1	0	0	1	0	55%	17%	28%
0.1	0.6	0.1	0.2	1	0	0	1	0	55%	17%	28%
0.1	0.7	0.1	0.1	1	0	0	1	0	16%	5%	80%

49%, the roads use decrease from 17% to 8% and the rail use go up from 28% to 43%.
As a result of our computational study on the ω_i variation (Table 4.3), we observed that the variation on the ω_i does not have significant effect neither on the number of facilities to open nor on transportation mode to use. Therefore, in this case study, it can be concluded that small fluctuations in the choice of ω_i would not significantly influence the results.

Total costs goal g_1 variation

In this section, we show the sensitivity of the numerical solution with respect to the g_1 values. We increased the total cost from 40 000 000 (€) to 90 000 000 (€).
As summarized in Table 4.4, we generate eleven instances where the first column shows the total cost goal level (g_1), the second column shows the real total cost goal level (g_1*) calculated by the model, then the potential facility locations (S_i). According to the results showed in Table 4.4, increasing g_1 the number of opened sites increase from 2 facilities to four sites to open. The table also shows that, changing g_1 value, we obtain other SC configuration. For example, for g_1=40 000 000 (€) the proposed SC configuration is $\{S_3, S_5\}$, for g_1=60 000 000 (€) the sites to open are $\{S_1, S_4\}$ and for g_1=90 000 000 (€) the proposed SC structure is $\{S_1, S_3, S_4, S_5\}$. The Figure 4.3 clearly shows that, the proposed

Table 4.4: Total costs goal g_1 variation

g_1 variation		Potential facilities					Transportation mode		
g_1	g_1*	S_1	S_2	S_3	S_4	S_5	W(%)	R(%)	T(%)
40 000 000	59 150 000	0	0	1	1	0	82%	2%	16%
45 000 000	59 150 000	0	0	1	1	0	82%	2%	16%
50 000 000	59 150 000	0	0	1	1	0	81%	2%	17%
55 000 000	59 150 000	0	0	1	1	0	82%	2%	16%
60 000 000	60 000 000	1	0	0	1	0	55%	17%	28%
70 000 000	74 096 000	1	0	0	1	1	71%	2%	26%
80 000 000	80 014 000	0	1	0	1	1	69%	2%	29%
90 000 000	90 000 000	1	0	1	1	1	64%	12%	24%

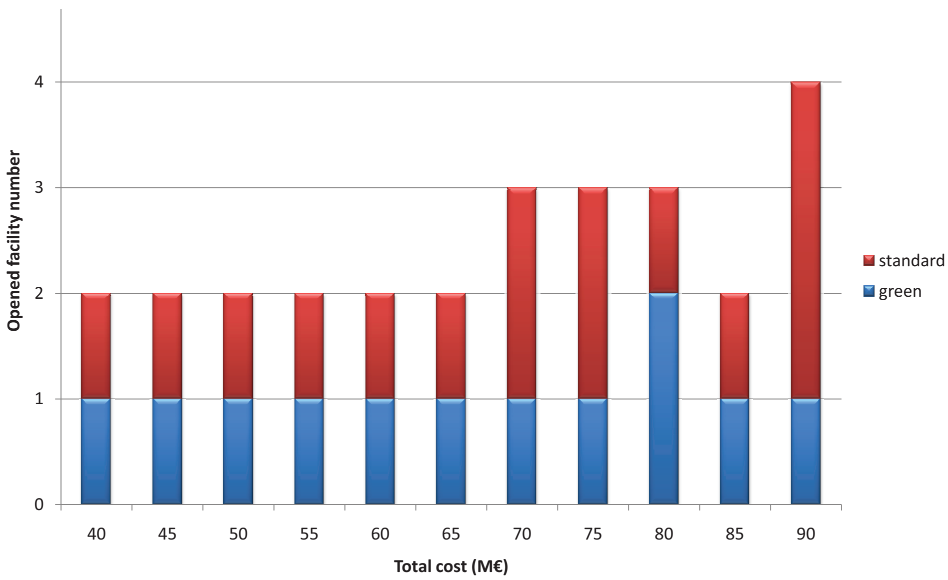

Figure 4.3: Number of opened facilities

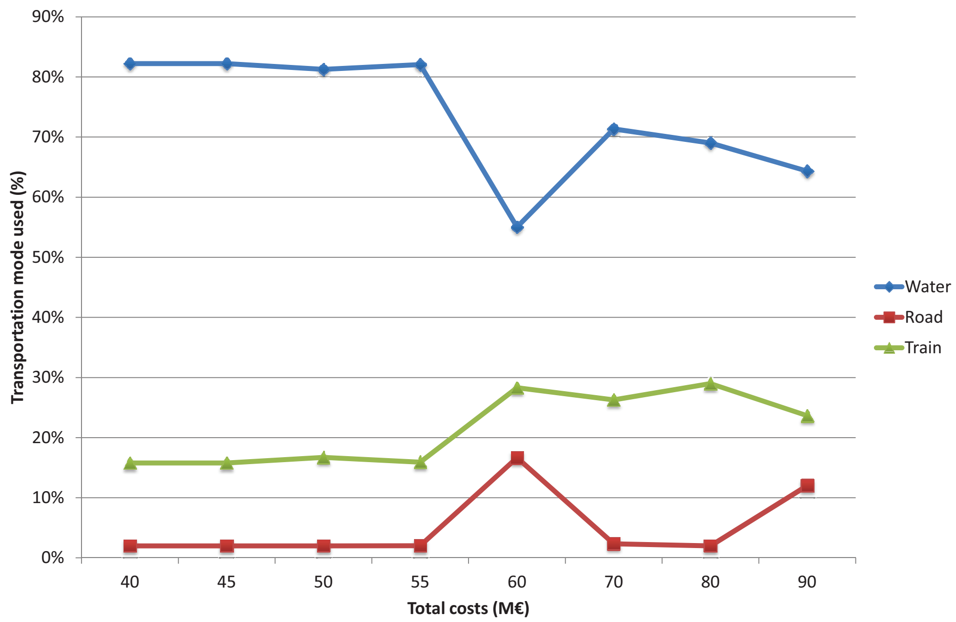

Figure 4.4: Total costs goal g_1 variation

SC configuration of all instances contain at least one green treatment facility. It seems that, the presence of a green treatment facility in all solutions, is due to the CO_2 emission goal value fixed to 250 (T), the energy consumption goal and the waste treatment goal.

Figure 4.4 shows that increasing the total cost value g_1, the percentage of goods shipped using rails (T%) and roads (R%) goes up.

Energy consumption goal g_2 variation

We now consider how the supply chain configuration and the transportation modes used behave as the g_2 level varies, which can be seen in Table 4.5. In this case g_2 varied from 3 500 000 (€) to 6 500 000 (€).

The optimal SC structure of each instance are illustrated in Table 4.5. It is found that 2 facilities are built up. They are $\{S_1, S_4\}$ or $\{S_2, S_5\}$, and in each solution we found a green site to build (S_2 or S_4). According to the results presented in Table 4.5, increasing the goal level g_2, the percentage of goods transported using waterways transportation mode decreases from 55% to 15%, the percentage of products shipped using roads transportation mode goes down from 17% to 0% and the use of rail to transport the goods rises from 28% to 85% (see, Figure 4.5).

Table 4.5: Energy consumption goal g_2 variation

g_2 variation		Potential facilities					Transportation mode		
g_2	g_2*	S_1	S_2	S_3	S_4	S_5	W(%)	R(%)	T(%)
3 500 000	4 552 000	1	0	0	1	0	55%	17%	28%
4 000 000	4 552 000	1	0	0	1	0	55%	17%	28%
4 500 000	4 550 000	1	0	0	1	0	55%	17%	28%
5 000 000	5 000 000	1	0	0	1	0	61%	20%	18%
5 500 000	5 500 000	0	1	0	0	1	15%	1%	84%
6 000 000	5 610 800	0	1	0	0	1	15%	0%	85%
6 500 000	5 610 800	0	1	0	0	1	15%	0%	85%

CO_2 emissions goal g_4 variation

The final aspect studied is CO_2 emissions variation impact on the supply chain structure. In this case, the carbon goal will increase (Figure 4.6) and all other parameters are fixed. As summarized in Table 4.6, we increase g_4 value from 100 to 15 000. The first column shows the CO_2 emission goal level (g_4), the second the real CO_2 emission goal level (g_4*) considered by the model and the rest of the columns have the same signification as in Tables presented before.

Regarding the computational results, it is important to note the following. As shown in Table 4.6 the number of facilities opened, is always equal to 2 sites and for each instance the solution contains at least a green building (S_2 or S_4), due to the impact of g_2 and g_4 goals, fixed by DM which forces the supply chain to use the green technology. Also, increasing the g_4 the use of waterways to transport goods increase from 39% to 100%, the percentage of goods transported using roads fluctuate between 0% and 58%, and the percentage of products shipped using train go down from 46% to 0%. Based on these results, we can conclude that g_4 value has influence in the SC configuration and the transportation mode to use.

Figure 4.6 confirms that the g_4 value variation has influence on the transportation mode selected.

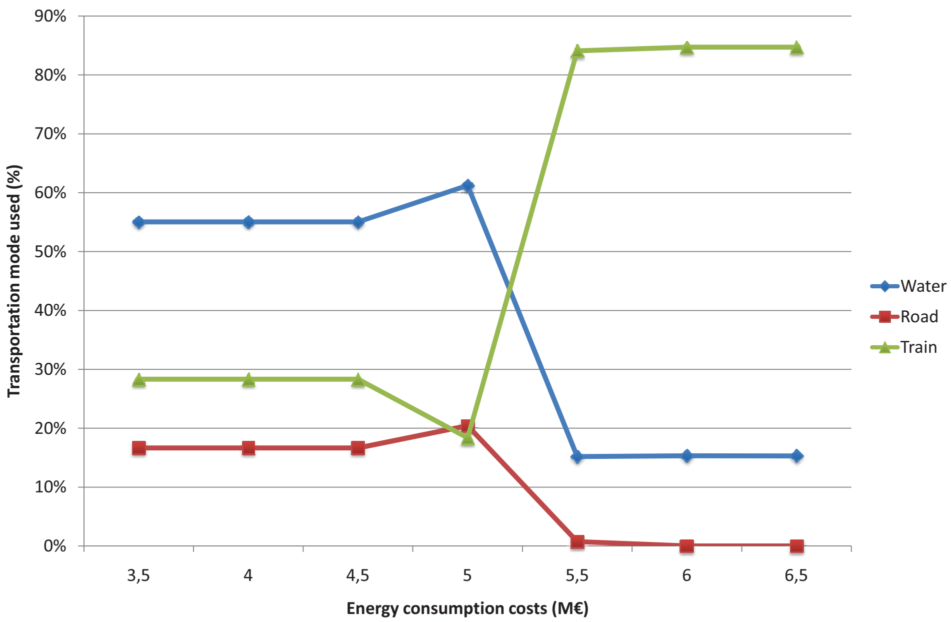

Figure 4.5: Energy Consumption Costs

Table 4.6: CO_2 emissions goal g_4 variation

g_4 variation		Potential facilities					Transportation mode		
g_4	g_4*	S_1	S_2	S_3	S_4	S_5	W (%)	R (%)	T(%)
100	140.75	1	0	0	1	0	39%	15%	46%
150	150	1	0	0	1	0	37%	15%	48%
200	200	1	0	0	1	0	50%	15%	35%
250	250	1	0	0	1	0	55%	17%	28%
300	300	0	1	1	0	0	57%	12%	32%
400	400	0	0	1	1	0	78%	12%	10%
500	500	0	0	1	1	0	80%	13%	7%
1 000	1 000	0	0	0	1	1	42%	58%	0%
1 500	1 500	0	1	0	0	1	38%	48%	13%
2 000	2 000	0	0	0	1	1	80%	20%	0%
3 000	3 000	0	0	0	1	1	48%	52%	0%
4 000	4 000	0	0	0	1	1	51%	49%	0%
5 000	5 000	0	0	0	1	1	91%	9%	0%
10 000	10 000	0	1	0	1	0	41%	0%	59%
15 000	15 000	0	1	0	1	0	100%	0%	0%

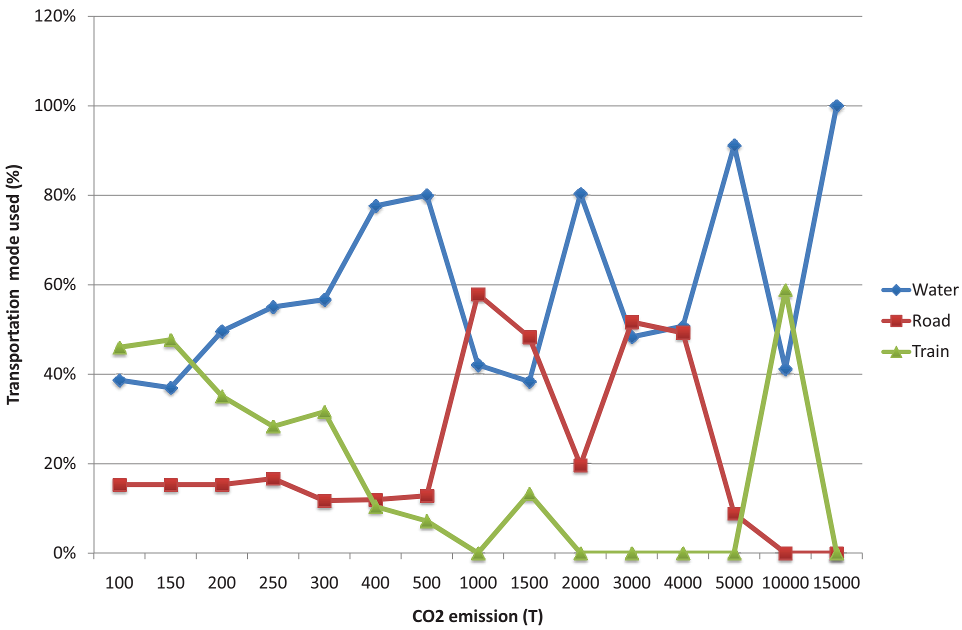

Figure 4.6: CO_2 emissions

4.5 Conclusions

In this Chapter, a multi-objective supply chain network design problem is addressed. The problem is formulated as a goal programming model which aims at achieving four objectives. The model represents a real case of supply chain network of an inland waterways company in France. In this work, an approach for designing environmental SC has been presented. The model consisted of a multi-objective optimization of economics and environmental goals. The model considered the long-term strategic decisions: treatment facility location, transportation modes and material flux.

Sensitivity analysis for the case study is conducted and we check that, improving the building technology and increasing the facility number in the supply chain can decrease CO_2 emission of the whole network. Regarding to the influence of some parameters on the SC configuration and transportation mode used, we find that small variability of goals weight ω_i does not affect the solution of our case study.

Finally, in next chapter, we will present a heuristic to solve large scale SCND problems.

Chapter 5

Heuristic Approach to large scale Supply Chain Network Design Problem

The Supply Chain Network (SCN) should be designed in the way that could meet the customer needs with an efficient cost. Nowadays, the structure of the supply chain network is complex and has a considerable size. However, Supply Chain Network Design (SCND) problems are hard to solve. Such network design problems belong to the class of NP-hard problems, as several other well-known NP-hard facility location problems(Bloemhof-Ruwaard et al. (1994), Cornuejols et al. (1991)).

In this chapter, a novel heuristic solution method is developed based on a decomposition technique, to solve large scale supply chain network design problems. This solution method, specifically, designed for real size SCN problems that exact methods failed to solve. The heuristic method is tested on real case instances, and it is compared to an exact method in solving small instances. Results show that our heuristic outperforms the exact method in terms of computational time and the size of problems solved.

5.1 Introduction

As we said in chapter 2, for small size supply chain network design problems, exact methods, such as Branch-and-Bound can be used to solve these problems. For large scale ones, exact methods fail because the size of the solution space increases exponentially with the number of constraints and variables in the network. In these cases heuristics methods based on Lagrangian relaxation (Pirkul and Jayaraman (1997), Fisher (1985)), Bender decomposition (Geoffrion and Graves (1974), Benders (1962)), Decomposition techniques (Sahina and Saral (2007), Jang et al. (2002)) and many others techniques were proposed to solve the SCND problems in a reasonable computation time.

To cope with this complexity, many researches divided the supply chain network into several stages, such as: Ereng et al. (1999), Pontrandolfo and Okogbaa (1999) and Vidal and Goetschalcks (1997).

To solve the supply chain network design problem, Jang et al. (2002) decomposed the entire supply chain network into three sub-networks: the inbound network, distribution network and outbound network. The first sub-problem consists of all suppliers to the manufacturing plants, the second one includes facilities where the final products are manufactured and the distribution facilities, the final sub-network consists of customers and distributors close to customers. Authors proposed solution methodologies based on the Lagrangian relaxation for each sub-network. They solved instances that have from 5 to 15 plants, from 10 to 20 warehouses, 10 customers and 10 products.

Lee and Dong (2008) explored the logistic network design for end-of-lease computer products recovery. Due to the problem complexity and the large number of variables and constraints, they developed a two-stage heuristic approach to decompose the integrated design of the multi-echelon forward and reverse logistics distribution networks into a location-allocation problem and a revised network flow problem. Authors generated computational results from a set of twenty-five test problems and the largest instance is composed of 30 potential treatment facilities, 40 potential hybrid facilities and 100 customers. Results suggested that the heuristic solution algorithm performs well in terms of solution quality and computational time. The average gap between the final solution obtained by the proposed heuristic approach and the lower bound obtained by CPLEX ranges from 4% to 12%.

Cheng and Wang (2009) presented a decomposition procedure to solve distribution problems. They proposed a heuristic approach in which they decomposed a complex global distribution problem into a combination of sub-problems with basic structures as independent as possible to each other. The idea of their heuristic decomposition procedure is to divide the large-scale global distribution into some identified sub-problems such as: facility location problem, location-allocation problem, hub location problem, transportation problem, travelling salesman problem, vehicle routing problem, etc. Then, each sub-problem is solved and the global solution is the sum of all these solutions.

Arntzen et al. (1995) presented a multi-period, multi-commodity mixed integer model to optimize a global supply chain. The objective function includes variable production, inventory, and shipping costs; fixed production costs, and savings from credit earned for re-exporting products. They claimed that they solved models that had from 2000 to 6000 constraints and from 5000 to 20000 variables. It is not clear from the article the exact method of solution applied, but they claimed that using non traditional methods, such as row factorization and cascaded problem solution, allowed them to get impressive results and always optimal solutions.

Cole (1995) presented a capacitate fixed-charge multi-commodity network flow model with side constraints. The side constraints are the non-linear inventory service level constraints resulting from the assumption of normally distributed demands. He suggested two solution procedures, and tested three example problems. The largest instance had 4 products, 9 customers, 3 potential plant locations, and 6 potential warehouse locations.

Goetschalckx et al. (1994) presented a generic model for the strategic design of production-distribution systems. To solve the generic model, they introduced heuristic method that significantly reduced the solution times compared to standard MIP solutions by a commercial solver. Other heuristic algorithms are presented by Fleischmann et al. (2001) and Geoffrion et al. (1978).

As evident from the above discussion, first, the decomposition resolution approach is less used in SCND problems. The lack of these decomposition schemes may be explained by the fact that due to the multi-level structure of a supply chain network and the interaction of strategic decisions across several levels, it becomes more difficult to decompose the problem into easier sub-problems. Second, the existing resolution approaches for supply chain design problems are suited for very small size problems.

How can we get a solution of large scale SCND problem in a reasonable time?

To answer this question, we propose a heuristic algorithm based on decomposition technique. Our current study represents a significant improvement over past research by presenting a unified model of the problem that includes numbers, locations and capacities of warehouses and distribution centers to open and goods quantities to transport throughout the supply chain network. Also, an efficient heuristic solution procedure based on decomposition approach is developed in order to get good solution in an acceptable CPU time. Computational tests with up to 1500 customers, 220 potential warehouses, 220 potential distribution centers and 220 suppliers are reported.

The rest of the chapter is organized as follows. In section 5.2, the mathematical model of the SCND problem is introduced. In section 5.3 the three-phase heuristic algorithm based on decomposition is explained in detail. Then the heuristic phases are discussed and applied to an application case in section 5.4. In section 5.5, some computational results about the performance of heuristic are presented. Finally, some concluding remarks are summarised in section 5.6.

5.2 Mathematical Model

In this section, we present the SCN problem and his mathematical formulation , then we show the first computational results of the model solved using a commercial solver like Cplex.

The potential design of a supply chain being considered (see Figure 5.1), is composed of suppliers, warehouses, distribution centres, and sellers. As depicted in Figure 5.1, products are shipped from suppliers to warehouses, where goods are prepared to be sent to the next level. Then, they are transported to distribution centers. The distribution centers insure the storage and the distribution of products to sellers. Warehouses are defined as the facility where products are received and married with goods going to the same destination, then shipped at the earliest opportunity, without going into long-term storage. They are located near suppliers and distribution centers. Distribution centers are ones located near customers and handled most products in four cycles (receive, store, pick, and ship).

The main assumptions used in the problem formulation are as follow:

–All demands of customers must be satisfied and no returned products from customers

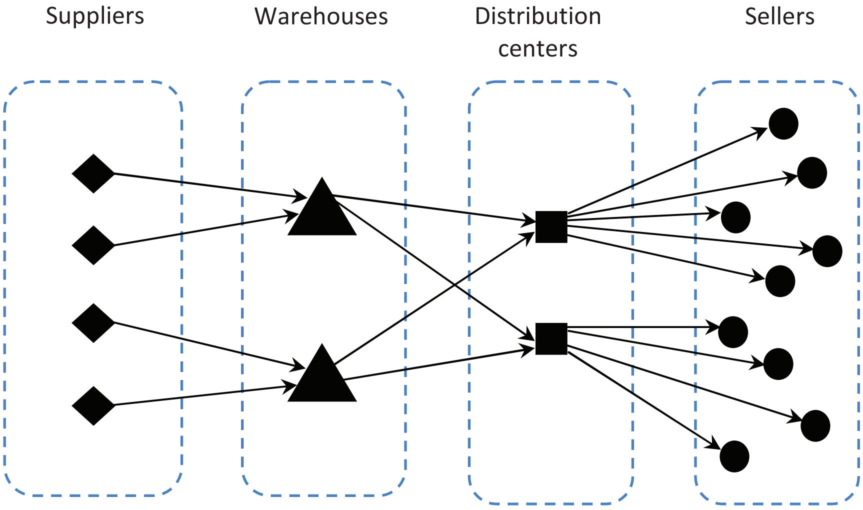

Figure 5.1: Supply Chain Network

must be collected.

–Products are shipped through a push mechanism in the supply chain network.

–The warehouse serves as a buffer between suppliers and distribution centers.

–Inventory is stored at the distribution centers.

–Products received in a distribution center will be stored before shipment to sellers and we attributed to each product a unit variable cost of (receive, store, and pick) that will be called unit storage costs in our case.

–Transportation costs from suppliers to warehouses are lower than from warehouses to distribution centers.

–Maximal warehouse treatment capacities, minimal treatment capacities are taken into consideration.

–Maximal distribution center storage capacities, minimal storage capacities are taken into consideration.

The strategic supply chain network we intend to elaborate should answer the following questions under uncertainty: (i) how many warehouses and distribution centers should be installed? (ii) where the new sites should be located? (iii) how much goods should each warehouse and distribution center handle? (iv) which sellers should be served by each distribution center? (v) quantities to transport throughout the supply chain network?

We use the same notations and parameters of the previous chapter.

The total cost (5.1) is composed of fixed warehouse opening costs, fixed distribution cen-

- Numbers:

m number of supplier locations.

n number of possible warehouse locations.

p number of possible distribution center locations.

q number of customer locations.

- Indices :

i supplier index.

j possible warehouse location indices.

k possible distribution center location indices.

l customer index.

- Parameters :

A_i capacity of supplier i.

fc_j fixed cost of opening warehouse j.

f_j processing costs at warehouse j.

F_j^{max} maximum processing capacity at warehouse j.

F_j^{min} minimum processing capacity at warehouse j.

dc_k fixed cost of opening distribution center k.

c_k storage costs at distribution center k.

C_k^{max} maximum storage capacity of distribution center k.

C_k^{min} minimum storage capacity of distribution center k.

μ_{ij} unit transportation costs of goods between supplier i and warehouse j.

μ_{jk} unit transportation costs of goods between warehouse j and distribution center k.

μ_{kl} unit transportation costs of goods between distribution center k and customer l.

ter opening costs, transportation costs of goods throughout the supply chain, production and storage costs. They are calculated in equation (5.1) as follows:

$$\begin{aligned} Minimize \quad & \Bigg[\sum_{j\in W}(fc_j \cdot x_j) + \sum_{k\in D}(dc_k \cdot y_k) + \sum_{i\in S}\sum_{j\in W}(\mu_{ij} + f_j)\cdot q_{ij} + \\ & \sum_{i\in S}\sum_{k\in D}(\mu_{ik} + c_k)\cdot q_{ik} + \sum_{j\in W}\sum_{k\in D}(\mu_{jk} + c_k)\cdot q_{jk} + \sum_{k\in D}\sum_{l\in C}\mu_{kl}\cdot q_{kl}\Bigg] \end{aligned} \tag{5.1}$$

μ_{ik} unit transportation costs of goods between supplier i and distribution center k.

$\tilde{D}_l$ demand of the customer l.

- Decision variables:

x_j =1 if warehouse j is opened, and = 0 otherwise.

y_k =1 if distribution center k is opened, and = 0 otherwise.

q_{ij} quantity of products transported from supplier i to warehouse j.

q_{jk} quantity of products transported from warehouse j to distribution center k.

q_{kl} quantity of products transported from distribution center k to customer l.

q_{ik} quantity of products transported from supplier i to distribution center k.

