TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

SC	Supply Chain
SCM	Supply Chain Management
DC	Distribution Centers
3PL	Third Party Logistics
AHP	Analytical Hierarchal Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
MCDM	Multi-Criteria Decision Making
SCD	Supply Chain Design
GP	Goal Programming
MILP	Mixed Integer Linear Programming
LCA	Life Cycle Assessment
ANP	Analytical Network Process
AHP	Analytic Hierarchy Process
TOPSIS	Technique for the Order of Prioritization by Similarity to Ideal Solution

INTRODUCTION

Nowadays, supply chain activities have significantly intensified due to the growing world population and globalization. As a result of this growth, natural resources are becoming scarce, and their demand will increase (PWC 2011). Nowadays, companies are obliged to apply environmentally friendly practices because of growing public concerns about climate change caused by greenhouse gas emissions (GHG). Additionally, due to pressures from consumers, community activists, various stakeholders, and government regulators, organizations must adopt a certain level of commitments to social issues (Hassini et al. 2012). Therefore, companies must pay more attention to the adaptation of sustainable supply chain practices which reduce the environmental damages and negative social impacts in order to achieve long-term economic viability. Sustainable supply chains planning is a novel approach which emerged based on this situation and aims to integrate economic, environmental and social decisions in supply chains at design time (Chaabane et al. 2012).

Sustainable supply chain management could be defined as following: "*Sustainable SCM is the management of material, information and capital flows as well as cooperation among companies along the supply chain while integrating goals from all three dimensions of sustainable development, i.e., economic, environmental and social, which are derived from customer and stakeholder requirements. In sustainable supply chains, environmental and social criteria need to be fulfilled by the members to remain within the supply chain, while it is expected that competitiveness would be maintained through meeting customer needs and related economic criteria*." (Seuring and Müller 2008). Management of a supply chain with consideration of sustainability has become a growing concern for a wide range of manufacturing and companies of all scales (Seuring 2013). However, sustainable practices can work for one industry, while they might not apply to other industries (Hassini et al. 2012). Sustainable supply chain management (SSCM) suggests that proactive sustainability yields economic benefits, competitiveness, and better corporate social responsibility.

The food industry is one of the sectors where we observe more and more attention to sustainability during the last years in different regions: Europe, North America and Asia (Manzini and Accorsi 2013). The food supply chain influences every individual in the world. The food supply chain (which is called food system or food industry), consists of food manufacturing, food processing, packaging, distribution, consumer procurement, consumer consumption, and end of product's life (Baldwin 2009).

The food industry is capable of providing nutritious, safe and flavorful products to a wide range of customers; also; agricultural production can prepare a range of products for nourishment (Baldwin 2009). Nevertheless, due to perishability and variation in the quality of food products, managing the production and distribution in food supply chains is dynamic (Grunow and van der Vorst 2010).

Growing concerns about the impacts of food products on the environment and society at large have led companies to deal with environmental and social issues associated with their supply chain design. Based on what the European Commission announced, more than 17 million workers and 32 million individuals are concerned with the food industry (Communities 2008). Ignoring of animal well-being, pesticide's emissions, large consumption of water and energy and wastes accumulation are only a few examples of the negative effects that food industries have caused. Therefore, moving toward sustainability in this sector is intensively required.

0.1 Problem statement

The food industry is composed of a complex supply chain including many actors: suppliers of raw materials, manufacturers, distributors, shippers (transportation), and retailers. The food sector consumes a tremendous amount of energy to keep the products fresh during storage and transportation activities. Food supply chains are heavily associated with social structures since many players and agents (i.e., consumers at one side and farmers from the other side) are involved in this system. Therefore, reducing environmental impact and promoting social responsibilities are of great importance in this sector.

Management and planning of a supply chain are associated with an integrated and complicated decision-making process. There are many indicators involved for measurement and evaluation of supply chain performance. To design and evaluate the performance of a sustainable food supply chain, different criteria and conflicting objectives must be integrated. Besides, different decisions need to be taken at different levels (strategic, tactical and operation) and supply chain stages (supplier, manufacturing, distribution, and transportation). However, the planning decisions on these three management levels are interlinked, and considering them at each of these levels in isolation from the other levels reduce efficiency and applicability of the decisions (Ivanov, 2009). Indeed, integration and alignment of decisions make the network design and planning more complicated. This is even more challenging when a supply chain deals with issues related to perishability, seasonality and sustainability-related issues.