Subject to

Constraint (5.2) imposes that all goods received by suppliers will be transported to warehouse:

$$\sum_{j\in W} q_{ij} + \sum_{k\in D} q_{ik} = A_i \qquad i \in S. \quad (5.2)$$

Constraint (5.3) enforces the flow conservation of products in warehouses level:

$$\sum_{i\in S} q_{ij} = \sum_{k\in D} q_{jk} \qquad j \in W. \quad (5.3)$$

Constraint (5.4) limits the warehouse treatment capacity :

$$F_j^{min} \cdot x_j \leq \sum_{i\in S} q_{ij} \leq F_j^{max} \cdot x_j \qquad j \in W. \quad (5.4)$$

Constraint (5.5) enforces flows conservation of products in distribution centers level:

$$\sum_{j\in W} q_{jk} + \sum_{i\in S} q_{ik} = \sum_{l\in C} q_{kl} \qquad k \in D. \quad (5.5)$$

Constraint (5.6) limits the distribution center capacity:

$$C_k^{min} \cdot y_k \leq \sum_{j\in W} q_{jk} + \sum_{i\in S} q_{ik} \leq C_k^{max} \cdot y_k \qquad k \in D. \quad (5.6)$$

Constraint (5.7) guarantees that customer's demand will be satisfied:

$$\sum_{k\in D} q_{kl} = D_l \qquad l \in D. \quad (5.7)$$

Constraints (5.8), and (5.9) enforce the binary nature of x_j and y_k :

$$x_j \in \{0,1\} \qquad j \in W. \tag{5.8}$$

$$y_k \in \{0,1\} \qquad k \in D. \tag{5.9}$$

Constraints (5.10), (5.11), (5.12) et (5.13) are standard non-negative constraints:

$$q_{ij} \geq 0 \qquad i \in S; j \in W. \tag{5.10}$$

$$q_{jk} \geq 0 \qquad j \in W; k \in D. \tag{5.11}$$

$$q_{kl} \geq 0 \qquad k \in D; l \in C. \tag{5.12}$$

$$q_{ik} \geq 0 \qquad i \in S; k \in D. \tag{5.13}$$

For example, in Table 5.1, where Exp represents instances, S denotes le suppliers number, W is the warehouses number, DC represents the distribution centers number and C denotes customers number. To solve a SCND problem with 11 suppliers, 40 potential

Table 5.1: Global MILP model limits

Exp	S	W	DC	C	Constraints	Variables	CPU Time (s)
D_1	11	10	10	10	732	641	0.22
D_6	11	10	10	103	1755	1571	3.58
D_7	11	16	20	103	3701	3469	51.59
D_{10}	11	40	63	103	16248	15815	36232
D_{13}	11	100	100	103	46510	45761	16012
D_{15}	11	140	140	140	82762	81761	OM*
D_{16}	11	160	160	160	107385	106241	OM*

*OM: Out of Memory

warehouses, 63 potential distribution centers and 103 customers using an exact method, we need 36 232 seconds to find the solution. Also, our computational experiences show that it's impossible to solve SCND problems using an exact method implemented on commercial solver like Cplex. Limits of the MILP model are recapitulated on Table 5.1. This is far of our objective, which is to solve a large scale application case with 1500 customers, 220 potential distribution centers, 220 potential warehouses and 220 suppliers.

In the following section, the heuristic algorithm based on decomposition technique is presented.

5.3 Heuristic Approach

In this section, we present a heuristic approach to solve the global supply chain problem. Our aim is to obtain good solutions for large scale SCND problems in a reasonable time. The core idea behind the heuristic method is to reduce each facilities set of the original supply chain network as small set. The network is then reduced to a medium size problem that could be solved using an exact method.

We build the heuristic on ideas developed in two works. We integrate the concept of decomposition as discussed in Cheng and Wang (2009), the idea of their heuristic decomposition procedure is to divide the large-scale global distribution into some identified sub-problems such as: facility location problem, location-allocation problem, hub location problem, transportation problem, travelling salesman problem, vehicle routing problem, etc. Then, each sub-problem is solved and the global solution is the sum of all these solutions.

We also use the concept of decomposition of the entire supply chain network as discussed in Jang et al. (2002), they decomposed the entire SCN into three sub-networks: The inbound sub-problem consists of all suppliers to the manufacturing plants, the distribution sub-problem includes facilities where the final products are manufactured and the distribution facilities, the outbound sub-network consists of customers and distributors close to customers. They used the Lagrangian relaxation to solve each sub-network.

To determine the reduced supply chain network of the original huge one presented in Figure 5.2, it is first decomposed into two-level sub-problems. Then, the well-known p-median model (Klose and Drexl (2005) and ReVelle et al. (2008)) is used to solve each sub-problem. Finally the reduced supply chain network is solved using the global MILP model (5.1)-(5.13). The heuristic are detailed in the following subsections.

5.3.1 Heuristic Structure

The heuristic approach consists of three phases as follows:

Phase 1: Decomposition phase: in this phase we decompose the huge supply chain network into small sub-networks with decomposition technique. The decomposition process continues until the problem is divided into two levels sub-problems that we can solve using the p-median model. The detail of this phase will be developed in Section 5.3.2.

Phase 2: Reduction sets phase: in this phase we reduce the huge facilities number of each set using p-median model in order to obtain the reduced potential sets. The detail of this phase will be presented in the Section 5.3.3.

Phase 3: Resolution phase : in this phase we solve the global MILP model with the reduced potential sets got in phase 2.

To clarify these phases, the heuristic method will be explained in the following para-

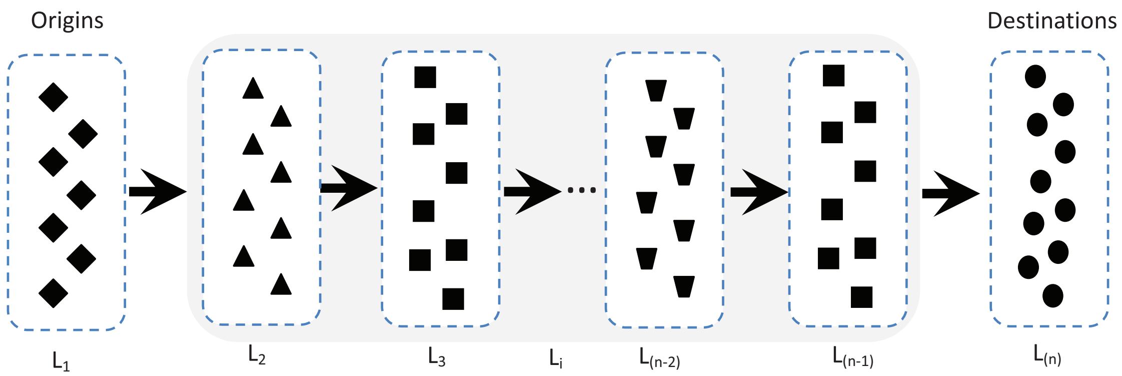

Figure 5.2: n level supply chain network

graphs. Consider the n level supply chain network represented in Figure 5.2. The network includes the origins level, destinations level and intermediate levels. Between origins and destinations, we specify levels in which location decisions are made. The edges represent the links between levels on which the goods are delivered and each level of facilities plays a specific role . We suppose that the flow of goods in this network is oriented from lower level to higher level facilities (Figure 5.2).

This SCN consists of n levels and each level of type i $(i = 1, 2, \cdots, n)$ can contain several facilities. In order to formulate the problem in mathematical expression, the following notations are introduced first :

L_1 denotes origins set of the supply chain network, L_n denotes destination set of the supply chain network. L_i presents the set of intermediate level i in the network, (i=2,$\cdots$, $n-1$).

5.3.2 Decomposition Phase

As said before, this heuristic phase is focused on dividing the original supply chain network into a set of two-level sub-networks (Sf_1, Sf_2, Sf_3, $\cdots$, $Sb_{(n-1)}$). This phase contains two steps: Forward step and Backward step. In forward step, we push the goods from the origins to destinations (Figure 5.3). In backward step, we push the products from destinations to origins, as shown in Figure 5.3. The number of sub-problems to form is m = 2$\times$(n-2), $n \geq 2$, where n is the levels number of the network.
To decompose the supply chain network (Figure 5.2), we compute the following heuristic algorithm (Algorithm 5.1). Figure 5.3 shows the decomposition phase. The output of this phase is a set of two-level sub problems Sf_i and Sb_j.

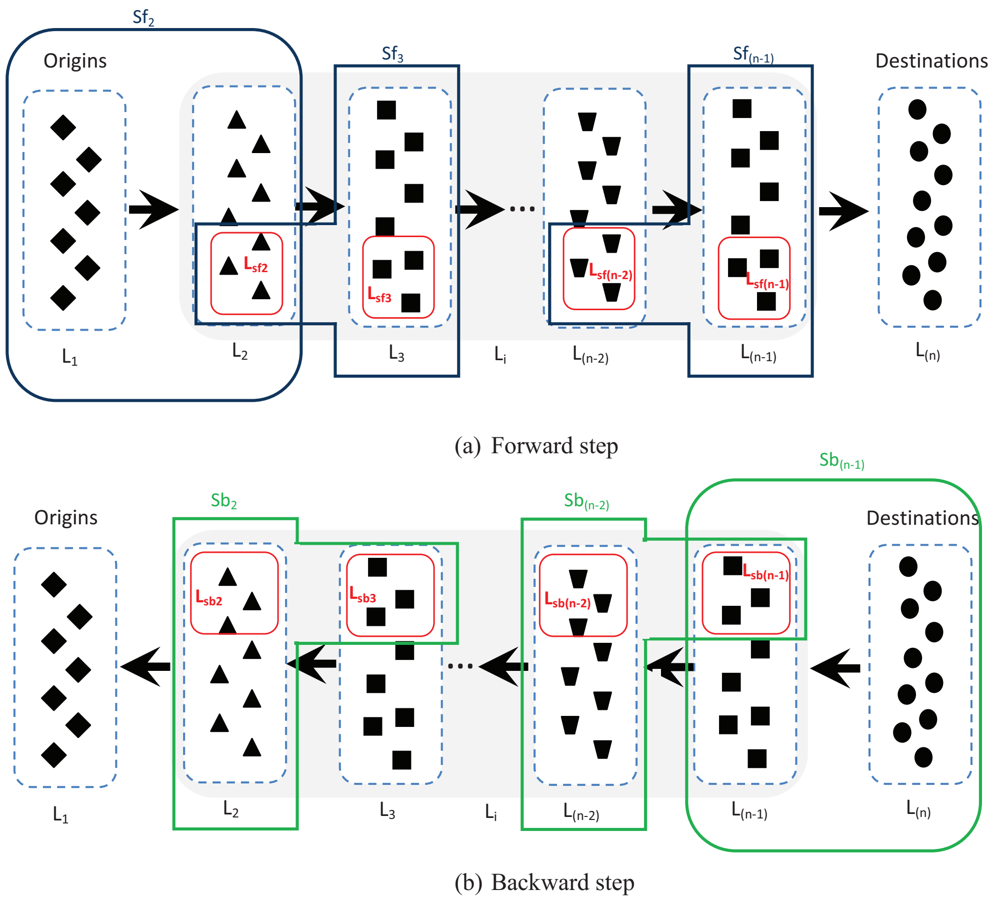

Figure 5.3: Heuristic steps:Decomposition phase and Reduction phase

Algorithm 5.1: DECOMPOSITION ALGORITHM

Input:

L_i: set of level i in the supply chain network.

Output:

Sf: forward sub-problems.

Sb: backward sub-problems.

begin
  /* Forward Step*/
  for $(i = 1$ ***to*** $i = n - 2)$ **do**
    if $(i = 1)$ **then**
      $Sf_{(2)} \longleftarrow \{L_1, L_2\}$
    $Sf_{(i+1)} \longleftarrow \{L_{Sf_{(i)}}, L_{(i+1)}\}$
  /* Backward Step*/
  for $(j = n$ ***to*** $j = 3)$ **do**
    if $(j = n)$ **then**
      $Sb_{(n-1)} \longleftarrow \{L_n, L_{(n-1)}\}$
    $Sb_{(j-1)} \longleftarrow \{L_{Sb_{(j)}}, L_{(j-1)}\}$
  Return (Sf, Sb)

5.3.3 Reduction Phase

We compute reduction algorithm (Algorithm 5.2) for each sub-problem Sf_i and Sb_i, in order to reduce the size of each potential set L_i to new reduced set Lr_i.

The idea of this step, is to keep the same costs or criteria used in the objective function of the global MILP model to locate warehouses ans distribution centers. This means that, to reduce the warehouses set, we integrate in the objective function of the p-median problem warehouse opening costs, production costs and transportation costs, because these costs are used in the global MIPL model to locate warehouses. Also, to reduce the distribution centers set, the objective function of the p-median problem contains distribution center opening costs, storage costs and transportation costs.

In order to calculate the p value, we solve the largest MILP model composed of suppliers

Algorithm 5.2: REDACTION ALGORITHM

Input:

Sf: forward sub-problems.

Sb: backward sub-problems.

Output:

L_{Sf}: reduced set of forward sub-problems.

L_{Sb}: reduced set of backward sub-problems.

Lr: reduced set.

begin

  /* Forward Step*/

  for $(i = 1$ ***to*** $i = (n-2))$ **do**

    $L_{Sf_{(i+1)}} \longleftarrow p - median(Sf_{(i+1)})$

  /* Backward Step*/

  for $(j = n$ ***to*** $j = 3)$ **do**

    $L_{Sb_{(j-1)}} \longleftarrow p - median(Sb_{(j-1)})$

  /* Reduced Sets*/

  for $(i = 2$ ***to*** $i = (n-1))$ **do**

    $Lr_i \longleftarrow L_{Sf_{(i)}} \cup L_{Sb_{(i)}}$

  Return (L_{Sf}, L_{Sb}, Lr)

set, p warehouses, p distribution centers and customers set, that we can solve using the commercial software Cplex.

A general p-median problem involves a set of customers and a set of facilities to serve customer demands (see Drezner and Hachamer (2004), ReVelle and Eiselt (2005), Klose and Drexl (2005) and ReVelle et al. (2008)).

Let us define parameters and variables of the p-median model (Figure 5.4): S represents suppliers set and W is potential facilities set. p denotes the number of facilities to open, f_j represents fixed cost of opening facility at candidate node j, c_j denotes unit cost of production goods at candidate facility j, μ_{ij} is the unit transportation costs of goods between node i and node j, d_i denotes quantities supplied by supplier i. X_j =1 if we

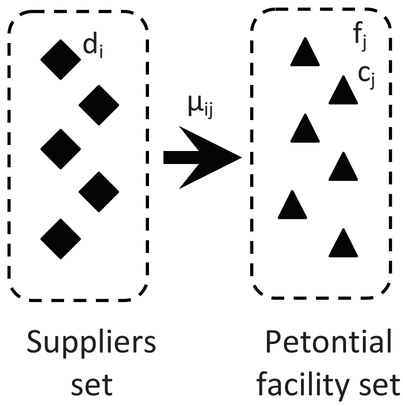

Figure 5.4: p-median network

locate facility at candidate site j, and $= 0$ else. Y_{ij} =1 if goods quantities at node i are received by a facility at candidate site j, and $= 0$ else.

$$Minimize \quad \sum_{j\in W}(f_j \cdot X_j) + \sum_{j\in W}\sum_{i\in S}(\mu_{ij} + c_j) \cdot d_i \cdot Y_{ij} \tag{5.14}$$

Subject to

Constraint (5.15) requires that exactly p facilities be located:

$$\sum_{j\in W} X_j = p \tag{5.15}$$

Constraint (5.16) ensures that every demand is assigned to some facility site:

$$\sum_{i\in S} Y_{ij} = 1 \qquad j \in W. \tag{5.16}$$

Constraint (5.17) allows assignment only to sites at which facilities have been located:

$$Y_{ij} - X_j \leq 0 \qquad i \in S; j \in W. \tag{5.17}$$

Constraints (5.18) and (5.19) are standard non-negative and integrity constraints:

$$X_j \in \{0, 1\} \qquad j \in W. \tag{5.18}$$

$$Y_{ij} \in \{0, 1\} \qquad i \in S; j \in W. \tag{5.19}$$

5.3.4 Resolution Phase

After the resolution of the previous two phases, the supply chain network system is reduced in complexity to the original SCN, due to reduction of the size of the potential sets to small size sets. In this phase, we solve the reduced supply chain network problem using the global MILP model (5.1)-(5.13).

5.4 Application Case

In this section, we apply the proposed heuristic approach to our application case, as shown in Figure 5.5. We consider a real life supply chain network consists of 220 suppliers, 220 potential warehouse locations, 220 potential distribution center locations , and 1500 sellers . In order to describe the supply chain network (Figure 5.5), we define notations as follows:

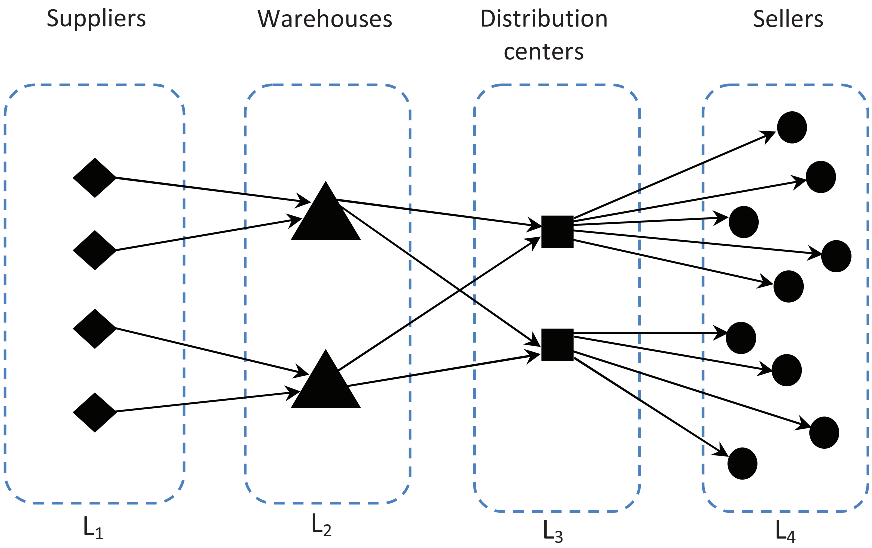

Figure 5.5: Supply Chain Network

we let L_1 denotes suppliers set and L_2 denotes warehouses set, L_3 presents distribution centers set, L_4 is customers set.

5.4.1 Decomposition Phase

To find a feasible solution for the SCND problem, we start by dividing the problem into four sub-problems: suppliers-warehouses sub-problem Sf_2={L_1,L_2} (see Figure 5.6 (a)), warehouses-distribution centers sub-problem Sf_3={L_{Sf_2},L_3} (see Figure 5.6 (b)), customers-distribution centers sub-problem Sb_3={L_4,L_3} (see Figure 5.6 (c)) and distribution centers-warehouses sub-problem Sb_2={L_{Sb_3},L_2} (see Figure 5.6 (d)).
As illustrated in Figure 5.6. Where L_{Sf_2} is the first potential warehouses set obtained solving sub-problem Sf_2. L_{Sb_3} denotes second potential distribution centers set obtained solving sub-problem Sb_3.

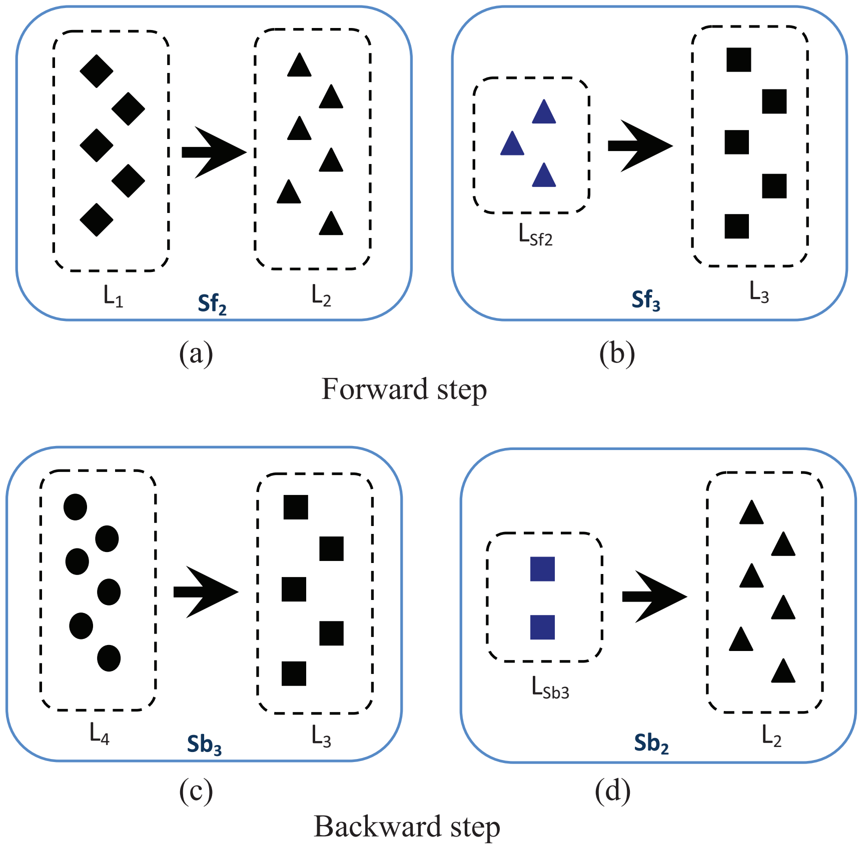

Figure 5.6: Decomposition phase

5.4.2 Reduction Phase

To reduce the huge size of the potential sets of the SCN, p-median model should be run for each sub-problem. In order to calculate the p value, we solve the largest MILP model composed of 220 suppliers, p warehouses, p distribution centers and 1500 customers. We find that p is equal to 14.

For this case, the reduction phase contains four steps as presented in Figure 6.2, which represent the number of sub-problem obtained in the previous phase. How this reduction can be achieved will be explained in the following steps.

Step 1

In this step, we apply the p-median model to the first sub-problem Sf_2 obtained in the decomposition phase. As we can see on Figure 5.8, the detail of this step, the sub-problem Sf_2 is composed of two sets: suppliers set L_1 and warehouses set L_2. To get the first potential warehouses set L_{Sf_2}, we solve the following mathematical model (5.20). In addition to parameters and variables defined in previous section, let's introduce those of

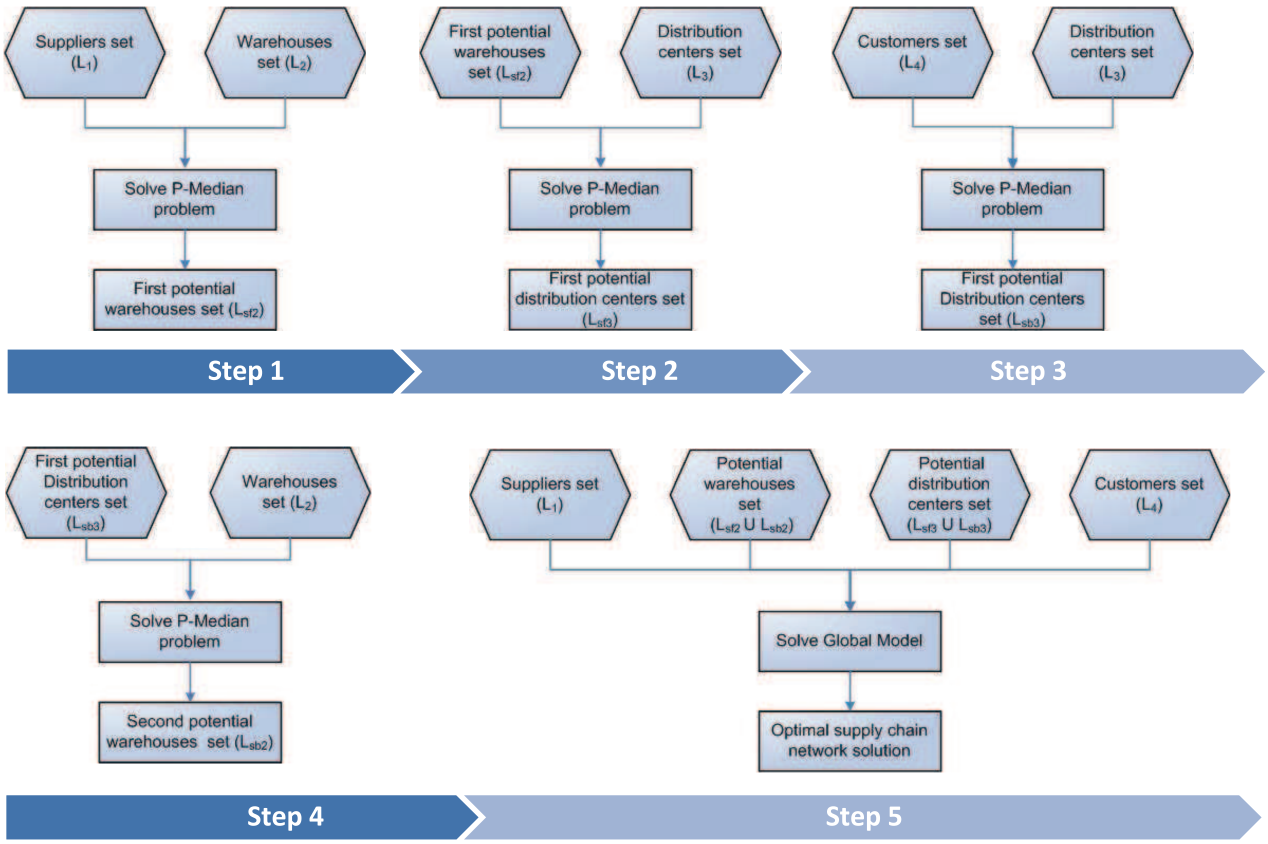

Figure 5.7: Heuristic steps: Decomposition phase and Reduction phase

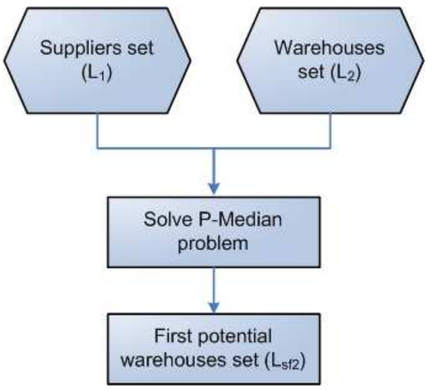

Figure 5.8: Step 1

the p-median model: p denotes the number of warehouses to open, which is equal to 7 in this step. d_i denotes quantities shipped from the supplier i. X_j =1 if we locate warehouse at candidate site j, and = 0 else. Y_{ij} =1 if goods at node i are served by a warehouse at candidate site i, and = 0 else.

$$Minimize \quad \sum_{j \in L_2} (fc_j \cdot X_j) + \sum_{i \in L_1} \sum_{j \in L_2} (\mu_{ij} + f_j) \cdot d_i \cdot Y_{ij} \tag{5.20}$$

Subject to

(5.15), (5.16), (5.17), (5.18), (5.19).

The output of this step is the first potential warehouses set L_{Sf_1} that we will use in step 4.

Step 2

In this step, we try to reduce potential distribution centers set L_3. However, we solve the p-median problem applied to the second sub-problem Sf_3 obtained in the decomposition phase. Figure 5.9 outlines the detail of this step, the sub-problem Sf_3 is composed of two sets: first potential warehouses set distribution centers set L_{Sf_2} and distribution centers set L_3. Parameters and variables used in the p-median model: p denotes the number

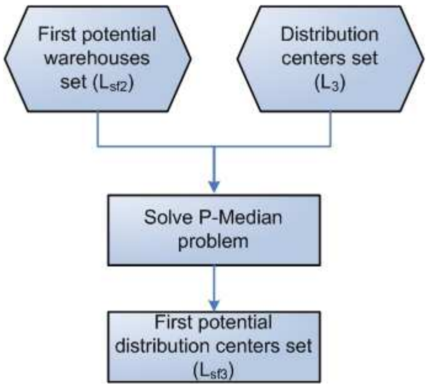

Figure 5.9: Step 2

of potential distribution centers to open. d_i denotes quantities supplied from warehouse i. X_j =1 if we locate distribution center at candidate site j, and = 0 else. Y_{ij} =1 if distribution center j are served by a warehouse at candidate site i, and = 0 else.

$$Minimize \quad \sum_{j \in L_3} (dc_j \cdot X_j) + \sum_{i \in L_{Sf_2}} \sum_{j \in L_3} (\mu_{ij} + c_j) \cdot d_i \cdot Y_{ij} \tag{5.21}$$

Subject to

(5.15), (5.16), (5.17), (5.18), (5.19).

We fix the number of potential distribution centers to open $p = 7$, then we solve the model. The output of this step is the first potential distribution centers set L_{Sf_3} that we will use in step 3.

Step 3

Figure 5.10 outlines the detail of this step. The sub-problem Sb_3 contains two sets: the first potential warehouses set L_{Sb1} and distribution centers set L_3. First, we fix the number of potential distribution centers to open p to 7. Then, we solve the following p-median problem (5.22) applied to Sb_3 sub-problem in order to get the second potential distribution centers set L_{Sb_3} . Before presenting the objective function of the p-median problem, let's

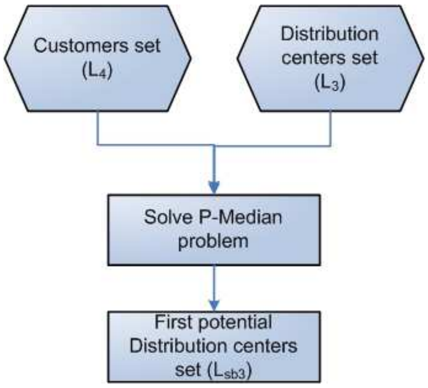

Figure 5.10: Step 3

define parameters and variables of this model: d_i denotes demand of customer i. X_j =1 if we locate distribution center at candidate site j, and = 0 else. Y_{ij} =1 if demand at customer i are served by distribution center at candidate site j, and = 0 else.

$$Minimize \quad \sum_{j \in L_4} (fc_j \cdot X_j) + \sum_{i \in L_4} \sum_{j \in L_3} (\mu_{ij} + f_j) \cdot d_i \cdot Y_{ij} \tag{5.22}$$

Subject to

(5.15), (5.16), (5.17), (5.18), (5.19).

Outputs of this step are the second potential distribution centers set L_{Sb_3} and Lr_3= L_{Sf_3} $\cup$ L_{Sb_3} that we will use in step 5.

Step 4

In this step, the sub-problem Sb_2 contains two sets: first potential distribution center set L_{Sb_3} and warehouses set L_2 (Figure 5.11). In order to get the second potential warehouses set L_{Sb_2}. We solve the p-median problem applied to this sub-problem

Parameters and variables of this model are: p denotes the number of potential distribution

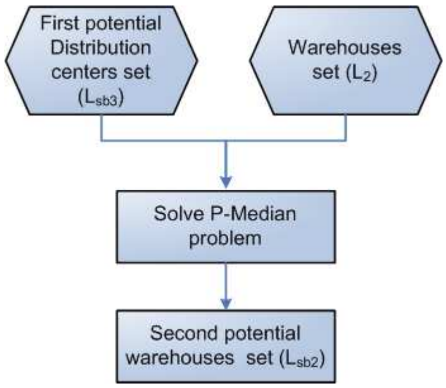

Figure 5.11: Step 4

centers to open, $p = 7$ in this step. d_i denotes quantities supplied from warehouse i. X_j =1 if we locate warehouse at candidate site j, and = 0 else. Y_{ij} =1 if warehouse j are served by a distribution center at candidate site i, and = 0 else.

$$Minimize \quad \sum_{j \in L_2} (dc_j \cdot X_j) + \sum_{i \in L_{Sb_3}} \sum_{j \in L_2} (\mu_{ij} + c_j) \cdot d_i \cdot Y_{ij} \tag{5.23}$$

Subject to

(5.15), (5.16), (5.17), (5.18), (5.19).

Outputs of this step are the second potential warehouses set L_{Sb_2} and Lr_2= L_{Sf_2} $\cup$ L_{Sb_2} that we will use in step 5.

5.4.3 Resolution Phase

Now, we have the reduced supply chain network. As we can see on Figure 5.12, this network is composed of : suppliers set A, reduced potential warehouses set Lr_2=\{L_{Sf_2} $\cup$

$L_{Sb_2}\}$, reduced potential distribution centers set Lr_3=$\{L_{Sf_3} \cup L_{Sb_3}\}$ and customers set D. We solve the MILP model (5.1)-(5.13) in order to find the optimal supply chain network solution.

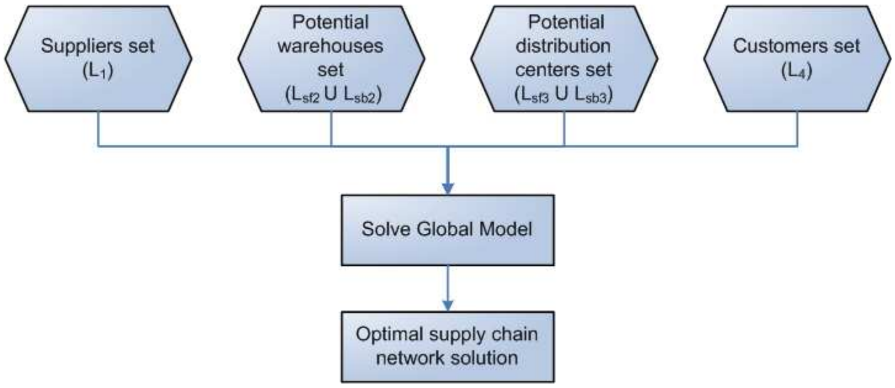

Figure 5.12: Step 5

5.5 Computational Results

In this section we describe numerical experiments using the heuristic algorithm for solving real case supply chain design problem. We first explain instances and some implementation details. Then, we highlight the computational efficiencies of our heuristic method. Finally, we outline the quality of the heuristic solutions in comparison to those obtained using a MILP model.

5.5.1 Data and Implementation

We consider a real life supply chain network. Our case consists of 220 suppliers, 220 potential warehouse locations, 220 potential distribution center locations , and 1500 sellers that the company serves. We generated 26 test problems from this real life SCN, to evaluate the performance of the heuristic methodology and the global MILP model (5.1)-(5.13). This means that, we reduced randomly the size of customers set from 1500 to 10 customers, the size of distribution centers set from 220 to 10 distribution centers, warehouses number from 220 elements to 10 warehouses and the size of suppliers set from 220 suppliers to 11 suppliers (Table 5.2).

These instances are complemented on Windows Vista 1.66 GHZ and 2 GB of memory and solved by commercial software ILOG OPL 6.3/ CPLEX 12.1.0 (ILOG (2011)).

To solve the Global MILP of some large instances, from instance D_{15} to instance D_{26}, we used some specific cuts in order to speed up the resolution (see Paquet et al. (2004)). Cuts proposed for the model presented here are related to numbers of distribution centres and warehouses to open. They are defined by equations (5.24) to (5.25). Equation (5.24) calculates the maximum number of warehouses to open and Equation (5.25) ensures that the maximum number of distribution centers to open is equal to 4.

$$\sum_{j \in W} x_j \leq 2 \tag{5.24}$$

$$\sum_{k \in D} y_k \leq 4 \tag{5.25}$$

The main characteristics of this SC networks are presented in Chapter 3.

5.5.2 Performance of Heuristic

In this subsection, we discuss the performance of the heuristic algorithm for solving SCND problems. To measure this performance, we select the following performance indicators: (i) constraints number; (ii) variables number; (iii) CPU Time.

Constraints number and variables number of the heuristic method obtained solving the last phase of the approach. The CPU Time of the heuristic presents the addition of the computational times of all heuristic phases.

Table 5.2 summarizes results of the two approaches global MILP and heuristic.

Results are described by providing suppliers number (S), the potential warehouse sites number (W), the potential distribution centers number (DC), the constraints number and variables number.

Table 5.2 reveals that the global MILP model contains more constraints and variables than the heuristic approach. As we can see, for small instances, from $D1$ to $D6$, variables and constraints number of both models are in the same number level, because the number of facilities in warehouses set and distribution centers set are static equal to 10. Increasing the number of facilities in these sets, the difference in number of constraints and variables between two models go up. For example, for $D20$ we find that constraints number is equal to 288 404 and 5 964 using MILP model and heuristic respectively.

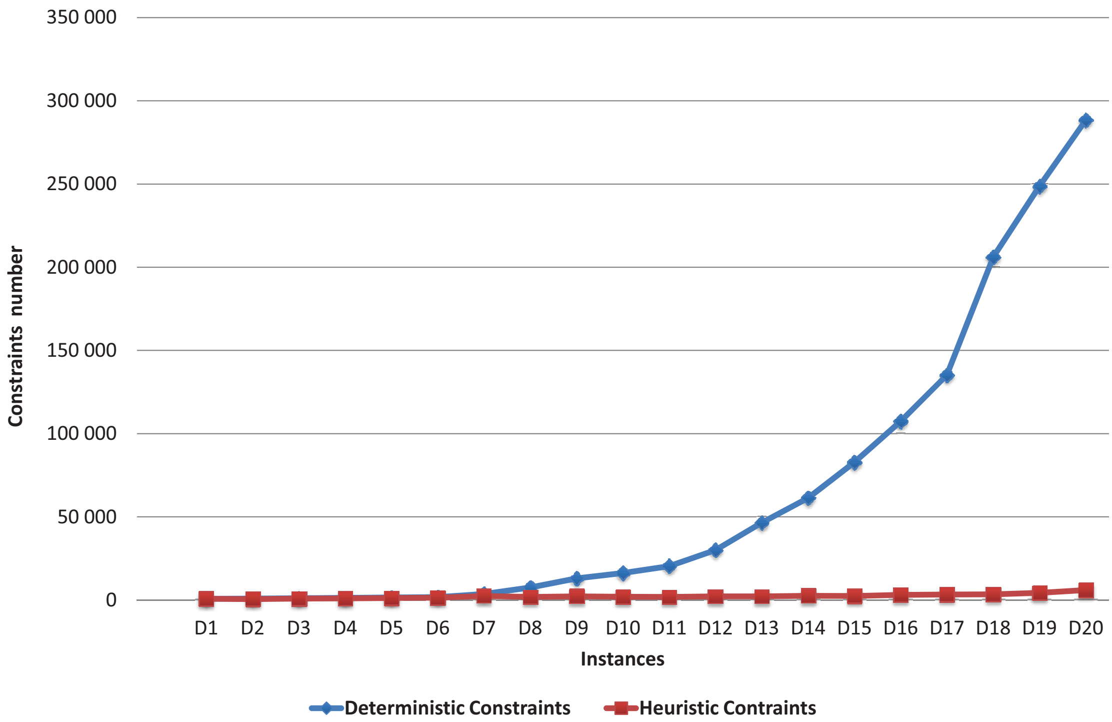

Figure 5.13: Constraints: MILP model vs Heuristic

It is clear that, the use of heuristic method help us to decrease the complexity of the problem by reducing constraints and variables number. Figure 5.13 shows the increase of constraints number of MILP model with the growth of the sample size. We compare the constraints number required for solving a MIL problem to the heuristic, for each experience. As we can see, the constraints number using MILP model goes up exponentially with the increase of the instance size, while it increases slowly with the network size using our heuristic.

Figure 5.14 depicts the increase of variables number of MILP model with the growth of instance size. We compare the variables number required for solving MILP using commercial solver to the heuristic, for each experience. It's clear that using our heuristic, increasing the instance size the variables number rises from 650 to 5 500 (Table 5.2), while it rises exponentially (from 641 to 238 481) with the increase of the instance size using the global MILP model. Figure 5.15 charts the increase of the computational time with the growth of the sample size. For each instance, we compare the CPU seconds required for solving the MILP model to the heuristic algorithm proposed in Section 5.2. The efficacy of the proposed heuristic is clearly observed. For more detail you can refer to Table 6.8.

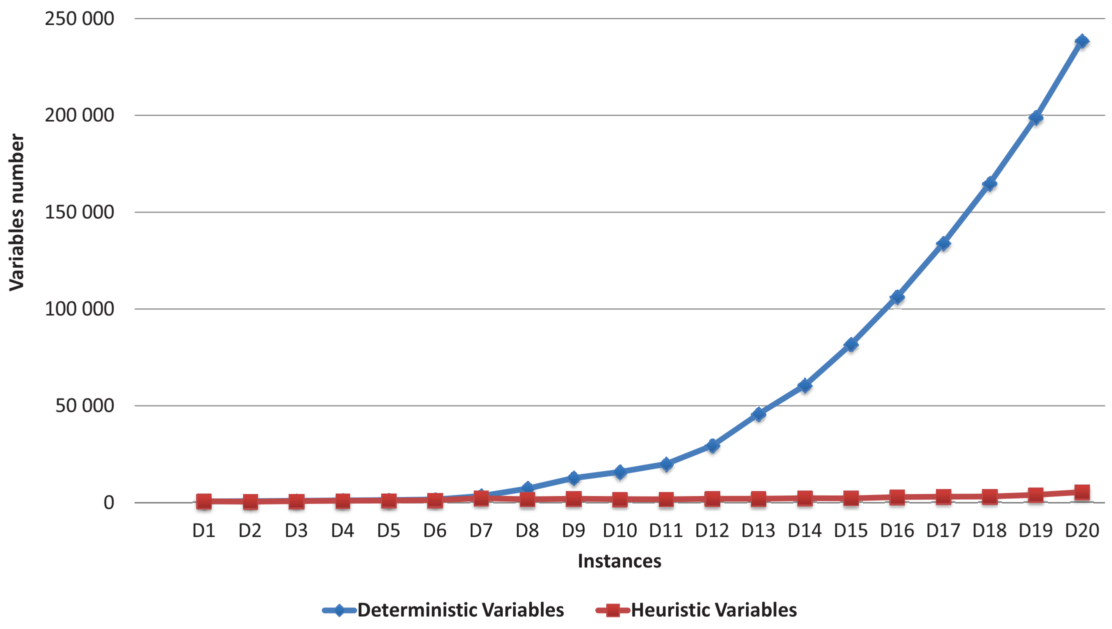

Figure 5.14: Variables: MILP model vs Heuristic

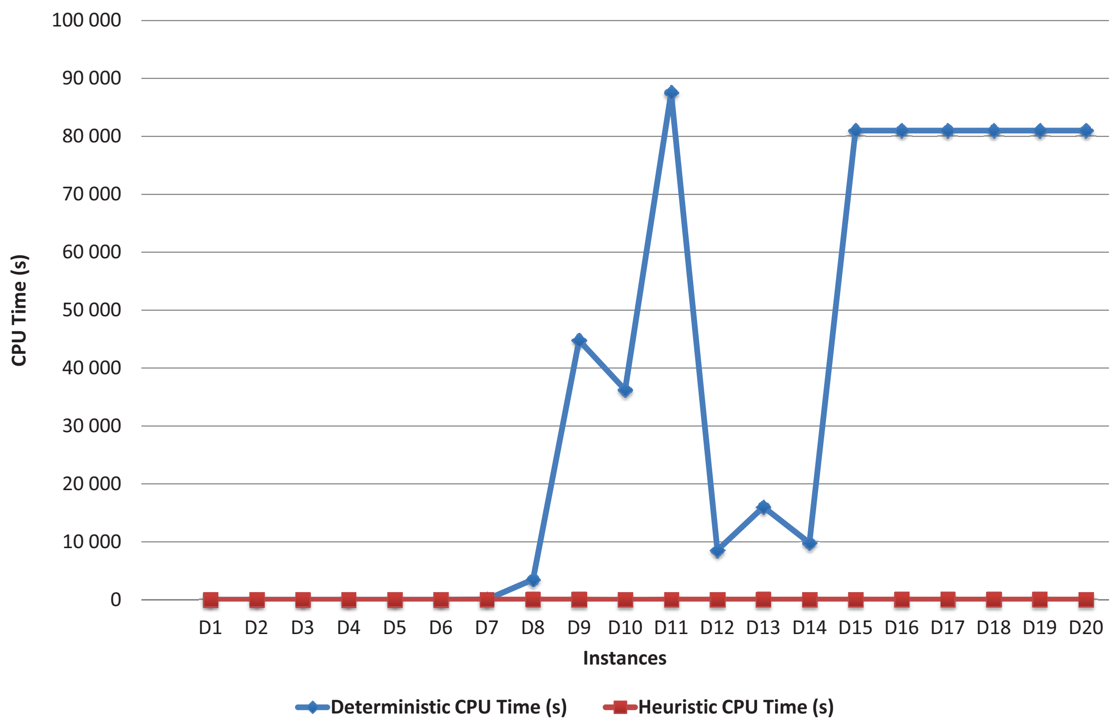

Figure 5.15: CPU time: MILP model vs Heuristic

Table 5.2 reveals that solutions of the heuristic approach are not only superior to MILP solution in terms of the CPU time, but these solutions also lead to smaller number of constraints and variables.

The computational experimentation compares performances of the proposed heuristic approach and the MILP approach. Limited computational results show that although the latter is more effective in solving smaller-sized test instances, the proposed heuristic approach appears to be more promising for larger test instances.

The quality of heuristic solutions are presented in the following subsection.

5.5.3 Quality of Heuristic Solutions

In this section we compare solutions of the heuristic algorithm to that of MILP model using the following performance indicators: (i) costs; (ii) Gap; (iii) SC configuration.

- *Costs:* refers to the sum of all costs that are generated : opening costs, processing costs, storage and transportation costs.

- *Gap:* refers to the percentage of cost difference between solutions.

$$Gap\ 1 = \left(\frac{Heuristic\ \ costs - Global\ \ MILP\ \ costs}{Global\ \ MILP\ \ costs}\right) \times 100 \tag{5.26}$$

$$Gap\ 2 = \left(\frac{Heuristic\ \ costs - Lower\ \ bound}{Lower\ \ bound}\right) \times 100 \tag{5.27}$$

Where *Global MIPL costs* represents the objective function value obtained solving the global MILP. The *Heuristic costs* is the objective function value of the last step of the heuristic method. The *Lower bound* represents the lower bound value of the global MILP calculated by solver Cplex.

- *SC configuration:* refers to the supply chain network structure proposed by the mathematical model.

In Table 6.8, we compare the solution obtained from the heuristic algorithm with the global MILP solution that we got using Cplex solver. We first solve small size instances, from $D1$ to $D7$, we find that the gap between the heuristic solution and the global MILP solution (Gap 1), for all these instances, is equal to zero percent. We conclude that using our heuristic, we can establish optimal solution to small sized problems, with an excellent quality. Then, we conduct further experiments to test the heuristic for medium size

Table 5.2: Constraints and variables numbers: Heuristic vs Global MILP model

					MILP Model		Heuristic	
Exp	S	W	DC	C	Constraints	Variables	Constraints	Variables
D1	11	10	10	10	732	641	732	641
D2	11	10	10	20	842	741	576	490
D3	11	10	10	40	1062	941	854	742
D4	11	10	10	60	1282	1141	1034	902
D5	11	10	10	80	1502	1341	1214	1062
D6	11	10	10	103	1755	1571	1421	1246
D7	11	16	20	103	3701	3469	2465	2263
D8	11	16	40	103	7581	7289	1859	1675
D9	11	16	63	103	13032	12671	2208	2015
D10	11	40	63	103	16248	15815	1965	1781
D11	11	63	63	103	20411	19909	1859	1675
D12	11	80	80	103	30046	29441	2166	1969
D13	11	100	100	103	46510	45761	2166	1969
D14	11	120	120	120	61342	60481	2546	2330
D15	11	140	140	140	82762	81761	2444	2214
D16	11	160	160	160	107385	106241	3106	2850
D17	11	180	180	180	135202	133921	3335	3062
D18	11	200	200	200	206024	164801	3414	3121
D19	11	220	220	220	248624	198881	4330	4005
D20	11	220	220	400	288404	238481	5964	5474
D21	11	220	220	600	-	-	7964	7274
D22	11	220	220	800	-	-	10315	9428
D23	11	220	220	1000	-	-	12715	11628
D24	50	220	220	1200	-	-	17428	16057
D25	100	220	220	1500	-	-	24411	22634
D26	220	220	220	1500	-	-	18724	16725

Table 5.3: CPU time: Heuristic vs Global MILP model

Exp	S	W	DC	C	MILP Model CPU Time (s)	Heuristic CPU Time (s)
D_1	11	10	10	10	0.22	0.23
D_2	11	10	10	20	0.28	0.53
D_3	11	10	10	40	1.12	1.94
D_4	11	10	10	60	2.2	2.42
D_5	11	10	10	80	2.14	2.12
D_6	11	10	10	103	3.58	2.06
D_7	11	16	20	103	51.59	22.34
D_8	11	16	40	103	3482	32.26
D_9	11	16	63	103	44777	36.44
D_{10}	11	40	63	103	36232	10.39
D_{11}	11	63	63	103	87548	16
D_{12}	11	80	80	103	8536	22
D_{13}	11	100	100	103	16012	28
D_{14}	11	120	120	120	9822	18
D_{15}	11	140	140	140	81000*	21
D_{16}	11	160	160	160	81000*	31
D_{17}	11	180	180	180	81000*	33
D_{18}	11	200	200	200	81000*	35
D_{19}	11	220	220	220	81000*	43
D_{20}	11	220	220	400	81000*	22
D_{21}	11	220	220	600	-	38
D_{22}	11	220	220	800	-	50
D_{23}	11	220	220	1000	-	76
D_{24}	50	220	220	1200	-	125
D_{25}	100	220	220	1500	-	350
D_{26}	220	220	220	1500	-	550

problems ($D8$ to $D14$). As we can see on Table 6.8, the Gap 1 for these problems ranges from 0% to 0.52%. To test the heuristic algorithm for large size problems, we increased suppliers number from 11 to 220, warehouses number from 120 to 220, distribution centers from 120 to 220 and customers number from 120 to 1 500. In these cases, the heuristic was able to find solutions in reasonable time. In contrast to the global MILP model that did not succeed to obtain any solution. The Gap 1 was impossible to calculate, because we didn't succeed to solve the problem using the exact MILP model. However, we will use Gap 2 to compare large size problems. The Gap between the best integer and the heuristic solution (Gap 2) ranges between 1.19% and 9.52%, the Gap 2 average is equal to 5.66%.

In Table 5.5, for instances $D1$ to $D7$, the CPU time varied significantly. The time spent to get the solution by the global MILP model using the solver is at least 10 times more than the time passed by heuristic approach. For these instances, the supply chain configurations proposed by the global MILP model and the heuristic are exactly the same. For example, the SC configuration obtained solving instance $D4$ using the global MILP model is: two distribution centres $\{CD13, CD35\}$ and one warehouse $\{F35\}$. We got the same SC configuration using our heuristic to solve the instance $D4$ (Table 5.5).
It's clear that using our heuristic, we can establish optimal solution to small sized problems, in a reasonable time, even faster than the global MILP model and the quality of the solution is equal to the global model one.
Then, the computing times using the heuristic to solve medium size instances ($D8$ to $D14$), are largely better than those using the global MILP. For example, the time that the global MILP model took to solve the problem $D9$ is equal to 44 777 seconds , while for the same problem the heuristic took only 37 seconds to get the optimal solution. Also, for instances $D8$ to $D14$, the SC configurations of the both approaches are equals or a small difference in one distribution center like in $D10$, the SC configuration proposed by the global MILP model is $\{CD35, CD96, CD137, CD49\}$ as distribution centers and $\{F137\}$ as warehouse, the SC configuration established by the heuristic algorithm is $\{CD35, CD96, CD137, CD219\}$ as distribution centers and $\{F137\}$ as warehouse.
For experiments $D15$ to $D26$, as we can see on Table 5.7, Table 5.8 and Table 5.9, it's impossible to solve these instances using global MILP model, all of them are out of mem-

ory (OM). But, using our heuristic we succeeded to obtain solutions in reasonable time. Finally, Tables 5.5, 5.6, 5.7, 5.8, 5.9 and 5.10 show the SC configuration and computing time obtained solving 26 instances using the heuristic algorithm and the global MILP model.