In a long-term decision planning, information is aggregated, and planning is done as a whole, leading to a moderate size decision model. However, even using data aggregation, solving a model with many criteria on a large scale is challenging and computationally expensive (Selim et al., 2008). Besides, aggregation of data in the upper decision levels (strategic and tactical) may cause infeasibility of decisions and sustainability goals in lower decision levels (tactical and operational). Increasing level of detail (from top to bottom) and degrees of aggregation (e.g., time, products, resources) might affect sustainability goals such as increasing amount of GHG emitted from transportation and warehousing activities, leading to the infeasibility of supply chain plan and a failure to fulfill the demand. Although sustainability targets are typically defined at long-term planning levels, managers should ensure that these targets are respected at lower levels, achieving decisions at short-term (Paradis et al. 2013).

Optimization is the primary approach to analyze supply chain performance and deal with multi-objective problems with conflicting goals (Ivanov 2010). Simulation, however, is a powerful tool to analyze the performance of proposed configuration further and evaluate the supply chain strategy resulted from an optimization model (Martins et al. 2017). The aforementioned complexity of integrated problems causes computational burden. Combination of simulation and optimization tools can help obtain a robust strategy towards a sustainable supply chain planning (Barbosa-Povoa et al., 2017). Simulation-based optimization can integrate optimization approaches into simulation analysis. Therefore, a more detailed representation of complex supply chains is obtained, which allows larger optimization problems to be solved in reasonable times (Martins et al. 2017).

The followings are the assumptions considered in this study. The structure of the supply chain under study is composed of the suppliers, manufacturing sites, distribution centers, and retailers, as well as transportation links between these nodes. Products are manufactured in manufacturing sites, and their raw material can be supplied from multiple suppliers. Products are delivered to customer sites either through distribution centers or directly from manufacturing sites. Products can be carried out using different transportation modes. Due to the availability of data, a case from a frozen food company is considered. Frozen products consume a huge amount of energy for temperature control during transportation and warehousing activities in order to guarantee food quality and safety. Besides, the demand for many frozen food products presents a highly seasonal pattern. To manage the demand variation, some companies match the production plan with demand by hiring and laying off workers which help to avoid the significant levels of inventory in low demand periods. We assume that the company is willing to identify the main environmental and social impacts as well as potential strategies to reduce these impacts.

The main supply chain decisions to be made include supplier selection, production quantity, material flow, DC locations, and transportation mode selection, considering the optimization of economic, environmental and social objectives. The decisions are taken in two planning levels, namely tactical and operational. At the tactical level, products are aggregated into periods. The number of workers determines production capacity at each period. The company produces multiple products; employ various transportation types, and aims to meet the demand over multiple time periods. The objective of the tactical optimization model is to optimize the SC configuration and flow of materials. At the operational level, the company has to decide on weekly production planning and the actual delivery to market-based on disaggregated demand. An overview of the supply chain environment is presented in Figure 0.1. As indicated in this figure, this study attempts to incorporate sustainability practices into the decision-making process. To ensure the feasibility of sustainable strategies, interdependency between planning levels should be taken into consideration (Paradis et al. 2013). This integration typically deals with multi-objective problems including a large number of decision variables. Therefore, the implementation of sustainable supply chains planning with tremendous amount of data is complicated, which leads to a large-scale optimization problem (Selim et al. 2008).