Table 5.4: Solutions: Heuristic vs Global MILP model

Exp	MILP costs (€)	Lower bound(€)	Heuristic costs (€)	Gap 1 (%)	Gap 2 (%)
D1	50 969 501	-	50 969 501	0,00%	-
D2	49 104 009	-	49 104 009	0,00%	-
D3	63 190 371	-	63 190 371	0,00%	-
D4	64 479 173	-	64 479 173	0,00%	-
D5	64 862 948	-	64 862 948	0,00%	-
D6	66 583 537	-	66 583 537	0,00%	-
D7	66 583 537	-	66 583 537	0,00%	-
D8	60 864 271	-	60 864 271	0,00%	-
D9	60 846 506	-	61 053 982	0,34%	-
D10	58 253 135	-	58 554 399	0,52%	-
D11	58 253 135	-	58 554 399	0,52%	-
D12	59 366 319	-	59 591 091	0,38%	-
D13	59 197 681	-	59 366 319	0,28%	-
D14	47 546 627	-	47 546 627	0,00%	-
D15	-	49 077 542	49 659 208	-	1,19%
D16	-	47 518 700	48 390 006	-	1,83%
D17	-	48 255 402	49 807 395	-	3,22%
D18	-	47 738 700	51 964 143	-	8,85%
D19	-	46 192 400	50 588 271	-	9,52%
D20	-	47 549 019	52 010 862	-	9,38%
			Average	0,15%	5,66%

Table 5.5: Configuration: Heuristic vs Global MILP (Part 1)

	Global MILP Model			Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D1	0,22	CD35(10000000); CD39(115160000)	F35(125160000)	0,23	CD35(10000000); CD39(115160000)	F35(125160000)
D2	0,28	CD35(45405000); CD39(79753000)	F35(125160000)	0,53	CD35(45405000); CD39(79753000)	F35(125160000)
D3	1,12	CD8(26596000); CD35(98562000)	F35(125160000)	1,94	CD8(26596000); CD35(98562000)	F35(125160000)
D4	2,2	CD13(84790000); CD35(40368000)	F13(125160000)	2,42	CD13(84790000); CD35(40368000)	F13(125160000)
D5	2,14	CD13(16006000); CD8(44538000); CD35(64555000)	F35(125160000)	2,12	CD13(16006000); CD8(44538000); CD35(64555000)	F35(125160000)
D6	3,58	CD13(16006000); CD35(64555000)	F35(125160000)	2,06	CD13(48877000); CD35(76281000)	F35(125160000)
D7	51,59	CD13(48877000); CD35(76281000)	F35(125160000)	22,34	CD13(48877000); CD35(76281000)	F35(125160000)

Table 5.6: Configuration: Heuristic vs Global MILP (Part 2)

	Global MILP Model			Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D8	3482	CD35(61823000); CD96(19152000); CD28(44184000)	F35(125160000)	32,26	CD35(61823000); CD96(19152000); CD28(44184000)	F35(125160000)
D9	44777	CD35(37884000); CD96(19152000); CD137(41848000); CD50(26274000)	F149(125160000)	36,44	CD35(42042000); CD96(19152000); CD137(44590000); CD219(19374000)	F13(125160000)
D10	36232	CD35(38239000); CD96(19152000); CD137(44410000); CD49(23357000)	F137(125160000)	10,39	CD35(38239000); CD96(19152000); CD137(44410000); CD219(23357000)	F137(125160000)
D11	875487	CD35(38239000); CD96(19152000); CD137(44410000); CD49(23357000)	F137(125160000)	16	CD35(38239000); CD96(19152000); CD137(44410000); CD219(23357000)	F137(125160000)

Table 5.7: Configuration: Heuristic vs Global MILP (Part 3)

Global MILP Model				Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D12	8536	CD3(16058000); CD8(8409200); CD137(51406000); CD166(20981000); CD171(28305000)	F149(125160000)	22	CD8(12088000); CD137(58460000); CD166(20981000); CD171(33630000)	F149(125159000)
D13	16012	CD137(50424000); CD166(20981000); CD171(29152000); CD89(24602000)	F149(125160000)	28	CD3(16058000); CD8(8409200); CD137(51406000); CD166(20981000); CD171(28305000)	F149(12516000)
D14	9822	CD7(27543000); DE722(54105000); DS513(43511000)	F66(12516000)	18	CD7(27543000); DE722(54105000); DS513(43511000)	F66(12516000)
D15	OM	-	-	21	CD8(42758000); CD123(36330000); CD133(46071000)	F66(12516000)

Table 5.8: Configuration: Heuristic vs Global MILP (Part 4)

Global MILP Model				Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D16	OM	-	-	31	CD71(40843000); CD123(29330000); CD133(54985000)	F66(12516000)
D17	OM	-	-	33	CD7(27396000); CD123(18348000); CD134(79415000)	F66(12516000)
D18	OM	-	-	35	CD123(21048000); CD134(71033000); CD197(33077000)	F153(12516000)
D19	OM	-	-	43	CD8(39996000); CD71(20421000); CD123(16048000); CD134(48693000)	F153(12516000)

Table 5.9: Configuration: Heuristic vs Global MILP (Part 5)

	Global MILP Model			Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D20	OM	-	-	22	CD8(39996000); CD71(20421000); CD123(16048000); CD134(48693000)	F66(12516000)
D21	OM	-	-	38	CD8(47366000); CD123(21277000); CD133(53793000)	F66(12516000)
D22	OM	-	-	50	CD8(39687000); CD123(26021000); CD133(62541000)	F129(128249000)
D23	OM	-	-	76	CD8(25389000); CD123(28517000); CD133(50519000); CD71(23353000)	F66(127778000)
D24	OM	-	-	125	CD8(42001000); CD123(24830000); CD133(48208000)	DE111(115039000)

Table 5.10: Configuration: Heuristic vs Global MILP (Part 6)

Global MILP Model				Heuristic		
Exp	CPU Time (s)	CD and capacities	W and capacities	CPU Time (s)	CD and capacities	W and capacities
D25	OM	-	-	350	CD71(34947000); CD123(30232000); CD134(64388000)	DEX07(83453000); ES423(46114000)
D26	OM	-	-	550	CD8(40726000); DE722(28210000); CD123(19442000); CD134(39197000)	DEX07(127575000)

5.6 Concluding Remarks

In this chapter, we have proposed a three-phase heuristic decomposition algorithm to solve a supply chain network design problem. The heuristic consists of three phases which we can generally define as decomposition phase, reduction phase and resolution phase. In the decomposition phase, decomposition methods have been introduced in order to divide the large scale of the SCN into small two-level networks. In reduction phase, a modified p-median model has been used to reduce the large potential sets into small reduced sets. In resolution phase, a global MILP model has been used to solve the reduced SCN.

In this chapter, we have developed a practical heuristic for large-scale supply chain network design problems. We have solved a real large-scale supply chain network composed of 220 suppliers, 220 warehouses, 220 distribution centers and 1 500 customers, in less than 550 seconds. Computational results are generated from a set of 26 test problems. The proposed heuristic CPU times increase almost slowly with the system size, which is favourable for large-scale implementation. The average of heuristic CPU Time is equal to 5 seconds for small size instances, 24 seconds for medium size problems and only 115 seconds for large scale instances. Moreover, the gap between the final solution obtained by the proposed heuristic approach and the lower bound of global MILP obtained by Cplex is equal to 0% in small size instances, less than 0.52% in medium size instances and in large size problems, the gap ranges from 1.19% to 9.52% and the average gap between the upper bound of the global MILP model and the solution of the heuristic is equal to 5.66%.

The numerical experiments have indicated that the proposed heuristic solution algorithm performs well in terms of solution quality and computational time consumed.

Since SCND decisions are strategic and long term in nature, the influence of customers demand in the establishment of the SCN and the effect of critical supply chain network parameters are important. We think that it will be useful to consider the uncertainty of these parameters, for example, by generating scenarios that capture future uncertainty of the customers demand and costs. In this regard, the stochastic programming will be the subject of the next chapter.

Chapter 6

Supply Chain Network Design under Uncertainty

The deterministic model discussed in the previous chapter provides a base for Supply Chain Network Design (SCND). Nevertheless, any network design obtained based on this model, which represents the optimal deterministic configuration, has no assurance of performance for any other future parameter fluctuation. Deterministic models do not handle uncertainties and information imperfections about expected probable future business environments (Sabri et Beamon (2000), Klibi et al. (2010), Santoso et al. (2005)). As we explained in Chapter 2, section 2.4.2, uncertainty modelling becomes an important challenge for more realistic SCN design.

Most SCND under uncertainty researches model Supply Chain (SC) parameters uncertainties with probability distributions that are usually predicted from historical data. (Alonso-Ayuso et al. (2003), Guillen et al. (2005), Gupta and Maranas (2003), Santoso et al. (2005)). However, whenever statistical data are unreliable, or are not even available, stochastic models may not be the best choice (Wang and Shu (2005)). The Possibility Theory (Zadeh (1978)) may provide an alternative which is easier and needs less data than the Probability Theory to deal with SC uncertainties (Dubois et al. (2003)). In this chapter, we extend the deterministic SCND model presented in chapter 5. We first assume that we got the statistical data of the customer demands, so, we use two-stage stochastic programming approach to model the supply chain network under demand uncertainty. After that, we address uncertainty in all SC parameters: opening costs, production costs, storage costs and customers demands. In this case, statistical data of all these parameters are not available. However, we use possibilistic linear programming approach to model the problem and we validate the approach in a large real case Textile supply chain network.

6.1 Stochastic Supply Chain Network Design

6.1.1 Introduction

Models discussed in the previous chapter suppose that supply chain design parameters are deterministic. Whereas, in most cases, the future business environment under which a supply chain network will operate is unknown and critical parameters such as customer demands, prices, and capacities are uncertain in the real world. However, the importance of uncertainty in supply chain design has encouraged researchers to address stochastic parameters in supply chain design, such as Cheung and Powell (1996), Van Landeghem and Vanmaele (2002), Yu and Li (2000).

In this part, we use two stages stochastic programming approach to model the problem. In this approach, uncertain parameters are considered as random variables with an associated probability distribution and the decision variables are classified into two stages. The first stage variables correspond to those decisions that need to be made first, before the realization of the uncertainty. The second stage corresponds to those decisions made after the uncertainty is announced. After the first stage decisions are taken and the random events realized, the second stage decisions are subjected to the constraints imposed by the second stage problem (Birge and Louveaux(1997)).

Santoso et al. (2005) proposed a two stage stochastic programming model and solution algorithm for solving supply chain network design problems. Their heuristic integrates the sample average approximation scheme with an accelerated Benders decomposition algorithm. Authors used the proposed solution approach for solving two realistic supply chain design problems. The first case network composed of 12 products, 6 suppliers, 17 warehouses, 8 manufacturing plants, 60 scenarios and 17 customers. The network structure of the second application case was: 13 products, 2 suppliers, 8 manufacturing plants, 60 scenarios and 238 customers. Azaron et al. (2008) developed a multi-objective stochastic programming approach for supply chain design under uncertainty. They considered numerous uncertain parameters such as: demands, supplies , processing, transportation, shortage and capacity expansion costs. Authors used the goal attainment technique, which is a variation of the goal programming technique, to solve the multi-objective SCND problem and to generate the Pareto-optimal solutions. Computational results on network involving 4 suppliers, 4 potential plants, 3 customers and 4 scenarios were presented. Another example of solving two-stage stochastic supply chain design problems is Alonso Ayuso et al. (2003). The authors proposed a branch-and-fix heuristic to solve a real problem. The networks involved 6 plants, 12 products, 24 markets, and 23 scenarios. Two-stage stochastic supply chain network design models were proposed by MirHassani et al. (2000), Tsiakis et al. (2001), Vila et al. (2007) and Vila et al. (2008).

As evident from the above discussion, there is a big deal of research in the supply chain network design under uncertainty, Owen and Daskin (1998). However, research addressing real size supply chain networks design problems is significantly small in number. Most of the stochastic supply chain network design literature considers simplified single criterion, single transportation mode. In addition, the existing stochastic programming approaches for supply chain design under uncertainty are suited for a very small number of scenarios. However, this section deals with the design of a multi-criteria, multi-level and multi-modal supply chain network under uncertainty in order to satisfy the customers demand and to respect the environmental, social, legislative, and economic requirements. We extend the second step of our methodology (see chapter 3), with a stochastic mathematical model. We validate this model on the case study concerning the recycling of sediment waterways presented in chapter 3.

In this chapter, we look for the optimal supply chain network design to fulfil uncertain customer demands using two-stage stochastic programming model. The objective is to minimize the sum of: opening facilities costs, storage costs, production costs and transportation costs. We determine location of treatment facilities and their capacities to satisfy an estimated annual demand of potential customers.

The remainder of this chapter is organized as follows. Fist, we discuss the modelling of the problem and indicate how the deterministic SCND model may be extended using stochastic programming method. Then, the results of the stochastic programming approach are discussed in Section 6.1.3. Finally, in Section 6.1.4 some concluding remarks are presented.

6.1.2 Model Development

In this section, we extend the deterministic Mixed Integer Linear Programming (MILP) model presented in Chapter 5, to a stochastic programming model, in order to design a supply chain network under uncertainty.

Consider the supply chain network presented in Chapter 5. In addition to the assumptions done before (Chapter 5), we assume that the customers demand are uncertain. As in Alonso-Ayuso et al. (2003), Guillen et al. (2005) and Santoso et al. (2005), we assume that we can predict from historical data the probability distributions of the demand uncertain parameter. As we have only one uncertain parameter, which is customers demand, and we have the probability distributions of this parameters, we use two stage stochastic programming approach to model the problem (Santoso et al. (2005)). For more details about this approach, you can refer to the Chapter 2. The potential design of a supply chain being considered (see Figure 6.1), is composed of suppliers, warehouses, distribution centres, and sellers. As depicted in Figure 6.1, products are shipped from suppliers to

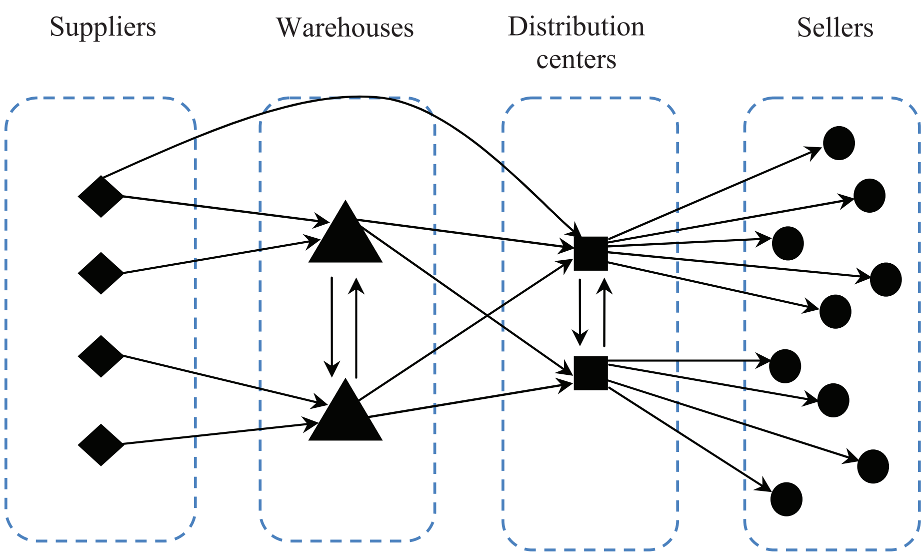

Figure 6.1: Supply Chain Network

warehouses, where goods are prepared to be sent to the next level. Then, they are transported to distribution centers. In some new products cases, $\beta\%$ of the goods should be shipped directly to distribution centers, this percentage are fixed by experts. The distribution centers insure the storage and the distribution of products to sellers. If the number of warehouses to open is more than one site,$\gamma\%$ of goods received from suppliers should be transported between warehouses in order to try to keep a quantity balance between sites. This percentage γ are assigned by experts. Warehouses are defined as the facility where the products are received and married with goods going to the same destination, then shipped at the earliest opportunity, without going into long-term storage. They are located near suppliers and distribution centers. Distribution centers are ones located near customers and handled most products in four cycles (receive, store, pick, and ship).
In this case it's very difficult to predict all uncertain SC parameters such as: transportation costs, opening costs, processing costs, storage costs and demand, because the collection of statistical data becomes increasingly unreliable and these information are unobtainable in a long time horizon. However, experts do not precisely know their values. Therefore, we will consider the knowledge of experts about the uncertain SC parameters as fuzzy data. The technique used to elaborate the fuzzy numbers will be explained in the next section.
The main assumptions used in the problem formulation are as follow:

We now model our supply chain as two-stage stochastic program. For reasons of simplicity, we denote

the set of feasible solution of first-stage decisions x_j and y_k by X and Y, the uncertain parameter in this formulation is: demand. The first stage consists of the deciding the configuration decisions x and y, and the second stage consists of treatment, storage, and the quantities of goods to transport throughout the supply chain network in an optimal way. Note that ξ represents the random vector corresponding to the uncertain demands. The design objective is to minimize the sum of investment costs and expected future

- Numbers:

m number of supplier locations.

n number of possible warehouse locations.

p number of possible distribution center locations.

q number of customer locations.

r number of scenarios.

- Indices :

i supplier index.

j,j' possible warehouse location indices.

k,k' possible distribution center location indices.

l customer index.

s scenarios index.

- Parameters :

A_i capacity of supplier i.

f_j^0 fixed cost of opening warehouse j.

α percentage of products transported from the suppliers to the distribution centre.

treatment, storage and transportation costs.

$$Minimize \left[\sum_{j \in W} (f_j^0 \cdot x_j) + \sum_{k \in D} (c_k^0 \cdot y_k) + \sum_{s \in R} \delta_s \cdot Q(x, y, \xi^s) \right] \tag{6.1}$$

Subject to

$$x \in X \subseteq \{0, 1\} \tag{6.2}$$

$$y \in Y \subseteq \{0, 1\} \tag{6.3}$$

With $Q(x,y,\xi^s)$ being the solution of the following second stage problem:

$$Q(x, y, \xi^s) = \sum_{i \in S} \sum_{j \in W} \mu_{ij} \cdot q_{ij}^s + \sum_{j \in W} f_j \sum_{i \in S} q_{ij}^s + \sum_{j \in W} \sum_{j' \in W} \mu_{jj'} \cdot q_{jj'}^s + \sum_{i \in S} \sum_{k \in D} \mu_{ik} \cdot q_{ik}^s + \tag{6.4}$$

$$\sum_{k \in D} c_k \sum_{i \in S} q_{ik}^s + \sum_{k \in D} \sum_{k'=1} \mu_{kk'} \cdot q_{kk'}^s + \sum_{j \in W} \sum_{k \in D} \mu_{jk} \cdot q_{jk}^s + \sum_{k \in D} c_k \sum_{j \in W} q_{jk}^s + \sum_{k \in D} \sum_{l \in C} \mu_{kl} \cdot q_{kl}^s$$

f_j unit processing costs at warehouse j.

F_j^{max} maximum processing capacity at warehouse j.

F_j^{min} minimum processing capacity at warehouse j.

γ percentage of products transported between warehouses.

c_k^0 fixed cost of opening distribution center k.

c_k unit storage costs at distribution center k.

C_k^{max} maximum storage capacity of distribut.center k.

C_k^{min} minimum storage capacity of distribution center k.

δ percentage of products transported between distribution centers.

μ_{ij} unit transportation costs of goods between supplier i and warehouse j.

μ_{jk} unit transportation costs of goods between warehouse j and distribution center$k$.

μ_{kl} unit transportation costs of goods between distribution center$k$ and customer l.

μ_{ik} unit transportation costs of goods between supplier i and distribution center k.

$\mu_{jj'}$ unit transportation costs of goods between warehouse j and warehouse $j^{'}$ $(j^{'} \neq j)$.

$\mu_{kk'}$ unit transportation costs of goods between distribution center$k$ and distribution center $k^{'}$ $(k^{'} \neq k)$.

θ_{kl} distance between distribution center k and customer l.

θ^{max} maximal distance between each customer effected to distribution center.

D_l^s demand of the customer l for scenario s.

δ_s probability of scenario s.

- Decision variables:

x_j =1 if warehouse j is opened, and $=0$ otherwise.

y_k $=1$ if distribution center k is opened, and $=0$ otherwise.

q_{ij}^s quantity of products transported from supplier i to warehouse j in scenario s.

q_{jk}^s quantity of products transported from warehouse j to distribution center$k$ in scenario s .

q_{kl}^s quantity of products transported from distribution center$k$ to customer l in scenario s.

q_{ik}^s quantity of products transported from supplier i to distribution center k in scenario s.

$q_{jj'}^s$ quantity of products transported from warehouse j to warehouse $j^{'}(j^{'} \neq j)$ in scenario s.

$q_{kk'}^s$ quantity of products transported from distribution center k to distribution center $k^{'}$ ($k^{'}$ $\neq k$) in scenario s.

Constraint (6.5) imposes that all goods received by suppliers will be transported to warehouse and/or distribution centre:

$$\sum_{j \in W} q_{ij}^s + \sum_{k \in D} q_{ik}^s = A_i \qquad i \in S; s \in R. \quad (6.5)$$

Constraint (6.6) guarantees the percentage of goods that will be transported directly from suppliers to distribution centers:

$$\sum_{k \in D} q_{ik}^s = \alpha \cdot A_i \qquad i \in S; s = 1, ..., r. \quad (6.6)$$

Constraint (6.7) enforces the flow conservation of the products between warehouses:

$$\sum_{i \in S} q_{ij}^s + \sum_{j^{'} \in W} q_{j^{'}j}^s = \sum_{k \in D} q_{jk}^s + \sum_{j^{'} \in W} q_{jj'}^s \qquad j \in W; s \in R; (j^{'} \neq j). \quad (6.7)$$

Constraint (6.8) guarantees the goods flow between warehouses:

$$\sum_{j^{'} \in W} q_{jj'}^s = \gamma \cdot \sum_{i \in S} q_{ij}^s \qquad j \in W; s \in R(j^{'} \neq j). \quad (6.8)$$

Constraint (6.9) limits the warehouse treatment capacity :

$$F_j^{min} \cdot x_j \leq \sum_{i \in S}^{m} q_{ij}^s + \sum_{j^{'} \in W}^{n} q_{j^{'}j}^s \leq F_j^{max} \cdot x_j \qquad j \in W; s \in R(j^{'} \neq j). \quad (6.9)$$

Constraint (6.10) enforces the flow conservation of the products between distribution centers:

$$\sum_{j \in W} q_{jk}^s + \sum_{i \in S} q_{ik}^s + \sum_{k^{'}=1} q_{k^{'}k}^s = \sum_{l \in C} q_{kl}^s + \sum_{k^{'}=1} q_{kk'}^s \qquad k \in D; s \in R; (k^{'} \neq k). \quad (6.10)$$

Constraint (6.11) guarantees the goods flow between distribution centers:

$$\sum_{k^{'}=1} q_{kk'}^s = \delta \cdot \left[\sum_{i \in S} q_{ik}^s + \sum_{j \in W} q_{jk}^s \right] \qquad k \in D; s \in R; (k^{'} \neq k). \quad (6.11)$$

Constraint (6.12) limits the distribution center capacity:

$$C_k^{min} \cdot y_k \leq \sum_{j \in W} q_{jk}^s + \sum_{i \in S} q_{ik}^s + \sum_{k' \in D} q_{k'k}^s \leq C_k^{max} \cdot y_k \qquad k \in D; s \in R; (k' \neq k). \quad (6.12)$$

Constraint (6.13) guarantees the response time from distribution centers to sellers:

$$q_{kl} \cdot (\theta^{max} - \theta_{kl}) \geq 0 \qquad k \in D; l \in C. \quad (6.13)$$

Constraint (6.14) guarantees that customers demand will be satisfied:

$$\sum_{k \in D} q_{kl}^s = D_l^s \qquad l \in C; s \in R. \quad (6.14)$$

Constraints (6.15) and (6.16) enforce the binary nature of x_j and y_k :

$$x_j \in \{0, 1\} \qquad j \in W. \quad (6.15)$$

$$y_k \in \{0, 1\} \qquad k \in D. \quad (6.16)$$

Constraints (6.17), (6.18), (6.19), (6.20), (6.21) and (6.22) are standard integrality and non-negativity constraints:

$$q_{ij}^s \geq 0 \qquad i \in S; j \in W; s \in R. \quad (6.17)$$

$$q_{jk}^s \geq 0 \qquad j \in W; k \in D; s \in R. \quad (6.18)$$

$$q_{kl}^s \geq 0 \qquad k \in D; l \in C; s \in R. \quad (6.19)$$

$$q_{ik}^s \geq 0 \qquad i \in S; k \in D; s \in R. \quad (6.20)$$

$$q_{jj'}^s \geq 0 \qquad j \in W; j' \in W; s \in R; (j' \neq j). \quad (6.21)$$

$$q_{kk'}^s \geq 0 \qquad k \in D; k' \in D; s \in R; (k' \neq k). \quad (6.22)$$

6.1.3 Computational results

In this section we describe numerical experiments using the proposed model for solving realistic supply chain design problem of an international textile company in Europe. We first describe the characteristics of the test problems and some implementation details, then comment on the quality of the two stage stochastic programming solution in comparison to those obtained using deterministic approach. Our application case consists of 11 suppliers, 16 possible warehouse locations , 63 possible distribution center locations , and 103 sellers that the company serves. Our deterministic model and two-stage stochastic programming model are complemented on Windows Vista 1.66 GHZ and 2 GB of memory and solved by commercial software ILOG OPL 6.3/ CPLEX 12.1.0. Four scenarios are generated for two-stage stochastic programming model and all of them are used individually for deterministic problem. To compare the performance of the deterministic and stochastic models under each scenario. First, the models were solved. Then, the configuration of the stochastic solution is assessed under each scenario by allowing the model to find his decision variables under each scenario.In order to generate a balanced network configuration between these various scenarios, we applied stochastic programming with equal probabilities. The Table 6.1 summarizes the results of the two models deterministic and stochastic.