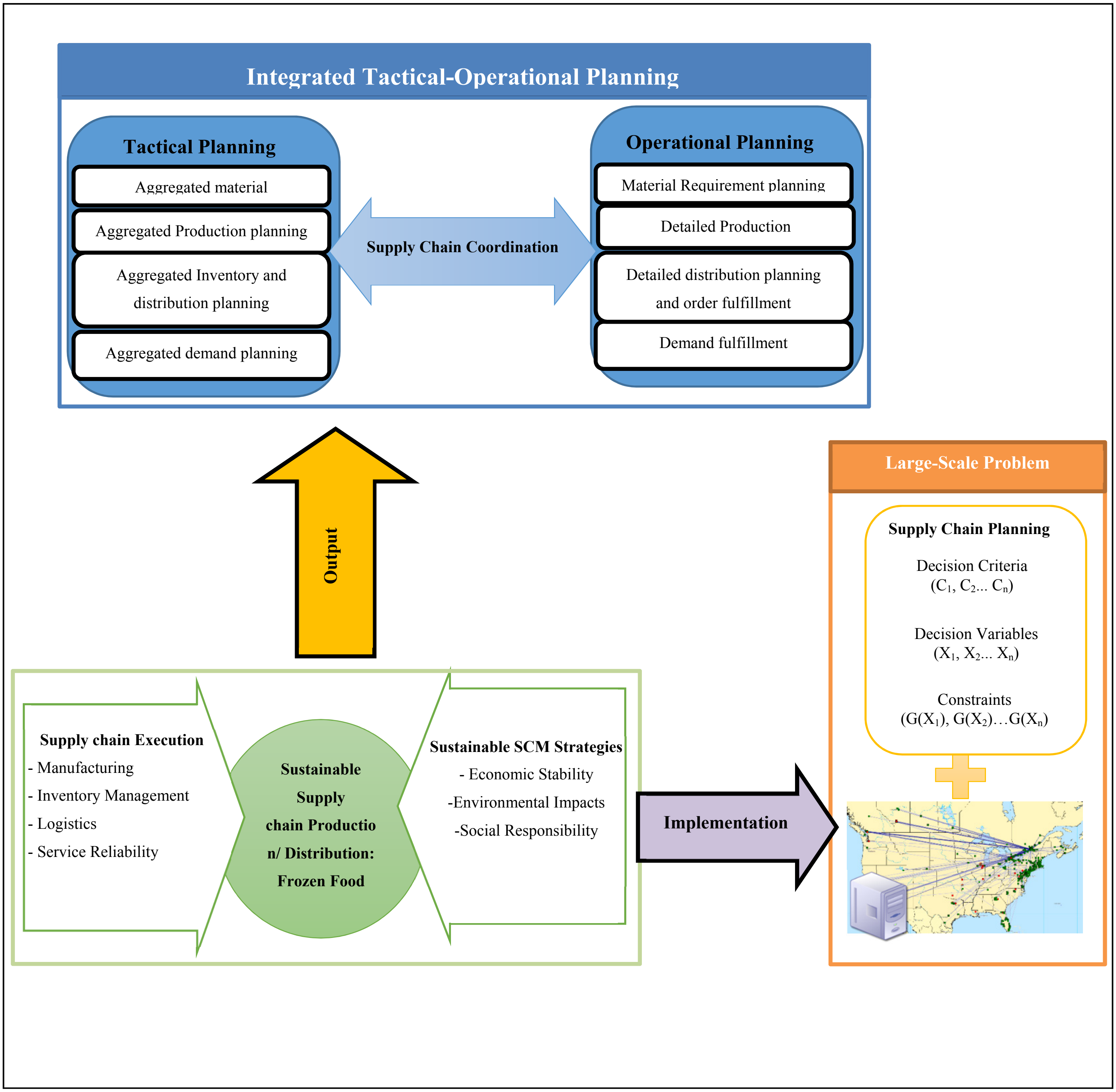


Figure 0.1 Supply chain environments of this study and objectives

0.2 Thesis Objective

The primary aim of this thesis is to develop an integrated tactical-operational decision approach to ensure the feasibility of a sustainable supply chain strategy set at tactical decision level.

To achieve this objective, two sub-objectives are defined. First is to develop a decision support tool for tactical planning of sustainable supply chains, achieving cost-effective, environmental and social friendly supply chain network. Second is to develop a solution methodology to cope with multiple conflicting objectives in reasonable solution time. Eventually, this study proposes an integrated tactical-operational approach to validate the decisions made at the tactical planning level and ensure the feasibility of sustainability goals in both planning levels.

Traditional tactical supply chain distribution planning in the food sector aimed at optimizing the economic objective, with little attention to environmental and social objectives and constraints. However, sustainable supply chain management requires decision makers to incorporate environmental and social factors into the decision making at the planning phase with energy consumption especially in the frozen food sector when food products need temperature-controlled distribution system and a balance between economic, environmental, and social should be found. Incorporating the sustainability factors may concern supply, manufacturing, distribution, etc. This leads us to our first research question:

RQ1: How to effectively develop an integrated sustainable production/distribution decision model for Frozen food supply chains?

To evaluate the sustainable production/distribution system, many different criteria throughout the supply chain must be taken into account. The tactical planning model developed for frozen food supply chains can be solved using traditional multi-objective optimization approaches such as e-constraint and weighted-sum method. However, there are barriers in the methods above to solve large-sized problems with multiple objectives in a reasonable computational time (Zhanguo et al. 2018). Supply chain optimization with multiple conflicting objectives is complex and often contains incommensurable goals. Therefore, developing a comprehensive framework where the critical tactical supply chain planning decisions and their interactions with supply chain performances are identified is needed. Given the complexity of supply chain planning and multiple conflicting objectives, a solution methodology needs to be developed to cope with this large-scale optimization problem. We formulated the second research question as follows:

RQ2: How to solve the sustainable supply chain distribution model with many variables and multiple conflicting objectives, leading to a large-scale multi-objective optimization problem?

Supply chain plans and strategies are formed based on the goals of higher levels of the supply chain. However, the plan set at an upper level (tactical) might not be achievable at lower decision level (operational). This could occur due to the detailed planning, increasing the delivery frequency and disaggregated demand in lower decision levels, which may cause infeasibility of sustainability goals, set by upper decisions levels. In this circumstance, integration of supply chain decision levels will help ensure the feasibility of decisions toward sustainable planning. The question arises of how to link, coordinate and optimize supply chain decisions in order to ensure the feasibility of sustainability goals at all planning levels. Thus, our third research question is stated as follows:

RQ3: How to integrate supply chain decision levels to ensure the feasibility of a sustainable supply chain strategy?

Thesis main objective
To develop an integrated tactical-operational decision approach
Thesis sub-objectives
1. To develop a decision support tool for tactical planning of sustainable supply chains
2. To develop a solution approach to cope with large-scale multi-objective optimization problems

The methodology proposed to address the above research questions is discussed in the following section.

0.3 Methodology

To answer the research above questions, a methodology is proposed. This methodology is based on the development of decision support tools using optimization and simulation tools. In this research, we use a case study of a North American Frozen Food Supply Chain to investigate and gain insight into the trade-off between conflicting objectives.
First, we use an optimization approach to simultaneously integrate the three sustainability dimensions (e.g. economic, environmental and social aspects) to support decision making at the tactical planning level. Then, we extend our research by doing further investigation on key indicators involved in supply chain planning to come up with a framework for evaluating the supply chain performances and ways to solve this large-scale optimization problem. Eventually, we get a greater perspective of the feasibility of plans set at a tactical level by integrating it with operational planning level. Figure 0.2 illustrates the proposed methodology. We describe the steps of methodology in detail as follows:

Step 1 Tactical planning for sustainable supply chains

The first step is designed to answer our first research question: How to effectively develop tactical planning for food supply chains, integrating three sustainability dimensions?

In this step, the objective is to achieve a supply chain configuration, which optimizes three sustainability dimensions using decision maker's preferences. To this end, we identify economic, environmental and social aspects, which are more relevant to the supply chain network under, study, i.e. those sustainability measures, which are mainly influenced by decisions made in the supply chain network. We investigate ways to integrate the sustainability aspects into the decision-making process of a food supply chain and translate them into objectives or constraints of the decision model. Through a case study, we run different scenarios to analyze the performance of the supply chain and identify actions to implement a sustainable supply chain strategy.

Step 2 Large-scale optimization problem

This steps focus on answering our second question: How to optimize a supply chain network with many variables and multiple conflicting objectives, leading to a large-scale optimization problem? In this step, we extend our study towards developing a framework, using key supply chain design indicators within the network. We identify relevant factors through literature; investigate their interaction with supply chain performances, and connect them with network decisions in quantified form. We also develop a solution methodology, which can cope with multiple objectives and decision variables in reasonable computational time.

Step 3 Integrated tactical-operational planning

The third step aims to answer our third research question: How to integrate supply chain decision levels to ensure the feasibility of a sustainable supply chain strategy?
To validate the sustainable supply chain strategies set at step 1, coordination and integration of decision levels must be taken into account. Decision makers must ensure the feasibility of lower decision plans when making decisions at upper levels. To highlight the need for an integrated model, we study tactical-operational planning using a case study. We analyze the model using different scenarios in order to stress the potential benefits of the integrated

approach, compared to the hierarchical approach. This enables decision-makers to validate decisions to make in sustainable supply chain strategies to implement.