Table 6.1: Computational Results

Scenarios	Variables	Constraints	CPU Time (s)	Optimal cost (€)	Distribution centers	Warehouses
S_1	12 608	17 820	353	55 533 302	CD7, CD21, CD31, CD50	F11
S_2	12 608	17 820	419	57 319 075	CD7, CD22, CD28, CD49	F3
S_3	12 618	17 820	629	58 543 342	CD7, CD22, CD24, CD50	F11
S_3	12 608	17 820	366	58 567 671	CD7, CD22, CD28, CD49	F3
Stochastic	50 280	71 280	285 976	57 739 990	CD7, CD22, CD28, CD49	F4

Table 6.1 reveal that the deterministic model contains 12 608 variables and 17 820 constraints, and the computational time is between 353 seconds and 629 seconds. The Stochastic two-stage programming model contains 50 280 variables and 71 280 constraints, however the computational time increase to 285 976 seconds. As we can see, for 4 scenarios

the CPU Time rise to 285 976 seconds, and it can easily go up with the growing of scenario numbers. In addition the number of variables and constraints for the models shows the higher degree of complexity of the stochastic model. The use of heuristics methods can help to use more scenarios and decrease this time, which is one of our future research topics. To satisfy customers demand and decrease the response time from distribution centers to sellers to less than 48 hours, the number of warehouses and distribution centers to open are: 1 and 4 respectively. The stochastic configuration differs from any of the deterministic configuration of individual scenario.

Table 6.2: Comparison of Deterministic cost to Stochastic cost.

Scenarios	Deterministic cost (€)	Stochastic cost(€)	Stochastic–Optimal (€)	% of Stochastic
S_1	55 533 302	55 697 279	163 977	0.30%
S_2	57 319 075	57 633 243	314 168	0.55%
S_3	58 543 342	58 902 208	358 866	0.61%
S_4	58 567 671	58 727 230	159 559	0.27%
Average	57 490 847	57 739 990	249 143	0.45%

Table 6.2 shows the differences between the cost given by the Deterministic solution of each scenario and the cost given by the Stochastic solution for the same scenario. The Stochastic solution generates more expensive costs than Deterministic solution for each scenario. The Stochastic average cost is 0.45% more expensive than the Deterministic average cost.

Values generated by the Deterministic solution and the worst cases are presented in

Table 6.3: Comparison of optimal Deterministic solutions to worst case solutions.

Scenarios	Deterministic cost (€)	Worst case cost(€)	Worst case-Deterministic (€)	% of worst case
S_1	55 533 302	56 157 021	623 719	1.12%
S_2	57 319 075	58 535 292	1 216 217	2.12%
S_3	58 543 342	59 414 125	870 783	1.49%
S_4	58 567 671	59 269 142	701 471	1.20%
Average	57 490 847	58 343 895	853 047	1.48%

Table 6.3.

In this comparison the average cost generated by the worst case is 1.48% bigger than the Deterministic average cost. From row 2 of Table 6.3, we see that the difference between worst case costs and Deterministic costs attends 1 216 217 (€), which represent 2.12% of the optimal Deterministic cost.

Table 6.4 compares optimal Stochastic solutions costs to worst case solutions costs.

It is clear that, the stochastic solution costs for all candidate stochastic programming

Table 6.4: Comparison of Stochastic cost to worst case cost.

Scenarios	Stochastic cost(€)	Worst case cost(€)	Worst case-Stochastic (€)	% of worst case
S_1	55 697 279	56 157 021	459 742	0.83%
S_2	57 633 243	58 535 292	902 049	1.57%
S_3	58 902 208	59 414 125	511 917	0.87%
S_4	58 727 230	59 269 142	541 912	0.92%
Average	57 739 990	58 343 895	603 905	1.05%

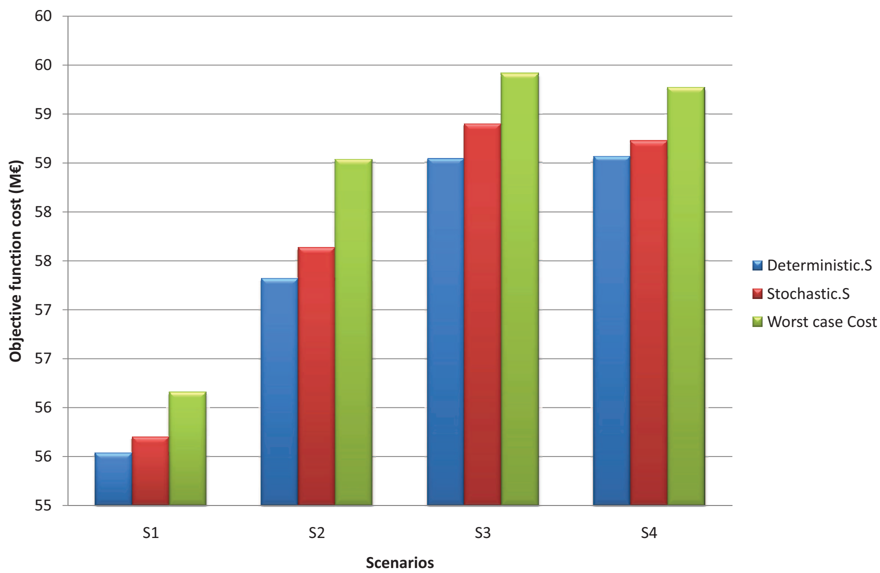

Figure 6.2: Solution costs comparison

solution are smaller than that of the worst case solution. From row 2 of Table 6.4, we observe that the cost corresponding to the stochastic programming solution 57 633 243 (€) is smaller than that of the worst case with approximately 900 000 (€), which represents 1.57% of the global cost.

The last row of Table 6.4 displays the average of the results, the stochastic solution is approximately 1.05% smaller than the worst case solution, which represents 500 000 (€). The Figure 6.2 shows the difference between the total costs of the optimal, stochastic and worst case solutions. The results show that the stochastic configuration is better than the worst case solution for all scenarios, and not far from the optimal solution of each scenario.

6.1.4 Concluding Remarks

Determining the optimal supply chain configuration is a difficult problem since a lot of factors and criteria must be taken into account when designing the network. Therefore, the practical methodology developed in this theses seems to be the best way of capturing the high complexity of sustainable supply chain network design problems under uncertainty. We presented a supply chain design problem model which includes explicitly demand uncertainty. The two stage stochastic programming formulation of the problem can be applied to any supply chain that consists of many levels. The results obtained point out, that supply chain design methods which do not include uncertainty obtain inferior results if compared with models that formalise it implicitly. The stochastic model could handle data uncertainty with a reasonable increase in total costs compared with the deterministic model and therefore it can be concluded that the proposed two-stage programming model can be used as a robust Model in real cases. In this first part, we assumed that we have only one uncertain parameter (demand) and that we can predict from historical data the probability distributions of the demand uncertain parameter. But, in reality, information data are unreliable or unobtainable and many critical SC parameters are uncertain such as : productions costs, storage cots, transportation costs, etc. With only 4 scenarios, the computational time of the two-stage stochastic programming model was equal to 285 976 seconds However, stochastic models may not be the best choice (Wang and Shu (2005)). In the next part of this chapter, we will try to address uncertainty in all SC parameters: opening costs, production costs, storage costs and customers demands assuming that we have not the historical data of these parameters. We will use possibilistic linear programming approach to model the problem.

6.2 Possibilistic Supply Chain Network Design

6.2.1 Introduction

In this section, we extend our model studied in this Chapter to a more complex case in which the supply chain parameters such as customers demand and costs are considered uncertain, especially as fuzzy numbers. Also, we consider two decision levels, warehouses to open in the the first level and distribution centers to locate in the second one.

This part has two important contributions. First, it presents a comprehensive possibilistic model for supply chain network design under uncertainty and an efficient solution procedure for finding solution to a possibilistic mixed-integer program. The need for such model by practitioners, in supply chain design, has been highlighted by many authors such as Sabri and Beamon (2000). And second, it introduces a real world application case. In our literature survey (Chapitre 2) we have felt a lack of studies in this field.

The complex nature and dynamics of the relationships between supply chain actors imply an important degree of uncertainty in SCND decisions and sources of these uncertainties may be environmental or originated from the system itself: lack of information, abundance of information, conflicting evidence, ambiguity, measurement and belief Zimmermann (2001). In the following, we describe these causes in detail:

- *Lack of information:* a lot of are situations characterized by a lack of information: (i) Decision under uncertainty is the situation in which a Decision Maker (DM) does not have any information about which of the possible states of nature will occur. (ii) Decision making under risk is situation in which the DM knows the probabilities for the occurrence of various states. (iii) Approximation: here one does not have to gather sufficient information to make an exact description, even though this might be possible. (iv) Ambiguity: certain linguistic information has entirely different meanings, human observer can normally easily interpret the word correctly if he knows the context of the word. (v) Measurement: we have some uncertainty about the real measure and we know only the indicated measure. The quality of measuring technology has increased with time and the further this technology improves, the more exactly it can measure physical features such as distance, transportation time, shipment speed, etc (Zimmermann (2001)).

- *Abundance of information :* this type of uncertainty is due to the limited ability of

human beings to perceive and process simultaneously large amounts of data (Newell and Simon (1972)). In that cases, generally DM transforms the available data into perceivable information by focusing their attention on those features which seems to him most important and neglecting all other information or by using coarser grid or rougher granularity.
- *Conflicting evidence :* uncertainty might also be due to conflicting evidence, there might be considerable information available pointing to a certain behaviour of a system and additionally there might also be information available pointing to another behaviour of the system. If the two classes of available information are conflicting, then an increase of information might not reduce uncertainty at all, but rather increase the conflict.
- *Belief :* is a cause of uncertainty situation in which all information available to the observer is subjective as a kind of belief in a certain situation. This situation is probably most disputable (Zimmermann (2001)).
In our real-world application case, a lot of supply chain parameters whose values are assigned by experts are uncertain in nature because some informations are unobtainable in a long time horizon. For example, it's difficult to predict numerous parameters such as: transportation costs, opening costs, processing costs, storage costs and demand, because the collection of statistical data becomes increasingly unreliable. However, experts do not precisely know their values. Therefore, it is useful to consider the knowledge of experts about the parameters as fuzzy data.
The main idea in this chapter is to model uncertain parameters as fuzzy triangular numbers. Then, to determine locations, numbers, capacities of warehouses capacities of distribution centers and materiel flow transported throughout the supply chain network by minimizing the fuzzy objective function composed of the sum of costs cited above.
This part is organized as follows: In section 6.2.2, an additional Possibilistic Linear Programming (PLP) literature review is presented. In section 6.2.3, basic fuzzy sets theory definitions need for the current study are highlighted, PLP model is set out and solution approach is outlined. Section **??**, includes application of the proposed model and offers an analysis of the computational results. Finally, conclusions are drawn and future lines of research are discussed in Section 6.2.5.

6.2.2 Possibilistic Linear Programming

In addition to the Possibilistic Linear Programming literature review presented in Chapter 2 (section 2.4), we try, in this section, to emphasize on research works in possibilistic supply chain network area.

Chen and Lee (2004) proposed a multi-objective optimisation for a supply chain network with uncertain market demands and product prices. The authors modelled the uncertain market demands as a number of discrete scenarios with known probabilities, and used the fuzzy sets for describing the sellers and buyers incompatible preference on product prices, and presented computational results on supply chain networks involving up to 1 plant site, 2 distribution centers, 2 retailers and 2 products.

In Wang and Hsu (2005) paper, a generalized closed-loop logistics model is proposed where the uncertainty is expressed by fuzzy numbers. They developed a mathematical programming model for this problem involving customer demands, recovery percentage and landfill rate as fuzzy parameters, and presented a numerical example composed of 3 suppliers, 5 production plants, 3 distribution centers, 2 recycling sites and 4 customers.

Wang and Shu (2007) suggested a possibilistic decision model to determine the supply chain configuration and inventory policies for new products with unreliable or unavailable statistical data. Fuzzy sets were used to model uncertain and flexible supply chain parameters such as total supply chain cost, demand, service time and lead time. Authors presented a case study of Computer Assembly Company to evaluate the performance of the entire supply chain.

Peidro et al. (2009) proposed a fuzzy mathematical programming model for supply chain planning which considers supply, demand and process uncertainties. The model formulated as a fuzzy mixed integer linear programming model where data are unknown and modelled by triangular fuzzy numbers. They tested the proposed PLP on a cars supply chain network involving: 44 suppliers, one manufacturing site, one assembly plant and a cars assembly plant. Chen and Lee (2004) proposed a multi-objective optimisation for a supply chain network with uncertain market demands and product prices. The authors modelled the uncertain market demands as a number of discrete scenarios with known probabilities, and used the fuzzy sets for describing the sellers and buyers incompatible preference on product prices, and presented computational results on supply chain networks involving up to one plant site, two distribution centers, two retailers and two products.

In Wang and Hsu (2010) paper, a generalized closed-loop logistics model is proposed where the uncertainty is expressed by fuzzy numbers. They developed a mathematical programming model for this problem involving customer demands, recovery percentage and landfill rate as fuzzy parameters, and presented a numerical example composed of 3 suppliers, 5 production plants, 3 distribution centers, two recycling sites and 4 customers. Pishvaee and Torabi (2010) showed a bi-objective possibilistic mixed integer programming model to deal with the design of closed-loop supply chain networks under uncertainty. To solve the proposed model, they introduced an interactive fuzzy solution approach by combining the Jimenez (1996), Jimenez et al. (2007), Torabi and Hassini (2008) and Selim and Ozkarahan (2008) methods.

6.2.3 Model Development

In this section, we introduce the basic idea of the possibilistic linear programming. Then, we present the steps of PLP method and the resolution approach. Figure 6.3 outlines the important steps of the modelling method and the resolution approach.

The starting point in Figure 6.3 is the formulation of the PLP model. Then, the imprecise coefficients and the fuzzy objective function are transformed into crisp ones. Finally, the resolution approach is applied. We will first describe the essentials of possibility approach and then explain all these steps in the following sections.

Uncertainty modeling

Before, we attempt to describe the detail of the steps introduced in (Figure 6.3), we present the definitions and the concepts of possibility theory suggested by Zadeh in 1965 (Zadeh (1965)).

To deal with the uncertainties, all fuzzy parameters are represented by the ($\sim$) sign over their symbols. According to Zadeh, a fuzzy set $\tilde{A}$ of a universe X is characterised by its membership function $\mu_{\tilde{A}}$.

$$\mu_{\tilde{A}} : X \longrightarrow [0, 1]$$

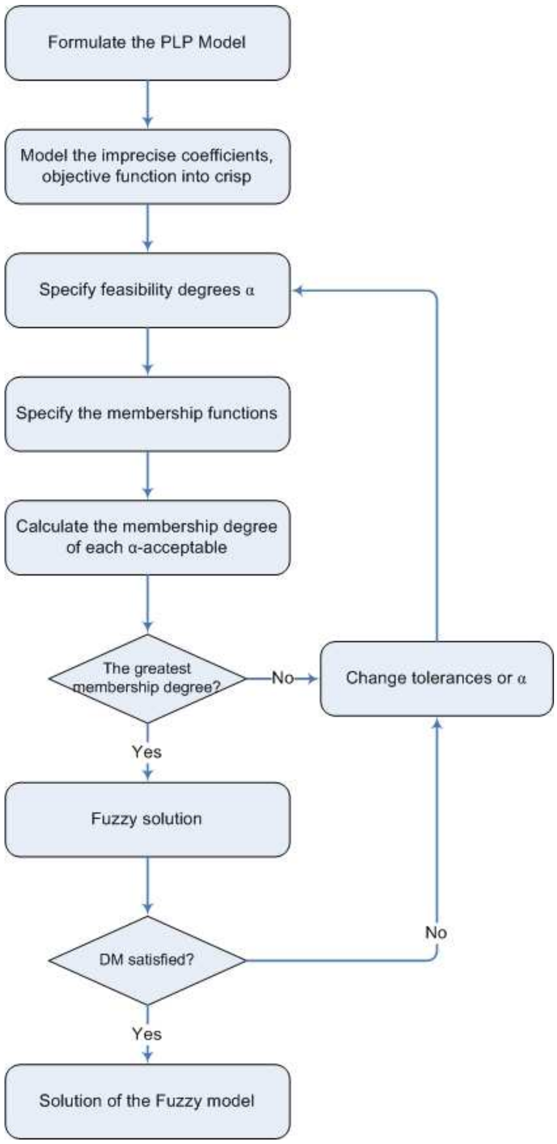

Figure 6.3: Modelling and resolution method

Where $\mu_{\tilde{A}}(x)$; $x \in X$, is the membership degree or grade of membership of x to $\tilde{A}$. A fuzzy set $\tilde{B}$ of a universe X is characterised by its membership function $\mu_{\tilde{B}}$.

$$\mu_{\tilde{B}} : X \longrightarrow [0, 1\,]$$

Where $\mu_{\tilde{B}}(x)$; $x \in X$, is the membership degree or grade of membership of x to $\tilde{B}$. The membership function $\mu_{\tilde{C}}(x)$ of *intersection* $\tilde{C}$=$\tilde{A} \cap \tilde{B}$ is defined by

$$\mu_{\tilde{C}}(x) = \min\{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, x \in X \tag{6.23}$$

The membership function $\mu_{\tilde{D}}(x)$ of *union* $\tilde{D}$=$\tilde{A} \cup \tilde{B}$ is defined by

$$\mu_{\tilde{D}}(x) = \max\{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, x \in X. \tag{6.24}$$

The membership function of the *complement* of a normalized fuzzy set $\tilde{A}$, $\mu_{\tilde{A}^c}(x)$ is defined by

$$\mu_{\tilde{A}^c}(x) = 1 - \mu_{\tilde{A}}(x), x \in X. \tag{6.25}$$

Assume that $\tilde{c}_{ij}$ is a triangular fuzzy number, c_{ij}^m it's the most likely value of this parameter, c_{ij}^L is the most pessimistic value and c_{ij}^R is the optimistic value. The following equation $\mu_{\tilde{c}_{ij}}(x)$ can be defined as the membership function of $\tilde{c}_{ij}$:

$$\mu_{\tilde{c}_{ij}}(x) = \begin{cases} f_{c_{ij}}(x) = \frac{x - c_{ij}^L}{c_{ij}^m - c_{ij}^L} & if \quad c_{ij}^L \leq x \leq c_{ij}^m \\ 1 & if \quad x = c_{ij}^m \\ g_{c_{ij}}(x) = \frac{c_{ij}^R - x}{c_{ij}^R - c_{ij}^m} & if \quad c_{ij}^m \leq x \leq c_{ij}^R \\ 0 & if \quad x \leq c_{ij}^L \quad or \quad x \geq c_{ij}^R \end{cases} \tag{6.26}$$

In practice, a Decision Maker (DM) can construct the triangular possibility distribution of $\tilde{c}_{ij}$ based on the three prominent data $(c_{ij}^L, c_{ij}^m, c_{ij}^R)$. Figure 6.4 presents the triangular possibility distribution of fuzzy number $\tilde{c}_{ij}$.

According to Heilpern (1992) and Jimenez et al. (2007), *expected interval* (EI) and

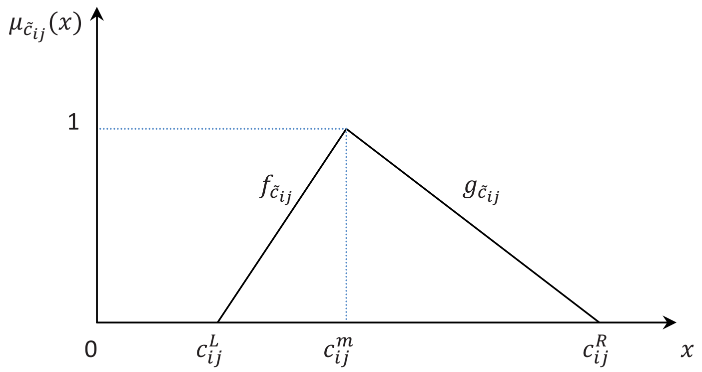

Figure 6.4: The triangular possibility distribution of $\tilde{c}_{ij}$

expected value (EV) of triangular fuzzy number $\tilde{c}_{ij}$ can be defined as follow:

$$E_1^{c_{ij}} = \int_0^1 f_{c_{ij}}^{-1}(x)\, dx = \frac{1}{2}(c_{ij}^L + c_{ij}^m) \tag{6.27}$$

$$E_2^{c_{ij}} = \int_0^1 g_{c_{ij}}^{-1}(x)\, dx = \frac{1}{2}(c_{ij}^m + c_{ij}^R) \tag{6.28}$$

$$EI(\tilde{c}_{ij}) = \left[E_1^{c_{ij}}, E_2^{c_{ij}}\right] = \left[\int_0^1 f_{c_{ij}}^{-1}(x)\, dx, \int_0^1 g_{c_{ij}}^{-1}(x)\, dx\right] = \left[\frac{1}{2}(c_{ij}^L + c_{ij}^m), \frac{1}{2}(c_{ij}^m + c_{ij}^R)\right] \tag{6.29}$$

$$EV(\tilde{c}_{ij}) = \frac{E_1^{c_{ij}} + E_2^{c_{ij}}}{2} = \frac{c_{ij}^L + 2c_{ij}^m + c_{ij}^R}{4} \tag{6.30}$$

Now we consider the following general fuzzy mathematical programming model in which all parameters are defined as triangular fuzzy numbers, where $\tilde{c}_{ij}$, $\tilde{a}_i$, $\tilde{b}_i$, represent, fuzzy parameters involved in the objective function and constraints, respectively. x is the crisp decision vector, z, is to be minimized in the sense of a given PLP problem.

$$\begin{aligned}
&Min \quad (z = \tilde{c}_{ij}x) \\
&s.t. \\
&\qquad \tilde{a}_i x \geq \tilde{b}_i, \quad i = 1, \ldots, l \\
&\qquad \tilde{a}_i x = \tilde{b}_i, \quad i = l+1, \ldots, m \\
&\qquad x \geq 0.
\end{aligned} \tag{6.31}$$

Using the definition of expected interval (6.29) , expected value (6.30) of a fuzzy number and α as feasibility degree. Feasibility degree reflects the DM preferences, we found 11 scales of α presented by Kaufmann and Gil Aluja (1992), they attributed to: 0 unacceptable solution, 0.1 practically unacceptable solution, 0.2 almost unacceptable solution, ..., 0.9 practically acceptable solution and 1 to completely acceptable solution. The equivalent crisp α-parametric model (6.32) of the model (6.31) can be written as follows:

$$\begin{aligned}
&Min \quad EV(\tilde{c}_{ij})x \\
&s.t. \\
&\qquad [(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]\, x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}, \quad i = 1, \ldots, l \\
&\qquad \left[(1-\tfrac{\alpha}{2})E_2^{a_i} + \tfrac{\alpha}{2}E_1^{a_i}\right] x \geq \tfrac{\alpha}{2}E_2^{b_i} + (1-\tfrac{\alpha}{2})E_1^{b_i}, \quad i = l+1, \ldots, m \\
&\qquad \left[\tfrac{\alpha}{2}E_2^{a_i} + (1-\tfrac{\alpha}{2})E_1^{a_i}\right] x \leq (1-\tfrac{\alpha}{2})E_2^{b_i} + \tfrac{\alpha}{2}E_1^{b_i}, \quad i = l+1, \ldots, m \\
&\qquad x \geq 0.
\end{aligned} \tag{6.32}$$

This model can not be solved directly. Therefore, a solution procedure is described in the following section.

Solution approach

There are different approaches to solve PLP problems (see Buckley and Feuring (2000) , Tanaka et al. (2000), Jimenez et al. (2007) , Sakawa (1993), Rommelfanger and Slowinski (1998)).

Usually a combination of some of this methods is necessary to obtain good results, as in

Jimenez et al. (2007).