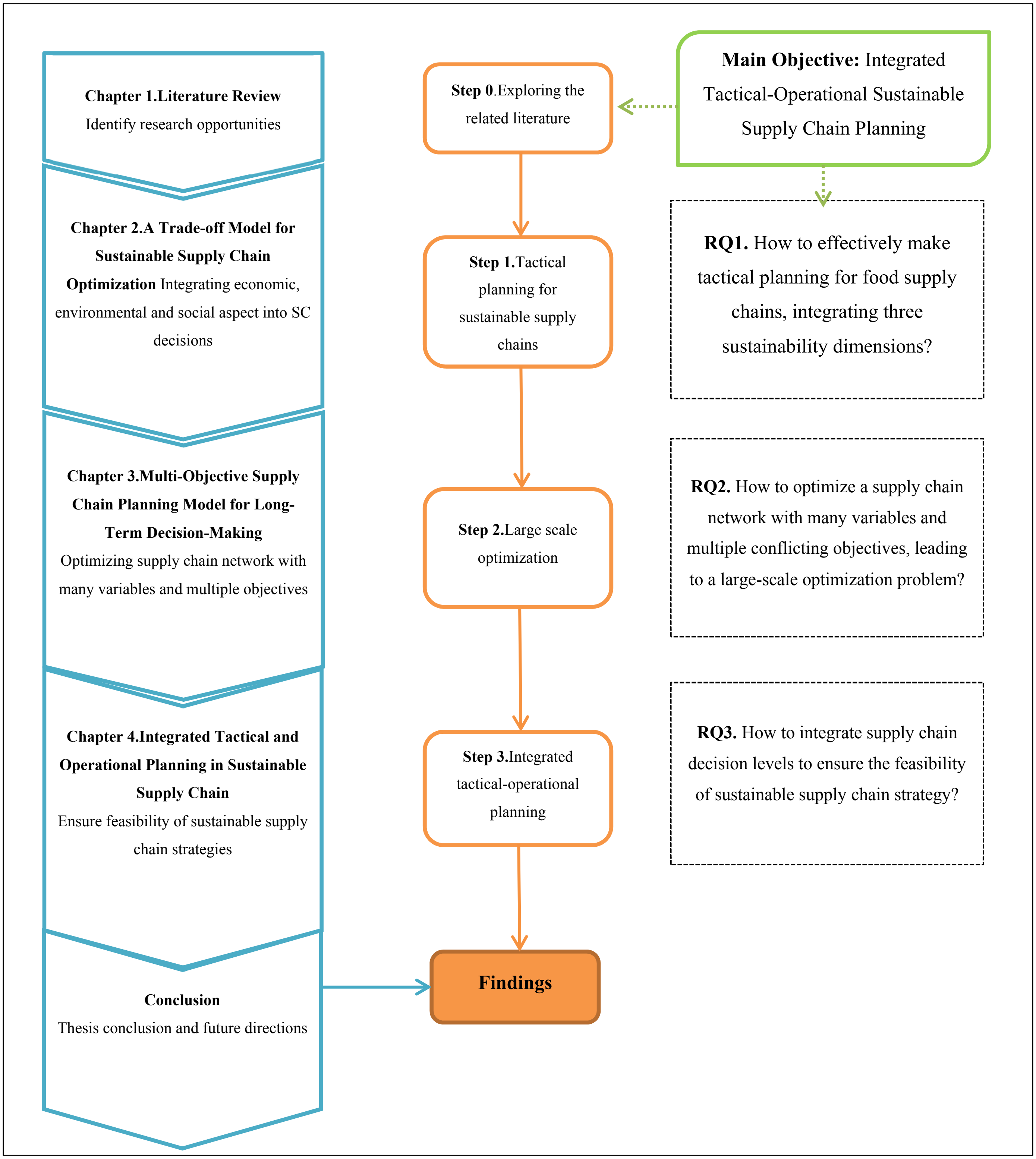


Figure 0.2 Proposed methodology

0.4 Thesis outline

This thesis is composed of four chapters. The first chapter focuses on a literature review about sustainable supply chain planning in general and more specifically on the food sector. The research gap is highlighted at the end of this chapter. In chapter 2, a multi-objective optimization model is proposed to support tactical decisions in a sustainable supply chain problem. In chapter 3, a solution methodology is proposed to optimize decisions over a long-term horizon and evaluate supply chain performances. Chapter 4 is devoted to addressing an integrated tactical-operational decision model to ensure sustainability in both planning levels. At the end of the thesis, we give concluding remarks and summary of major contributions, along with limitations and future implications of our research.

CHAPTER 1

BACKGROUND AND LITERATURE REVIEW

In this chapter, we review mainly the quantitative approaches to supply chains management with a focus on the food supply chain and connect them to ongoing challenges in this sector. Our focus is mainly on three aspects; sustainable supply chain planning, multi-objective optimization models, and integrated decision models.