Jimenez et al. (2007) proposed to solve possibilistic problem in an interactive way. The main steps of this approach are explained below:

In the first step, we solve the crisp linear program (6.32) for each α_k (feasibility degree). We obtain the space $S = \ x^0(\alpha_k),\alpha_k\ $ of the α_k-acceptable optimal solution of the problem (6.31) and the possibility distribution of objective value z : $z^0(\alpha_k)$. Then the Decision Maker is asked to specify the goal g and its optimist value G. If $z \leq g$ the DM will find it totally satisfactory and if $z \geq G$, DM satisfaction degree will be null. $\tilde{G}$ membership function is as follows:

$$\mu_{\tilde{G}}(z) = \begin{cases} 1 & if \quad z \leq g \\ \lambda = \frac{G-z}{G-g} & if \quad g \leq z \leq G \\ 0 & if \quad z \geq G \end{cases} \tag{6.33}$$

In the second step, we compute the degree of satisfaction of the fuzzy goal $\tilde{G}$ by each α-acceptable optimal solution. There are several methods to do this, we suggest using an index proposed by Kabak and Ulengin(1979).

$$K_{\tilde{G}}(z^0(\alpha)) = \frac{\int_{-\infty}^{+\infty} \mu_{\tilde{G}}(z) \cdot \mu_{\tilde{z}^0(\alpha)}(z)dz}{\int_{-\infty}^{+\infty} \mu_{\tilde{z}^0(\alpha)}(z)dz} \tag{6.34}$$

In the third step of Jimenez et al. (2007), we have to look for a balanced solution between the feasibility degree and the degree of satisfaction. We define two fuzzy sets $\tilde{M}$ and $\tilde{N}$ with the following membership functions: $\mu_{\tilde{M}}(x^0(\alpha_k)) = \alpha_k$ and $\mu_{\tilde{N}}(x^0(\alpha_k)) = K_{\tilde{G}}(z^0(\alpha_k))$, respectively.

Then we find the fuzzy decision $\tilde{D} = \tilde{M} \cap \tilde{N}$:

$$\mu_{\tilde{D}}(x^0(\alpha_k)) = \alpha_k \cdot K_{\tilde{G}}(z^0(\alpha_k)) \tag{6.35}$$

As we want to have a crisp decision, we propose as a solution to the fuzzy linear program, those with the highest membership degree in the fuzzy set decision:

$$\mu_{\tilde{D}}(x^*) = \max_{\alpha_k}\{\alpha_k \cdot K_{\tilde{G}}(z^0(\alpha_k))\} \tag{6.36}$$

We now present a real application case, where we test both, the PLP model and the solution approach.

Problem definition and possibilistic model

This section presents a possibilistic linear programming formulation of a supply chain network design problem. We consider the potential supply chain network illustrated in Figure 6.5, which includes suppliers, warehouses, distribution centers, and sellers.

These questions are answered by the proposed possibilistic model.

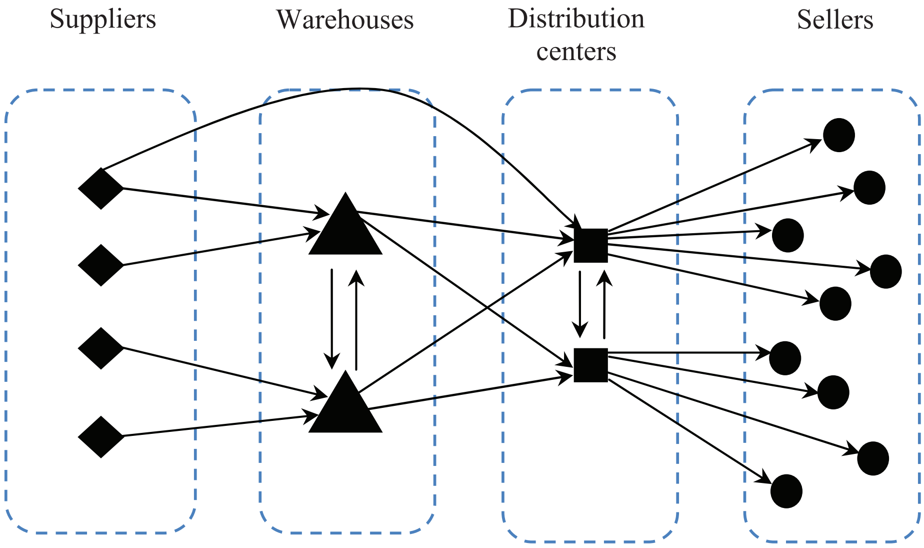

Figure 6.5: Supply Chain Network

Consider a supply chain network $\mathbf{N} = (O, A)$, where O is the set of nodes and A is the set of arcs. The set O consists of the set of suppliers S, the set of potential warehouse locations W, the set of potential distribution center locations D and the set of customers C. The supply chain configuration decisions consist of deciding which of the warehouses and distribution centers to open and determining flow of goods throughout the supply chain network. We associate a binary variable x_i to the first decisions, x_i=1, if warehouse i is opened, and 0 otherwise. We associate a binary variable y_i to the second decisions, y_i=1, if distribution center i is opened, and 0 otherwise. The flow decisions concern the flow of goods from the supplier to the customers. We let q_{ij} denote the flow of goods from a node i to a node j. $\tilde{dc}_i$ denotes fixed cost of opening distribution center i, $\tilde{fc}_i$ denotes fixed cost of opening warehouse i and $\tilde{\mu}_{ij}$ denotes unit transportation costs of goods from a node i to a node j. Let $\tilde{f}_i$ be the unit processing costs of products at warehouse i and $\tilde{c}_j$ the unit storage costs of goods at distribution center j.

The related cost coefficients in the objective function (6.37) are imprecise in nature because some parameters are unobtainable in a long time horizon. Accordingly, the objective function of the proposed model is composed of fixed warehouse opening costs, fixed distribution center opening costs, transportation costs of goods throughout the supply chain, treatment and storage costs. They are calculated in equation (6.37) as follows:

$$Minimize \sum_{j\in W}(\tilde{fc}_j \cdot x_j) + \sum_{k\in D}(\tilde{dc}_k \cdot y_k) + \sum_{i\in S}\sum_{j\in W}(\tilde{\mu}_{ij} + \tilde{f}_j)\cdot q_{ij} +$$
$$\sum_{j\in W}\sum_{j'\in W}\tilde{\mu}_{jj'}\cdot q_{jj'} + \sum_{i\in S}\sum_{k\in D}(\tilde{\mu}_{ik} + \tilde{c}_k)\cdot q_{ik} + \sum_{k\in D}\sum_{k'\in D}\tilde{\mu}_{kk'}\cdot q_{kk'} +$$
$$\sum_{j\in W}\sum_{k\in D}(\tilde{\mu}_{jk} + \tilde{c}_k)\cdot q_{jk} + \sum_{k\in D}\sum_{l\in C}\tilde{\mu}_{kl}\cdot q_{kl} \tag{6.37}$$

Subject to

Constraint (6.38) imposes that all goods produced by suppliers i, denoted by $\tilde{A}_i$, should be transported to warehouse and/or distribution center j:

$$\sum_{j\in W} q_{ij} + \sum_{k\in D} q_{ik} = \tilde{A}_i \qquad i\in S \tag{6.38}$$

Constraint (6.39) guarantees the percentage of goods β that should be transported directly from supplier i to distribution center j:

$$\sum_{k\in D} q_{ik} = \beta\cdot\tilde{A}_i \qquad i\in S \tag{6.39}$$

Constraint (6.40) enforces the flow conservation of the products between warehouses:

$$\sum_{i\in S} q_{ij} + \sum_{j'\in W} q_{j'j} = \sum_{k\in D} q_{jk} + \sum_{j'\in W} q_{jj'} \qquad j\in W,(j'\neq j) \tag{6.40}$$

Constraint (6.41) guarantees percentage of products γ that should be transported between warehouses i :

$$\sum_{j'\in W} q_{jj'} = \gamma\cdot\sum_{i\in S} q_{ij} \qquad j\in W,(j'\neq j) \tag{6.41}$$

Constraint (6.42) limits the warehouse processing capacities, where F_j^{max} denotes maximum processing capacity of products at warehouse j and F_j^{min} represents the minimum processing capacity of goods at the same warehouse j:

$$F_j^{min}\cdot x_j \leq \sum_{i\in S} q_{ij} + \sum_{j'\in W} q_{j'j} \leq F_j^{max}\cdot x_j \qquad j\in W(j'\neq j) \tag{6.42}$$

Constraint (6.43) enforces the flows conservation of the products between distribution centers:

$$\sum_{j \in W} q_{jk} + \sum_{i \in S} q_{ik} + \sum_{k' \in D} q_{k'k} = \sum_{l \in C} q_{kl} + \sum_{k' \in D} q_{kk'} \qquad k \in D, (k' \neq k) \tag{6.43}$$

Constraint (6.44) guarantees the percentage of products δ that should be transported between distribution centers j :

$$\sum_{k' \in D} q_{kk'} = \delta \cdot \left[\sum_{i \in S} q_{ik} + \sum_{j \in W} q_{jk} \right] \qquad k \in D, (k' \neq k) \tag{6.44}$$

Constraint (6.45) limits the distribution center capacities, where C_k^{max} presents the maximum storage capacity of products at distribution center k and C_k^{min} denotes the minimum storage capacity of goods at distribution center k:

$$C_k^{min} \cdot y_k \leq \sum_{j \in W} q_{jk} + \sum_{i \in S} q_{ik} + \sum_{k' \in D} q_{k'k} \leq C_k^{max} \cdot y_k \qquad k \in D, (k' \neq k) \tag{6.45}$$

Constraint (6.46) guarantees that $\tilde{d}_i$ demand of each customer i should be satisfied:

$$\sum_{k \in D} q_{kl} = \tilde{d}_l \qquad l \in C \tag{6.46}$$

Constraints (6.47), and (6.48) enforce the binary nature of x_j and y_k :

$$x_j \in \{0, 1\} \qquad j \in W \tag{6.47}$$

$$y_k \in \{0, 1\} \qquad k \in D \tag{6.48}$$

Constraints (6.49) are standard integrality and non-negativity constraints:

$$q_{ij} \geq 0 \qquad (ij) \in A \tag{6.49}$$

Equivalent crisp model

Using the above descriptions (6.31)-(6.32), the equivalent auxiliary crisp model of the SCND model (6.37)-(6.49) can be formulated as follows:

$$
\begin{aligned}
Min\quad & z\\
z = \quad & \Bigg[\sum_{j\in W}\left(\frac{fc_j^L+2fc_j^m+fc_j^R}{4}\right)\cdot x_j+\sum_{k\in D}\left(\frac{dc_k^L+2dc_k^m+dc_k^R}{4}\right)\cdot y_k\\
&+\sum_{i\in S}\sum_{j\in W}\left(\frac{\mu_{ij}^L+2\mu_{ij}^m+\mu_{ij}^R+f_j^L+2f_j^m+f_j^R}{4}\right)\cdot q_{ij}\\
&+\sum_{i\in S}\sum_{k\in D}\left(\frac{\mu_{ik}^L+2\mu_{ik}^m+\mu_{ik}^R+c_k^L+2c_k^m+c_k^R}{4}\right)\cdot q_{ik}\\
&+\sum_{j\in W}\sum_{k\in D}\left(\frac{\mu_{jk}^L+2\mu_{jk}^m+\mu_{jk}^R+c_k^L+2c_k^m+c_k^R}{4}\right)\cdot q_{jk}\\
&+\sum_{j\in W}\sum_{j'\in W}\left(\frac{\mu_{jj'}^L+2\mu_{jj'}^m+\mu_{jj'}^R}{4}\right)\cdot q_{jj'}+\sum_{k\in D}\sum_{k'\in D}\left(\frac{\mu_{kk'}^L+2\mu_{kk'}^m+\mu_{kk'}^R}{4}\right)\cdot q_{kk'}\\
&+\sum_{k\in D}\sum_{l\in C}\left(\frac{\mu_{kl}^L+2\mu_{kl}^m+\mu_{kl}^R}{4}\right)\cdot q_{kl}\Bigg]
\end{aligned}
\tag{6.50}
$$

Subject to

$$\sum_{j\in W}q_{ij}+\sum_{k\in D}q_{ik}\geq\frac{\alpha}{2}\left(\frac{A_i^m+A_i^R}{2}\right)+\left(1-\frac{\alpha}{2}\right)\left(\frac{A_i^L+A_i^m}{2}\right)\qquad i\in S \tag{6.51}$$

$$\sum_{j\in W}q_{ij}+\sum_{k\in D}q_{ik}\leq\left(1-\frac{\alpha}{2}\right)\left(\frac{A_i^m+A_i^R}{2}\right)+\frac{\alpha}{2}\left(\frac{A_i^L+A_i^m}{2}\right)\qquad i\in S \tag{6.52}$$

$$\sum_{k\in D}q_{ik}\geq\beta\left[\frac{\alpha}{2}\left(\frac{A_i^m+A_i^R}{2}\right)+\left(1-\frac{\alpha}{2}\right)\left(\frac{A_i^L+A_i^m}{2}\right)\right]\qquad i\in S \tag{6.53}$$

$$\sum_{k\in D}q_{ik}\leq\beta\left[\left(1-\frac{\alpha}{2}\right)\left(\frac{A_i^m+A_i^R}{2}\right)+\frac{\alpha}{2}\left(\frac{A_i^L+A_i^m}{2}\right)\right]\qquad i\in S \tag{6.54}$$

$$and\quad (6.39),(6.40),(6.41),(6.42),(6.43),(6.44),(6.45).$$

$$\sum_{k\in D}q_{kl}\geq\frac{\alpha}{2}\left(\frac{D_l^m+D_l^R}{2}\right)+\left(1-\frac{\alpha}{2}\right)\left(\frac{D_l^L+D_l^m}{2}\right)\qquad l\in C \tag{6.55}$$

$$\sum_{k\in D}q_{kl}\leq\left(1-\frac{\alpha}{2}\right)\left(\frac{D_l^m+D_l^R}{2}\right)+\frac{\alpha}{2}\left(\frac{D_l^L+D_l^m}{2}\right)\qquad l\in C \tag{6.56}$$

$$and\quad (6.46),(6.47),(6.48),(6.49).$$

6.2.4 Application to the real case

To validate the proposed model and illustrate the usefulness of the proposed solution method, several experiments are established and the related results are reported in this section. The application case concerns the design of a supply chain of an international textile company in Europe. The potential SCN consists of 11 suppliers, 16 potential warehouse locations, 63 potential distribution center locations, and 103 sellers that the company serves. To solve the models, we used commercial software ILOG OPL 6.3 and CPLEX 12.1.0. We made all test runs on a PC based on a windows Vista 1.66 GHz processor equipped with 2 GB RAM.

To simplify, we suppose that we have β, γ and δ are equal to zero. To compare the behaviour of the proposed possibilistic model with its deterministic version. First, the models are solved. We obtain two solutions: Possibilistic and Deterministic configurations. Then, the configuration of the PLP solution is assessed to the deterministic model and solved under each test problem to find his decision variables. To validate the consistency of the proposed model, twenty two experiments (Table 6.8) were made in which different parameter values are changed. The corresponding results obtained by both deterministic and possibilistic methods are compared with each other on these test problems.

The following performance indicators have been selected to be measured: (i) the total costs, (ii) average service level, (iii) used capacity level, (iv) computational efficiency, (v) budget using level and (vi) penalty costs.

- *Total costs:* refers to the sum of all the costs that are generated : opening costs, processing costs, storage and transportation costs.

- *Average Service Level (ASL):* refers to the percentage of the amount of goods that can be supplied to costumers, where q, D_l^R, D_l, represent, number of customers, the amount of goods that can be send to customer l and the demand of customer l, respectively.

$$ASL = \left(\frac{1}{q}\right) \cdot \sum_{l=1}^{q} \frac{D_l^R}{D_l} \times 100 \tag{6.57}$$

- *Used Capacity Level (UCL):* refers to the percentage of the capacity used to serve costumers demand.

$$UCL = \frac{Used\ capacity}{Total\ capacity} \times 100 \tag{6.58}$$

- *Computational efficiency:* measures the computational effort necessary for the resolution of each one of the models: the number of variables, the number of constraints and the CPU time.

- *Used Budget Level (UBL):* refers to the percentage of budget or the amount of money that can be used.

$$UBL = \frac{Real\ budget}{Estimated\ budget} \times 100 \tag{6.59}$$

- *Penalty Costs (PC):* refers to the amount of money that is paid to customers due to not respect the delivery quantity, ρ present the unit penalty cost.

$$PC = \rho \times \sum_{l=1}^{q}(D_l - D_l^R) \tag{6.60}$$

To generate the triangular fuzzy parameters, the three prominent points $(c_{ij}^L, c_{ij}^m, c_{ij}^R)$ are estimated for each imprecise parameter. The Decision Maker has already adopted the pattern of triangular possibility distribution for all imprecise coefficients. To do so, the most likely value (c_{ij}^m) of each parameter is firstly generated using the data of the company, then the most pessimistic (c_{ij}^L) and optimistic (c_{ij}^R) values of a fuzzy number $(\tilde{c}_{ij})$ are calculated as follows:

$c_{ij}^L = (1 - \theta^L) \cdot c_{ij}^m$.

$c_{ij}^R = (1 + \theta^R) \cdot c_{ij}^m$.

Where θ^L and θ^R are left and right percentages. These values are assigned by experts.

Deterministic and Possibilistic solutions:

In this section, we apply the resolution method to the real case in oredr to find the possibilistic solution.

In Table 6.5, we present the feasibility degree α that the DM considerd and the solutions of the crisp model generated by varying α. The column Distribution centers proposes the distribution centers to open for each α. Warehouses column gives the set of warehouses to open. The possibility distribution of the fuzzy objective function are shown in the last column.

Now, we have the possibility distribution of objective values in Table 6.5. According to equation (6.33) we will suppose that the DM is fully satisfied with an objective value lower than $55 \cdot 10^6$ (€) and that he will not be able to assume more than $65 \cdot 10^6$ (€) as

Table 6.5: α-acceptable optimal solutions (part 1)

α	Distribution centers	Warehouses	Possibility distribution of objective		
			$z^L(\alpha)$	$z^m(\alpha)$	$z^R(\alpha)$
0.1	CD7, CD22, CD24, CD49	F9	41 584 000	51 080 000	77 970 000
0.2	CD7, CD22, CD24, CD49	F9	42 180 000	51 825 000	79 088 000
0.3	CD7, CD22, CD24, CD49	F9	42 777 000	52 571 000	80 206 000
0.4	CD7, CD22, CD24, CD49	F9	43 373 000	53 316 000	81 324 000
0.5	CD7, CD22, CD24, CD49	F9	43 969 000	54 062 000	82 442 000
0.6	CD7, CD22, CD24, CD49	F9	44 566 000	54 807 000	83 560 000
0.7	CD7, CD22, CD24, CD49	F9	45 162 000	55 552 000	84 679 000
0.8	CD7, CD22, CD24	F9, F3	47 530 000	57 613 000	89 119 000
0.9	CD7, CD22, CD24	F9, F3	48 124 000	58 355 000	90 232 000
1	CD7, CD22, CD24	F9, F3	48 718 000	59 097 000	91 346 000

global cost. For simplicity we suppose that the membership function is linear, the goal will be expressed as following:

$$\mu_{\tilde{G}}(z) = \begin{cases} 1 & if \quad z \leq 55 \cdot 10^6 \\ \frac{65 \cdot 10^6 - z}{65 \cdot 10^6 - 55 \cdot 10^6} & if \quad 55 \cdot 10^6 \leq z \leq 65 \cdot 10^6 \\ 0 & if \quad z \geq 65 \cdot 10^6 \end{cases} \tag{6.61}$$

We refer to equations (6.34) and (6.35) to calculate the compatibility index of each solution with DM's aspirations (see equation (6.34)) and the membership degree of each α-acceptable optimal solution (see equation (6.35)), as shown in Table 6.6. In agreement with equation (6.36), the solution of the PLP model is the one which has the greatest membership degree. We can see in Table 6.6 that the greatest membership degree correspond to 0.32 and the 0.7-feasible optimal solution (Table 6.5) will be the best configuration of the PLP problem.

In Table 6.7, we provide the number of variables, number of constraints, CPU Time, total costs, distribution centers to open and warehouses to open for the deterministic model and the probabilistic one. The capacity of each facility are presented between brackets.

Table 6.7 reveals that the deterministic model contains 12 671 variables and 18 765 constraints, and the computational time is equal to 912 seconds. The Possibilistic pro-

Table 6.6: α-acceptable optimal solutions (Part 2)

Feasibility degree α	Satisfaction degree K	$\alpha.K$	Optimal cost (€)
0.1	0.66	0.07	55 878 466
0.2	0.63	0.13	56 679 765
0.3	0.60	0.18	57 481 063
0.4	0.56	0.23	58 282 362
0.5	0.53	0.27	59 083 661
0.6	0.50	0.30	59 884 960
0.7	0.46	0.32	60 686 259
0.8	0.35	0.28	63 868 562
0.9	0.32	0.28	64 666 512
1	0.29	0.29	65 464 462

gramming model contains 12 671 variables and 18 868 constraints, the computational time is 419 seconds. As we can see, the number of variables and constraints for the models shows that they have the same degree of complexity. In addition, to satisfy customers demand the warehouses and distribution centers to open are the same for the two models with different capacities which are {F9} and {CD7, CD22, CD24, CD49} respectively.

Sensitivity analyses

To validate the consistency of the proposed model, twenty two experiments (Table 6.8) were made in which different parameter values are changed. In the first experiments (1-11), we analysed the effect of demand changes by changing the demand value and fixing all other parameters. The next experiments (12-17) are set up to carry out the effect of costs variations. Experiments (18-22) are designed to evaluate the variation of demand and costs. Table 6.8 introduces details of the experiments.

The results of these experiments are given in (Table 6.9). We see that the possibilistic model, in general, obtains better performance indicators (UCL, ASL, PC) and UBL) than the deterministic model. Figure 6.6 presents the UBL values of each test problem. As we can see, for deterministic model, 14 experiments have a budget using level more than 100%, which represents 64% of cases. This means that the budget fixed using the

Table 6.7: Computational Results

Model	Variables	Constraints	CPU Time (s)	Total costs (€)	Distribution centers	Warehouses
Deterministic	12 671	18 765	912	55 493 965	CD7 (37 900 000)	F9
					CD22 (19 200 000)	
					CD24 (44 410 000)	
					CD49 (23 720 000)	
Possibilistic	12 671	18 868	419	60 686 259	CD7 (39 740 000)	F9
					CD22 (19 600 000)	
					CD24 (45 410 000)	
					CD49 (24 250 000)	

deterministic model (55 493 965 €) is not enough to satisfy the costumers in 64% of these experiments. Whereas, only 5 test problems have exceeded the budget proposed by the possibilistic model (60 686 259 €), therefore approximately 23% of test problems passed the estimated budget. It is clear that the budget fixed by the PLP model is better than the one proposed by the deterministic model, because with the first one, we succeed to finance 77% of test cases and satisfy all customers, but with the second one, only 36% of experiments are feasible to satisfy all customers. Although the possibilistic solution is 9.3% more expensive than the deterministic one, this difference let us to get a robust supply chain configuration that can absorb the uncertainty of environment, like price and demand regulations, at the same time meet changing market requirements.

It can be seen from Table6.9 that the UBL average of deterministic configuration is equal to 102%, so the majority of the UBL values are more than 100% (Figure 6.6), thus implying that there is no sufficient money to take control of parameters uncertainties. The UBL average of possibilistic solution (94%) reveals the flexibility and robustness of the PLP solution in an uncertain environment.

Figure 6.7 shows the evolution of used capacity level varying the demand. As we can see, increasing the demand the UCL of deterministic and possibilistic configurations rise until to reach a peak (100%). The deterministic structure (125.23×10^6 pcs) attends capacity peak before the possibilistic one (129×10^6 pcs). According to the results presented in Table 6.9, the deterministic UCL average (96%) is bigger than the possibilistic one (94%).

Table 6.8: Experiments

N	Experiment	Description
1		The demands used in solving deterministic model
2		The demands are decreased by 3%
3		The demands are increased by 3%
4		The demands are increased by 5%
5	*Demands*	The demands are decreased by 5%
6		The demands are increased by 10%
7		The demands are decreased by 10%
8		The demands are increased by 20%
9		The demands are decreased by 20%
10		The demands are increased by 30%
11		The demands are decreased by 30%
12		The costs are decreased by 10%
13		The costs are decreased by 5%
14		The costs are increased by 5%
15	*Costs*	The costs are increased by 10%
16		The costs are increased by 15%
17		The costs are increased by 20%
18		The costs are increased by 2% and demands increases by 2%
19		The costs are increased by 3% and demands increases by 3%
20	*Demands and Costs*	The cots are increased by 5% and demands are decreased by 5%
21		The cots are increased by 10% and demands are decreased by 8%
22		The cots are increased by 20% and demands are decreased by 13%

Table 6.9: Possibilistic vs Deterministic Results

Exp	Deterministic				Possibilistic			
	UCL (%)	ASL (%)	PC (€)	UBL (%)	UCL (%)	ASL (%)	PC (€)	UBL (%)
1	100%	100%	0	100%	97%	100%	0	91%
2	97%	100%	0	98%	94%	100%	0	89%
3	100%	94%	748 200	102%	100%	100%	0	94%
4	100%	90%	1 252 200	104%	100%	98%	502 000	95%
5	95%	100%	0	96%	92%	100%	0	88%
6	100%	82%	2 508 200	108%	100%	94%	1 758 000	98%
7	90%	100%	0	92%	87%	100%	0	84%
8	100%	67%	5 006 200	115%	100%	86%	4 256 000	105%
9	80%	100%	0	85%	78%	100%	0	77%
10	100%	54%	7 509 412	123%	100%	79%	6 759 212	113%
11	70%	100%	0	77%	68%	100%	0	70%
12	100%	100%	0	90%	97%	100%	0	82%
13	100%	100%	0	95%	97%	100%	0	87%
14	100%	95%	1 233 199	105%	97%	100%	0	96%
15	100%	90%	2 466 398	110%	97%	99%	158 712	101%
16	100%	85%	3 699 597	115%	97%	94%	1 391 911	105%
17	100%	81%	4 728 260	119%	97%	90%	2 420 573	109%
18	100%	96%	500 540	104%	99%	100%	0	95%
19	100%	94%	750 856	105%	100%	100%	0	96%
20	95%	99%	239 348	101%	92%	100%	0	92%
21	92%	97%	800 508	103%	89%	100%	0	94%
22	87%	91%	1 979 624	108%	84%	100%	0	99%
Average	96%	92%	1 453 126	102%	94%	97%	749 844	94%

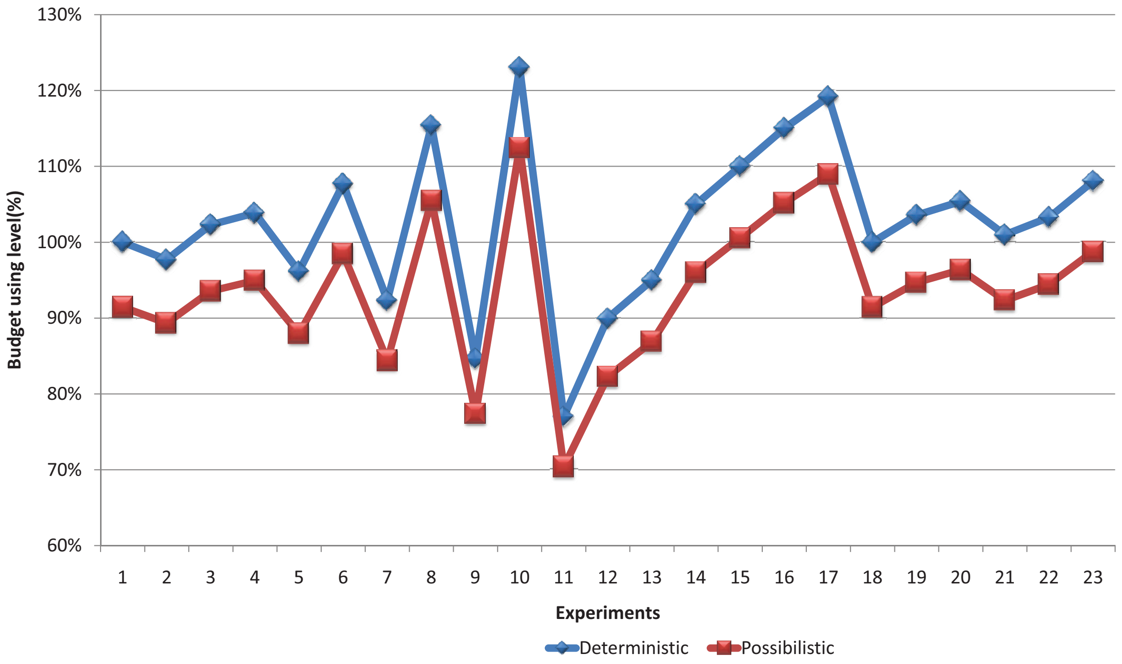

Figure 6.6: Used budget level: Possibilistic vs Deterministic

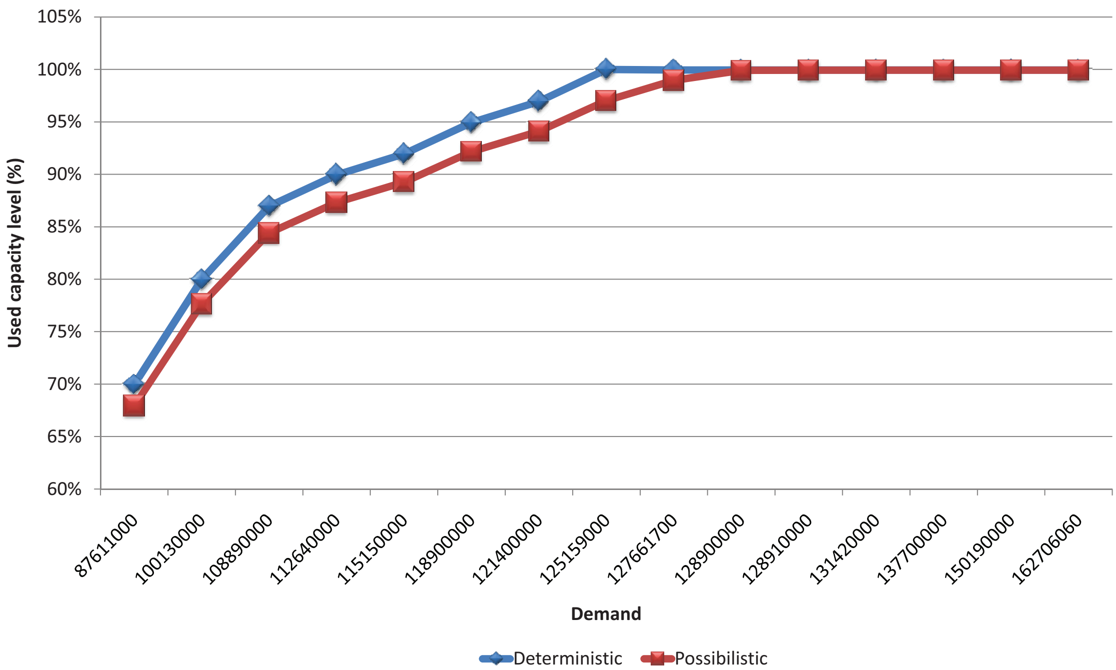

Figure 6.7: Used capacity level: Possibilistic vs Deterministic

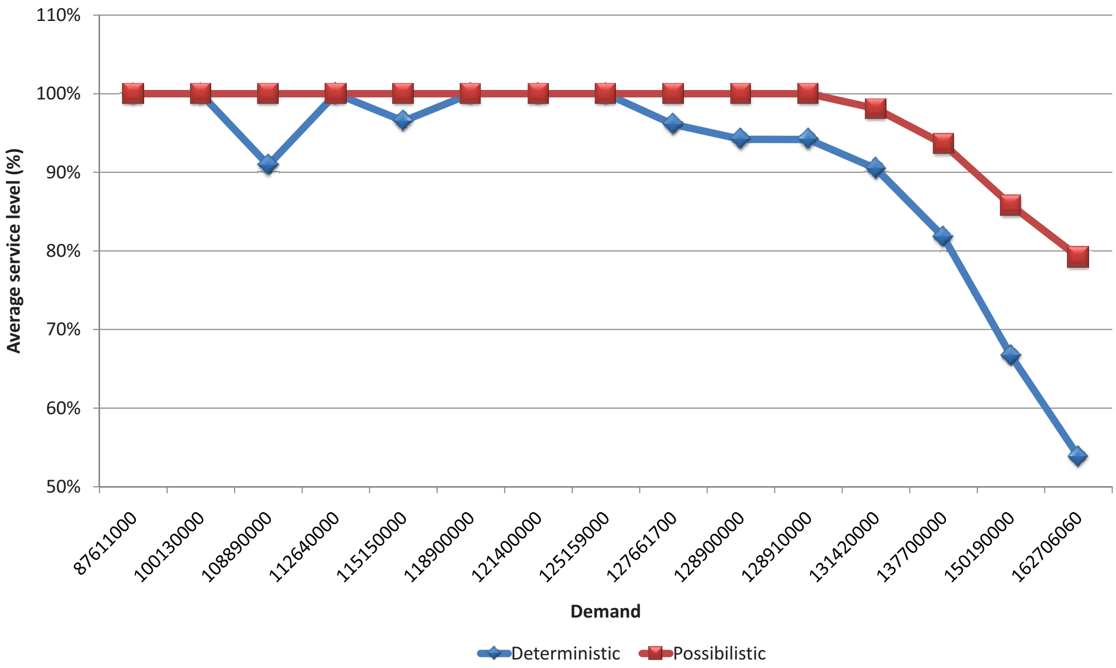

Figure 6.8: Average service level: Possibilistic vs Deterministic

As a result, this capacity abundance in possibilistic solution is necessary to control the environment uncertainty, especially when the demand increases. Figure 6.8 exhibits the average service level of deterministic and PLP models increasing the demand. We note that for demand between 87.6×10^6 to 129×10^6 pcs the possibilistic ASL is equal to 100%, when the demand attends maximal capacity of the structure (129×10^6) the service level starts decreasing to attend approximately 80% when demand goes up to 162.7×10^6. For the deterministic configuration, ASL is between 94% and 100% growing the demand from 87.6×10^6 to 125.23×10^6 pcs, then the level begins to go down (54%) increasing demand from 125.23×10^6 to 162.7×10^6. These fluctuations are due to the insufficient budget proposed by the deterministic model although, in these cases we have enough capacity. As seen in Table 6.9, the PLP models obtain ASL (97%) that are better than the deterministic model (92%). In all cases, this possibilistic model is more better adapted to the existing uncertainties in input parameters considered in this work.

Figure 6.9 resumes experiments where the company should pay penalties. The exper-

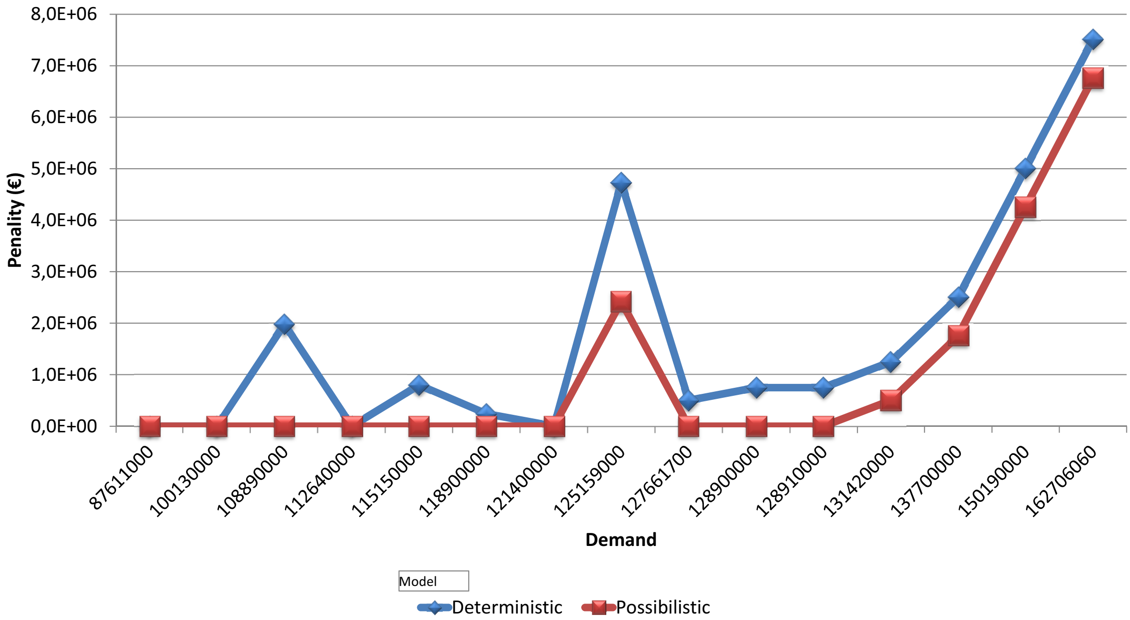

Figure 6.9: Penality: Possibilistic vs Deterministic

iments related to Possibilistic model show that when the demand increases from approximately 88×10^6 to 129×10^6, the penalty is equal to zero, exception one test problem the penalty is equal to 2 420 573 (€) which is due to budget insufficiency to satisfy customers demand. For demand values bigger than 129×10^6, when the demand increases, then the penalty costs increase significantly. On the other hand, the PC of deterministic model fluctuates between zero and 4 728 260 (€) when the demand is increasing from approximately 88×10^6 to 129×10^6, then when the demand increases , the penalty value also increases. In addition, we should pay penalty only five times in the possibilistic case, which represents 34% of cases, but for the deterministic model we should do it in more than 73% of cases, as can be seen in Figure 6.9.

6.2.5 Concluding Remarks

Determining the optimal supply chain configuration is a difficult problem since a lot of factors and parameters must be taken into account when designing the network under uncertainty. Since most of the parameters in such a problem have imprecise nature, a

PLP approach was used to model a supply chain network and, a possibilistic programming resolution method was proposed, which is able to find an efficient solution based on decision maker preferences.

The proposed model has been tested by using data from a real life textile SCN, hence the results demonstrate the effectiveness of a Possibilistic Linear Programming approach for SCND under uncertainty. In addition, this model controls the uncertainty sources identified in SCN problems given lack of information such as demands, costs, process and supply uncertainties.

The proposed possibilistic formulation is better than the deterministic methods for handling the real situations where precise or certain future informations are not available for SCND. Additionally, the possibilistic model supply chain performance indicators have been seen to be clearly better than those of deterministic model, as previously shown. For example, the average service level of PLP models (97%) are better than the deterministic model (92%). The investment budget proposes by the first model is more important than the second model, approximately 77% of the test cases are satisfied using the PLP configuration and only 36% of them are feasible using the deterministic solution. Furthermore, the possibilistic model has not generated an excessive increment of computational efficiency, then the possibility to model and solve a real life size supply chain problems under uncertainty.

In the next Chapter, we will present the general conclusions of this thesis.

Chapter 7

Conclusions and Perspectives

The work presented in this thesis is a relative small contribution in the Supply Chain research ocean. However, we think that design multi-criteria Supply Chain under uncertainty is really a contemporary issue in many application domains.
Chapter 2 presented a review of mathematical programming models and resolution methods for Supply Chain Network Design (SCND). We have proposed a classification based on the analysis of three aspects: supply chain network structure, decision level, supply chain modeling approach. The conclusions drawn from this chapter affirm that: (i) papers integrating multiple periods, multiple products, multiple criteria, multiple transportation modes, multiple objective and uncertainty in SCND context are still scarce, (ii) the most widely used modeling approach is mixed integer linear programming, where the use of heuristic algorithms and meta-heuristics to solve the approach stands out, (iii) more proposed models are validated using small numerical examples and the number of case studies applied to real supply chains are still scare.

Chapter 3 studied our new multi-criteria supply chain network design methodology. We have integrated many aspects in the design of the optimal sustainable supply chain, such as: economical, social, environmental and legislative aspects.
Our methodology consists of two different steps. In the first step, we find the best potential facility locations where the future facilities could be established and different criteria are satisfied. To model this step, we have combined the Geographic Information System (GIS) and the AHP method. The second step establishes the optimal supply chain design

to achieve customer demands and economic criteria using Mixed Integer Linear Programming model.

A computational real case study has demonstrated the methodology's efficiency, and has shown that using GIS model to locate potential facilities in the design of sustainable supply chain network is very useful. In fact, it has provided a good way for integrating many criteria and constraints such as: location sites far from the urban areas; sites should be close to commercial zones, roads, railways and landfills; plants should be far from natural area, airports and agriculture area, etc. Also, the GIS model has reduced the potential set of locations from the entire country or region to small sustainable locations set. This speeds up the process of finding the optimal supply chain configuration in the next step.

Our second contribution in this chapter is the study of CO_2 emission impacts in the SCND. We have shown that the integration of the environmental costs and multi-modality in the mathematical model changes the structure of the supply chain network. It depends on the environmental policy of the Company. This means that using the model, supply chain managers could be able to see the impact of integration of the CO_2 taxes and multi-modal transportation network in the strategic decisions of supply chain. That will help them to select the best strategic supply chain network. From this chapter we have learned that integration of environmental taxes in the model can be an efficient way to achieve environmental goals, by choosing the best SCN and clean transportation modes. These results have also confirmed that to reduce CO_2 emissions, we should take into account multi-modal transport network, in the design of the supply chain.

Therefore, many possible future research avenues can be defined in this context. For instance, GIS has the potential to speed up the process of finding potential locations and to permit sensitivity analysis that will examine the impact of varying some of the criteria in a mapping exercise. The results of this analysis can be used to identify general areas to be further evaluated on a site specific basis using more detailed market place information. As job opportunities or population features change due to actual development, the model can be easily revised to reflect these changes. In addition, the second step model should have objectives to evaluate the impact quality, lead-time and service level in supply chain design problem. Also, we think that it is very important to compare the results of our methodology to the existent SCND framework.

Chapter 4 presented an extension of the second step of the methodology proposed in Chapter 3. We have proposed a multi-objective supply chain network design problem. We have formulated the problem as a Goal Programming model which aims at achieving four economics and environmental goals which are respectively: (i) total costs goal, (ii) energy consumption costs goal, (iii) waste treatment costs goal and (iv) CO_2 emissions goal. We have conducted a sensitivity analysis for the case study and we have observed that, improving the building technology and increasing the facility number in the supply chain can decrease CO_2 emission of the whole network. Also, the total cost increase is expected to be in conflict with the other three goals that aim to reduce the CO_2 emission, energy consumption and waste treatment of the supply chain. Regarding to the influence of some parameters on the SC configuration and transportation mode used, we have found that small variability of goals weight ω_i does not affect the solution.
Our further research direction is to consider more factors in supply chain, such as social criteria, quality criteria and taking into account the product life cycle. On the other hand, we can also extend our research through designing new solution methods to solve this multi-objective supply chain network design model, such as heuristics and meta-heuristics.

Chapter 5 proposed a three-phase heuristic decomposition algorithm to solve large-scale supply chain network design problems. The heuristic consists of three phases which are: (i) decomposition phase, (ii) reduction phase and (iii) resolution phase. In the decomposition phase, we divide the large scale supply chain network into small two-layer networks. In reduction phase, we use a modified p-median model to reduce the large potential sets into small reduced sets. In resolution phase, we use a global MILP model to solve the reduced supply chain network.
Very large problems can indeed be solved in a reasonable amount of time with the heuristic, whereas they cannot be solved with conventional MIP tools within a reasonable amount of computational time. We have solved a real large-scale supply chain network composed of 220 suppliers, 220 warehouses, 220 distribution centers and 1 500 customers, in less than 550 seconds. The numerical experiments have indicated that the proposed heuris-

tic solution algorithm performs well in terms of solution quality and computational time consumed. For example, the average of heuristic CPU Time is equal to 5 seconds for small size instances, 24 seconds for medium size problems and only 115 seconds for large scale instances. Moreover, the gap between the final solution obtained by the proposed heuristic approach and the lower bound of global MILP obtained by Cplex is equal to 0% in small size instances, less than 0.52% in medium size instances and in large size problems, the gap ranges from 1.19% to 9.52% and the average gap between the lower bound of the global MILP model and the solution of the heuristic is equal to 5.66%.
Future research could consider systems that faced not only deterministic parameters but also stochastic parameters. The proposed solution approach can be adapted to other SCN problems such as reverse logistic network design problem. In addition, it would be interesting to apply this algorithm to more complex supply chains with more stages and considering the SC parameters uncertainty. Furthermore it is possible to compare the performance of this heuristic to others resolution methods presented in the literature. Another unexplored extension of this algorithm is the consideration of a more complex SCND model with multiple products, multiple periods, multiple objectives and uncertain SC parameters.

Chapter 6 presented a supply chain design problem which includes explicitly demand uncertainty. We use two-stage stochastic programming formulation to model the problem. The results obtained pointed out, that supply chain design methods which do not include uncertainty obtain inferior results if compared with models that formalise it implicitly. The stochastic model could handle data uncertainty with a reasonable increase in total costs compared with the deterministic model and therefore it can be concluded that the proposed two-stage programming model can be used as a robust model in real cases. Many possible future research directions can be defined in the area of logistic network design under uncertainty. For example addressing uncertainty for all variable costs and potential locations of customers may be attractive direction for future research. Moreover, time complexity is not addressed in this chapter. However, since the computational time increases when the size of the problem and the number of scenarios increase. We also need to reduce the runtime further in order to include more scenarios and add more facilities to the supply chain design decisions. Therefore, developing efficient exact or heuristic solution methods is also a critical need in this area.

Since most of the parameters in our problem have imprecise nature and the complexity to solve it by using the two-stage stochastic programming, we have proposed Possibilistic Linear Programming (PLP) approach to model a supply chain network and which is able to find an efficient solution based on decision maker preferences in a reasonable time.

The proposed model in this Chapter has been tested by using data from a real life textile SCN, hence the results have demonstrated the effectiveness of a Possibilistic Linear Programming approach for SCND under uncertainty. In addition, this model has controlled the uncertainty sources identified in SCN problems given lack of information such as demands, costs, process and supply uncertainties.

The proposed possibilistic formulation is better than the deterministic methods for handling the real situations where precise or certain future informations are not available for SCND. Additionally, the possibilistic model supply chain performance indicators have been seen to be clearly better than those of deterministic model, as previously shown. Furthermore, the possibilistic model has not generated an excessive increment of computational efficiency, then the possibility to model and solve a real life size supply chain problems with more uncertain parameters.

An interesting future research topic is to integrate into the proposed supply chain model other aspects, such as multi-period, multi-product and multi-objective. In addition, the CPU time was not an issue in our numerical experiments. However, in other large scaled practical problems it might be an issue. Therefore, developing an efficient heuristic or meta-heuristic algorithm to solve the corresponding PLP models should be helpful in reaching efficient solutions in reasonable time.

This concludes our thesis. Our hope is that it will at least stimulate discussion among researcher working in Supply Chain Network Design , about the usefulness of considering Multi-criteria aspect and data uncertainty mixed approaches.

Appendix A

Figures and Tables

A.1 AHP Example

We start by presenting the AHP example, then we explain how to elaborate the pairwise comparison matrix and how to calculate the importance ratios.

A company wishes to buy a new production equipment and has defined many aspects to chose the machine. We assume a firm has three criteria: cost, quality and delivery-time. The high level in the hierarchy graph concerns the effective selection of the best equipment; the following level represents criteria that correspond to the firm objectives; and the last level with the selection of the alternative suppliers.

What weights should you put on each of these equipments? Is the A, B or C the ultimate machine? Can you ignore any of these criteria ? It's time for the AHP.

We first provide a matrix for the company's pairwise comparisons using the evaluation scale to make pairwise comparisons between criteria importance according to objective achievement. Let us say that we compared all these criteria and come up with this table (Table A.1). Table.A.1 is read as follows:

- 1, indicates the equal importance of the criteria.
- 5, indicates that cost is considerably more important than quality.
- 9, indicates that cost is strongly more important than delivery-time.
- 3, indicate that the quality is moderately important than delivery-time.

A little matrix now lets us to turn these comparisons into numerical weight. First, we want to normalize all weights to a common references, by adding up the weights in a

Table A.1: Comparison between criteria

Preference signification	Cost	Quality	Delivery-time
Cost	1	5	9
Quality	0.2	1	3
Delivery-time	0.11	0.33	1
Total	1.61	6.33	13

column; then we divide each weight by its column sum. For example, as we can see on Table A.1, the sum of the weights in the Delivery time column is 13. Then we divide each weight in Delivery time column by 13 so the weight for cost is 9/13 or 0.69. This normalizes all weights to a common references. The next step is to calculate the average

Table A.2: Relative importance ratios

Preference signification	Cost	Quality	Delivery-time	Raw average
Cost	0.76	0.79	0.69	0.75
Quality	0.15	0.16	0.23	0.18
Delivery-time	0.08	0.05	0.08	0.07
Total	1	1	1	1

of the normalized weights of each criteria to obtain the raw average column in Table A.2. For example, the weight of the quality criteria is equal to 0.18 (Table A.2).

The AHP has revealed that for this company the cost is the most important criteria. Without AHP, may we have assumed hat the ultimate criteria was Quality or Delivery time.

A.2 Figures and Tables

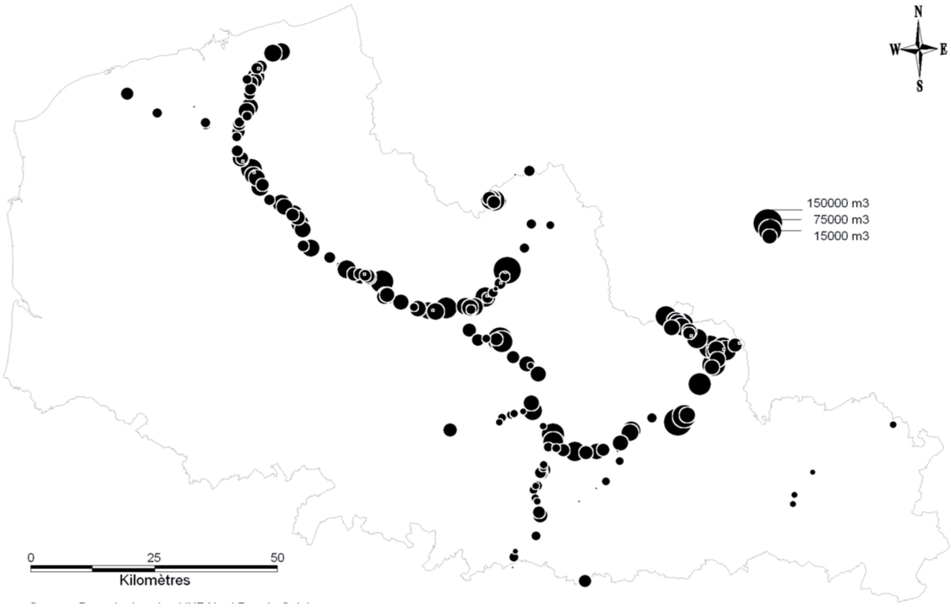

Figure A.1: Sediments depots in NPDC region

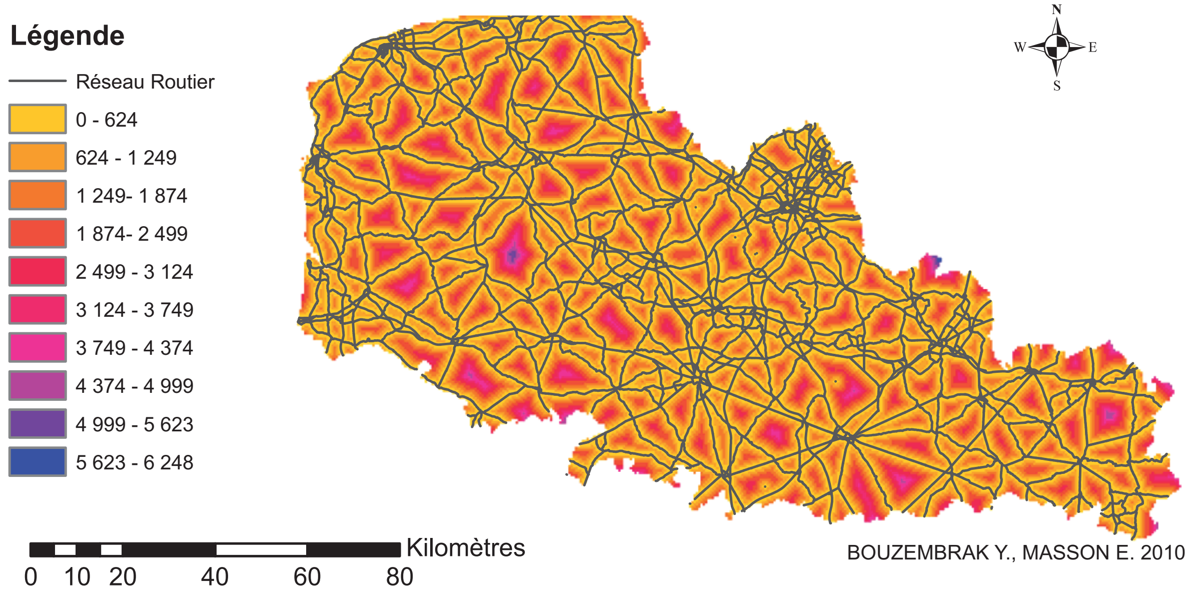

Figure A.2: Roads network classes in NPDC region

Table A.3: Roads network classes and weights

Classes	Weights	Classes	Weights
0 – 624	9	3 124 - 3 749	5
624 – 1 249	9	3 749 - 4 374	4
1 249 - 1 874	8	4 374 - 4 999	3
1 874 - 2 499	7	4 999 - 5 623	2
2 499 - 3 124	6	5 623 - 6 248	1

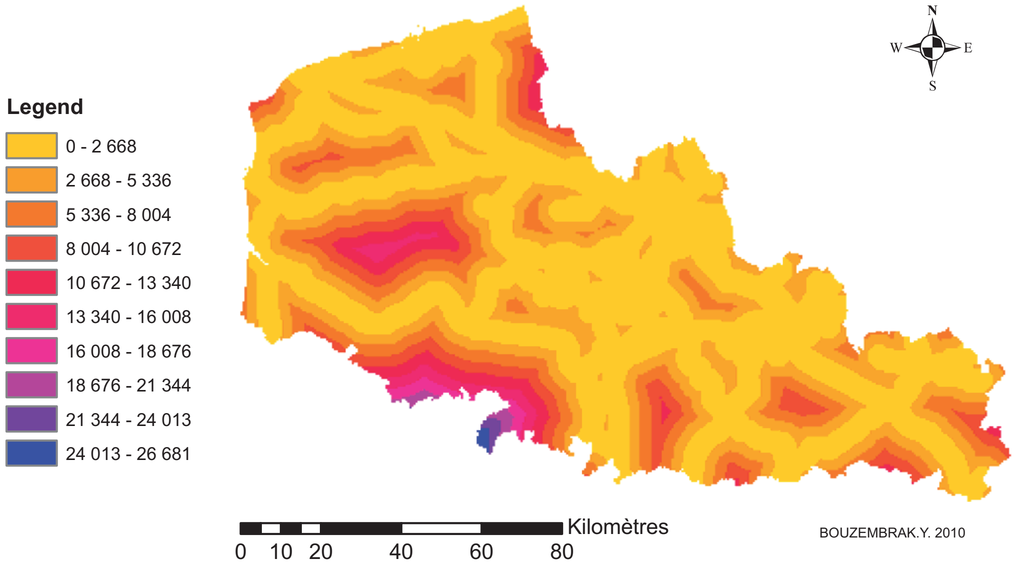

Figure A.3: Railways network classes in NPDC region

Table A.4: Railways network classes and weights

Classes	Weights	Classes	Weights
0 - 2 668	9	13 340 - 16 008	5
2 668 - 5 336	9	16 008 - 18 676	4
5 336 - 8 004	8	18 676 - 21 344	3
8 004 - 10 672	7	21 344 - 24 013	2
10 672 - 13 340	6	24 013 - 26 681	1

Table A.5: Waterways network classes and weights

Classes	Weights	Classes	Weights
0 - 6 206	9	31 032 - 37 238	5
6 206 - 12 412	9	37 238 - 43 445	4
12 412 - 18 619	8	43 445 - 49 651	3
18 619 - 24 825	7	49 651 - 55 858	2
24 825 - 31 032	6	55 858 - 62 064	1

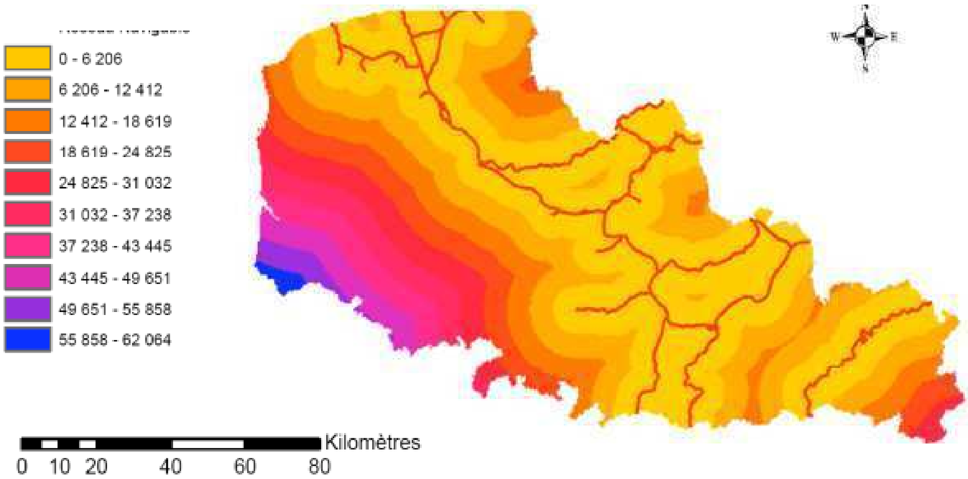

Figure A.4: Waterways network classes in NPDC region

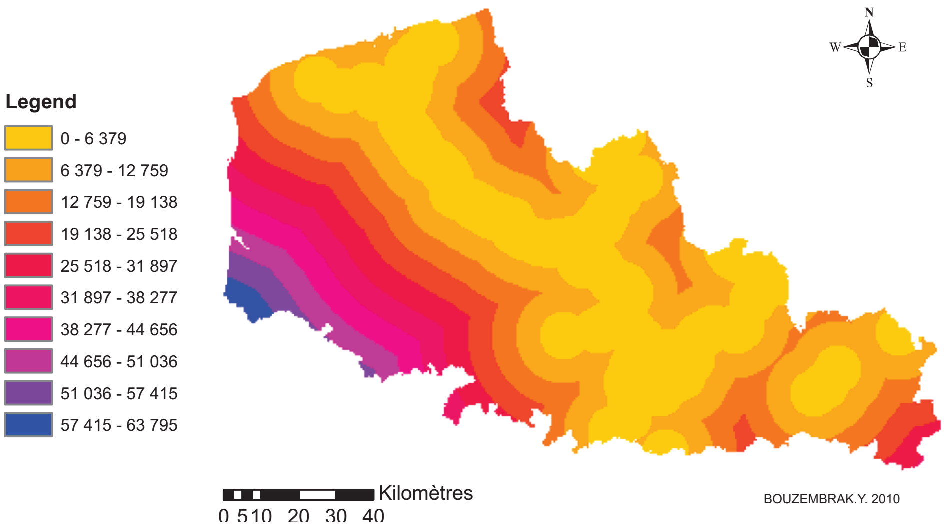

Figure A.5: VNF landfills classes

Table A.6: Landfills classes and weights

Classes	Weights	Classes	Weights
0 - 6 379	9	31 897 - 38 277	5
6 379 - 12 759	9	38 277 - 44 656	4
12 759 - 19 138	8	44 656 - 51 036	3
19 138 - 25 518	7	51 036 - 57 415	2
25 518 - 31 897	6	57 415 - 63 795	1

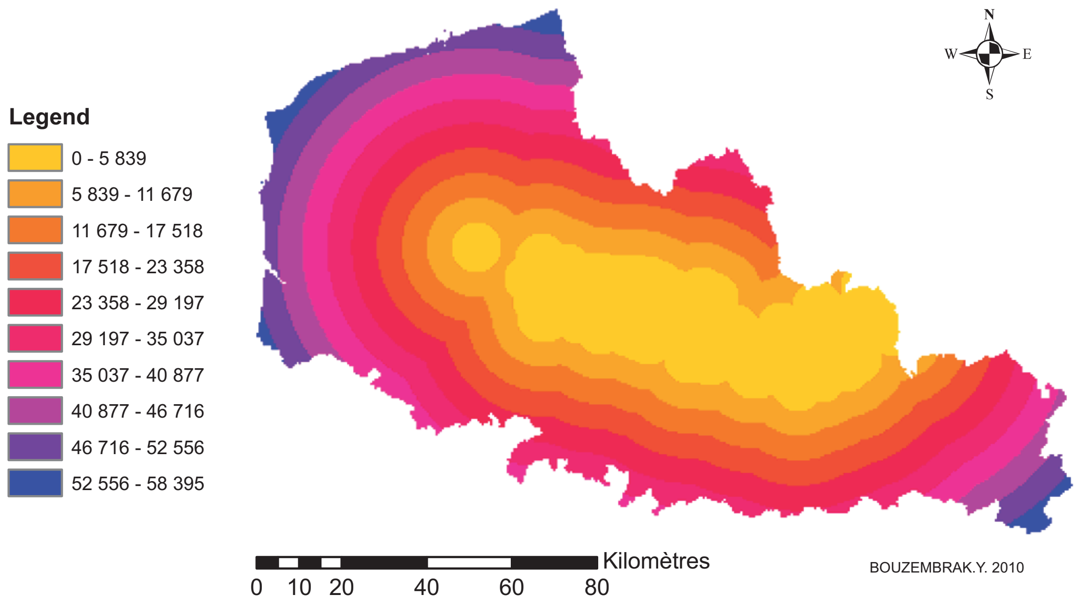

Figure A.6: Brownfield classes in NPDC region

Table A.7: Brownfield classes and weights

Classes	Weights	Classes	Weights
0 - 5 839	9	29 197 - 35 037	5
5 839 – 11 679	9	35 037 - 40 877	4
11 679 – 17 518	8	40 877 - 46 716	3
17 518 - 23 358	7	46 716 - 52 556	2
23 358 - 29 197	6	52 556 - 58 395	1

Table A.8: Supply chain configuration varying CO_2 taxes

N Difference(€)	CO_2 taxes	Potential locations					Objective function (€)		
		T_1	T_2	T_3	T_4	T_5	$\gamma \neq 0$	$\gamma = 0$	
1	0	0	0	0	T_4	T_5	48 509 520	48 509 520	0.0%
2	10	0	0	0	T_4	T_5	48 509 822	48 509 520	0.0%
4	100	0	0	0	T_4	T_5	48 511 474	48 509 520	0.0%
6	200	0	0	0	T_4	T_5	48 515 341	48 509 520	0.0%
7	300	0	0	0	T_4	T_5	48 518 166	48 509 520	0.0%
9	400	0	0	0	T_4	T_5	48 520 968	48 509 520	0.0%
10	500	0	0	0	T_4	T_5	48 523 771	48 509 520	0.0%
15	1000	0	0	0	T_4	T_5	48 536 488	48 509 520	0.1%
21	2000	0	0	0	T_4	T_5	48 560 014	48 509 520	0.1%
22	3000	0	0	0	T_4	T_5	48 583 363	48 509 520	0.2%
23	4000	T_1	0	0	0	T_5	48 606 223	48 509 520	0.2%
24	5000	T_1	0	0	0	T_5	48 628 834	48 509 520	0.2%
29	10000	T_1	0	0	0	T_5	48 731 450	48 509 520	0.5%
30	11000	T_1	0	0	0	T_5	48 751 955	48 509 520	0.5%
31	12000	T_1	0	0	0	T_5	48 772 441	48 509 520	0.5%
32	13000	T_1	0	0	0	T_5	48 792 915	48 509 520	0.6%
33	14000	T_1	0	0	T_4	0	48 809 384	48 509 520	0.6%
34	15000	T_1	0	0	T_4	0	48 825 785	48 509 520	0.7%
35	16000	T_1	0	0	T_4	0	48 842 185	48 509 520	0.7%
36	17000	T_1	0	0	T_4	0	48 857 682	48 509 520	0.7%
37	18000	T_1	0	0	T_4	0	48 873 001	48 509 520	0.7%
38	19000	T_1	0	0	T_4	0	48 888 320	48 509 520	0.8%
39	20000	T_1	0	0	T_4	0	48 903 639	48 509 520	0.8%
40	21000	T_1	0	0	T_4	0	48 918 958	48 509 520	0.8%
41	22000	T_1	0	0	T_4	0	48 934 277	48 509 520	0.9%
42	100000	T_1	0	0	T_4	0	50 129 100	48 509 520	3.3%
43	200000	T_1	0	0	T_4	0	50 660 861	48 509 520	6.5%

Table A.9: CO_2 Emissions varying CO_2 taxes

N	CO_2 taxes	Potential locations					CO_2 Emissions (T)		
		T_1	T_2	T_3	T_4	T_5	$\gamma \neq 0$	$\gamma = 0$	Difference (%)
1	0	0	0	0	T_4	T_5	980	980	0.0%
2	10	0	0	0	T_4	T_5	302	980	69.2%
4	100	0	0	0	T_4	T_5	290	980	70.4%
6	200	0	0	0	T_4	T_5	286	980	70.8%
7	300	0	0	0	T_4	T_5	280	980	71.4%
9	400	0	0	0	T_4	T_5	280	980	71.4%
10	500	0	0	0	T_4	T_5	280	980	71.4%
15	1000	0	0	0	T_4	T_5	240	980	75.5%
21	2000	0	0	0	T_4	T_5	235	980	76.0%
22	3000	0	0	0	T_4	T_5	233	980	76.2%
23	4000	T_1	0	0	0	T_5	226	980	76.9%
24	5000	T_1	0	0	0	T_5	205	980	79.0%
29	10000	T_1	0	0	0	T_5	205	980	79.1%
30	11000	T_1	0	0	0	T_5	205	980	79.1%
31	12000	T_1	0	0	0	T_5	205	980	79.1%
32	13000	T_1	0	0	0	T_5	205	980	79.1%
33	14000	T_1	0	0	T_4	0	164	980	83.3%
34	15000	T_1	0	0	T_4	0	164	980	83.3%
35	16000	T_1	0	0	T_4	0	164	980	83.3%
36	17000	T_1	0	0	T_4	0	153	980	84.4%
37	18000	T_1	0	0	T_4	0	153	980	84.4%
38	19000	T_1	0	0	T_4	0	153	980	84.4%
39	20000	T_1	0	0	T_4	0	153	980	84.4%
40	21000	T_1	0	0	T_4	0	153	980	84.4%
41	22000	T_1	0	0	T_4	0	153	980	84.4%
42	100000	T_1	0	0	T_4	0	153	980	84.4%
43	200000	T_1	0	0	T_4	0	153	980	84.4%

Table A.10: Transportation modes used varying CO_2 taxes

N	CO_2 taxes	Potential locations					Transportation Modes			Optimal Solution (€)
		T_1	T_2	T_3	T_4	T_5	% Roads	% Waters	% Trains	
1	0	0	0	0	T_4	T_5	9.3%	80.7%	10%	48 509 520
2	10	0	0	0	T_4	T_5	0.0%	78%	22%	48 509 822
4	100	0	0	0	T_4	T_5	0%	75.3%	24.7%	48 511 474
6	200	0	0	0	T_4	T_5	0%	74.7%	25.3%	48 515 341
7	300	0	0	0	T_4	T_5	0%	54.7%	45.3%	48 519 567
9	400	0	0	0	T_4	T_5	0%	54.7%	45.3%	48 523 771
10	500	0	0	0	T_4	T_5	0%	54.7%	45.3%	48 526 526
15	1000	0	0	0	T_4	T_5	0%	53.3%	46.7%	48 538 824
21	2000	0	0	0	T_4	T_5	0%	52.0%	48.0%	48 583 363
22	3000	0	0	0	T_4	T_5	0%	36.7%	63.3%	48 606 223
23	4000	T_1	0	0	0	T_5	0.7%	36.7%	62.7%	48 628 834
24	5000	T_1	0	0	0	T_5	0.7%	36.7%	62.7%	48 649 368
29	10000	T_1	0	0	0	T_5	0.7%	36.7%	62.7%	48 751 955
30	11000	T_1	0	0	0	T_5	0.7%	36.7%	62.7%	48 772 441
31	12000	T_1	0	0	0	T_5	0.7%	36.7%	62.7%	48 792 915
32	13000	T_1	0	0	0	T_5	1.3%	25.3%	73.3%	48 809 384
33	14000	T_1	0	0	T_4	0	1.3%	25.3%	73.3%	48 825 785
34	15000	T_1	0	0	T_4	0	1.3%	25.3%	73.3%	48 842 185
35	16000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 857 682
36	17000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 873 001
37	18000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 888 320
38	19000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 903 639
39	20000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 918 958
40	21000	T_1	0	0	T_4	0	2.0%	25.3%	72.7%	48 934 277
41	22000	T_1	0	0	T_4	0	2.0%	24.7%	73.3%	50 129 100
42	100000	T_1	0	0	T_4	0	2.0%	24.7%	73.3%	51 660 861
43	200000	T_1	0	0	T_4	0	50 660 861	48 563 113	48 509 520	0%

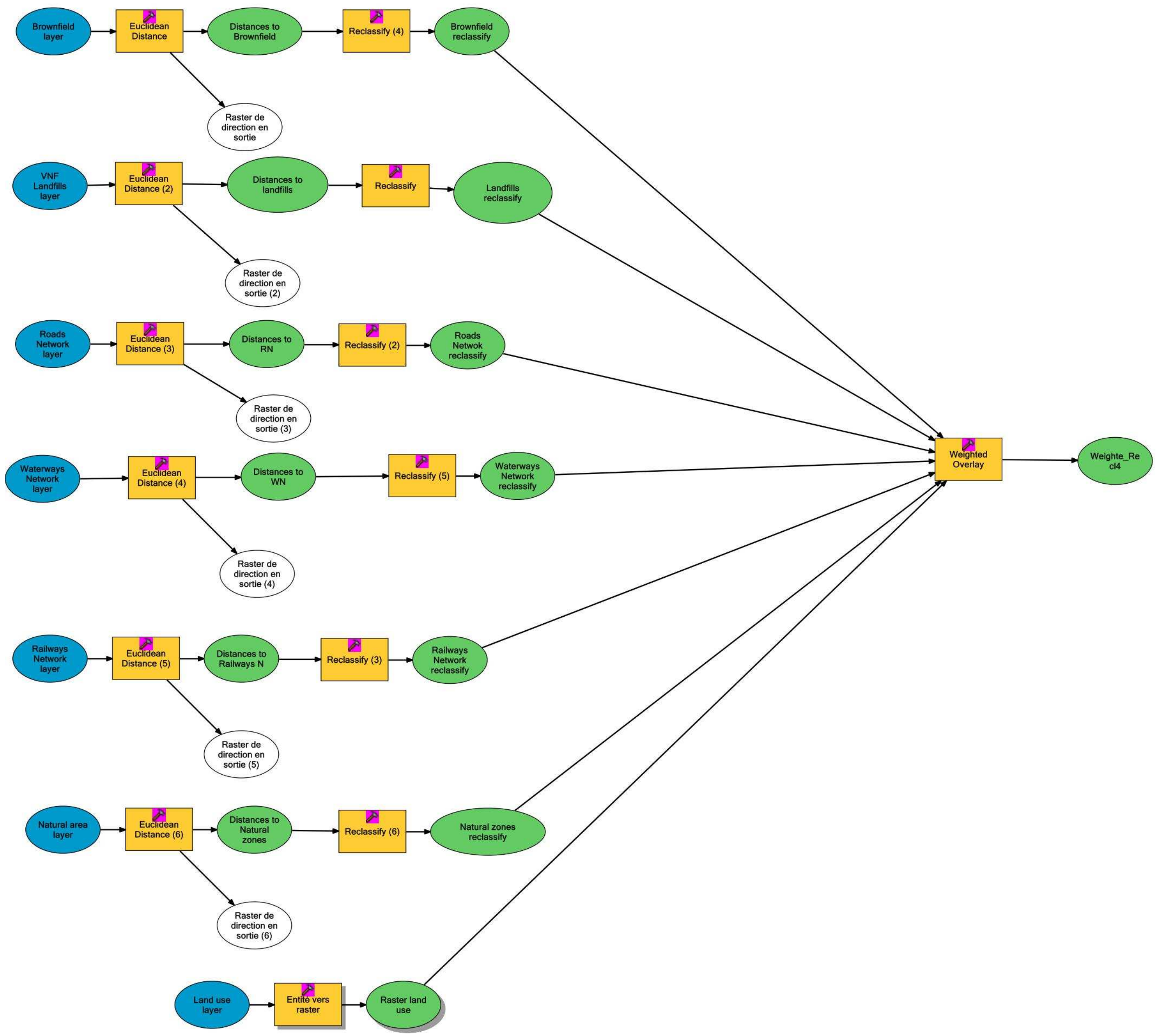

Figure A.7: GIS Model

Table A.11: Law demand case

		Treatment facility				
Scenarios	Optimal solution cost (€)	T_1	T_2	T_3	T_4	T_5
S_1	21 499 647	0	0	0	0	1
S_2	22 371 138	1	0	0	0	0
S_3	22 663 786	0	0	0	0	1
S_4	23 190 979	0	0	0	0	1
S_5	22 734 047	0	0	0	0	1
S_6	22 557 098	1	0	0	0	0
S_7	22 136 323	0	0	0	0	1
S_8	22 915 831	0	0	0	0	1
S_9	22 373 920	1	0	0	0	0
S_{10}	22 880 011	0	0	0	0	1
S_{11}	22 663 442	1	0	0	0	0
S_{12}	21 497 861	0	0	0	0	1
S_{13}	21 845 157	0	0	0	0	1
S_{14}	22 014 339	1	0	0	0	0
S_{15}	22 841 817	0	0	0	0	1
S_{16}	22 416 860	0	0	0	0	1
S_{17}	21 890 644	0	0	0	0	1
S_{18}	22 862 889	0	0	0	0	1
S_{19}	22 840 508	0	0	0	0	1
S_{20}	22 511 297	0	0	0	0	1
S_{21}	22 685 309	1	0	0	0	0
S_{22}	22 011 263	0	0	0	0	1
S_{23}	21 669 811	0	0	0	0	1
S_{24}	22 607 973	1	0	0	0	0

Table A.12: Medium demand case

		treatment facilities				
Scenarios	Objective Value (€)	T_1	T_2	T_3	T_4	T_5
S_{25}	51 537 458	0	0	0	1	1
S_{26}	47 741 375	1	0	0	0	1
S_{27}	48 164 175	0	0	0	1	1
S_{28}	49 404 226	0	0	0	1	1
S_{29}	51 771 159	1	0	0	0	1
S_{30}	47 241 512	0	0	0	1	1
S_{31}	48 872 672	1	0	0	0	1
S_{32}	51 381 933	1	0	0	0	1
S_{33}	48 471 592	1	0	0	0	1
S_{34}	46 914 566	0	0	0	1	1
S_{35}	49 214 544	0	0	0	1	1
S_{36}	46 952 201	1	0	0	0	1
S_{37}	47 050 298	0	0	0	1	1
S_{38}	49 170 072	0	0	0	1	1
S_{40}	48 368 435	1	0	0	0	1
S_{41}	47 266 430	1	0	0	0	1
S_{42}	46 956 496	0	0	0	1	1
S_{43}	49 962 501	1	0	0	0	1
S_{44}	67 772 882	1	0	0	1	1
S_{45}	47 581 870	0	0	0	1	1
S_{46}	46 315 504	0	0	0	1	1
S_{47}	48 817 042	0	0	0	1	1
S_{48}	46 963 658	0	0	0	1	1
S_{49}	67 421 795	1	0	0	1	1

Table A.13: High demand case

		Treatment facility				
Scenarios	Objective Value (€)	T_1	T_2	T_3	T_4	T_5
S_{50}	74 846 906	1	0	0	1	1
S_{51}	76 158 613	1	0	0	1	1
S_{52}	76 181 000	1	0	0	1	1
S_{53}	74 754 634	1	0	0	1	1
S_{54}	74 195 625	1	0	0	1	1
S_{55}	77 318 660	1	0	0	1	1
S_{56}	71 685 345	1	0	0	1	1
S_{57}	76 215 353	1	0	0	1	1
S_{58}	74 372 451	1	0	0	1	1
S_{59}	76 026 390	1	0	0	1	1
S_{60}	76 804 009	1	0	0	1	1
S_{61}	72 449 642	1	0	0	1	1
S_{62}	75 644 260	1	0	0	1	1
S_{63}	73 683 304	1	0	0	1	1
S_{64}	74 667 875	1	0	0	1	1
S_{65}	76 076 986	1	0	0	1	1
S_{66}	75 289 961	1	0	0	1	1
S_{68}	73 296 110	1	0	0	1	1
S_{69}	73 296 110	1	0	0	1	1
S_{70}	73 335 197	1	0	0	1	1
S_{71}	76 956 521	1	0	0	1	1
S_{72}	75 403 173	1	0	0	1	1
S_{73}	76 787 453	1	0	0	1	1
S_{74}	75 981 418	1	0	0	1	1

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