1.1 Measuring sustainability performance

Elkington (1998) for the first time introduced the three dimensions of sustainability. He called these dimensions as the triple bottom lines (3BL), which are profit, people, and the planet. A visual representation of these three dimensions is shown in figure 1.1. There are activities at the intersection of economic, environmental and social performance in which not only positively impact the environment and society but also could make economic benefits for companies in the long-term horizon (Carter and Rogers 2008). Sustainability criteria can be integrated into every component within the supply chain network including source, production, distribution, and transportation. If any of the dimensions is missing, the entire system is not sustainable.

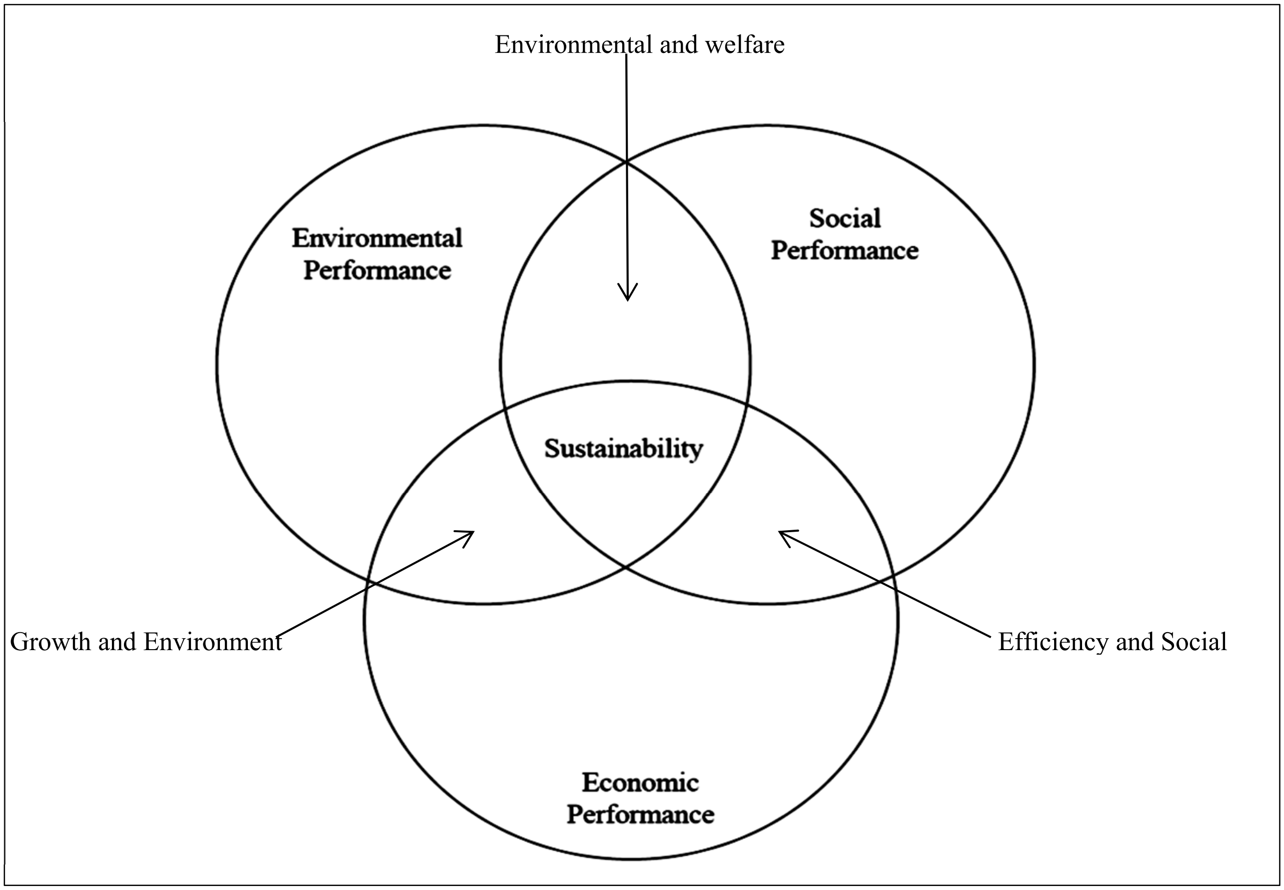


Figure 1.1 Sustainability Dimensions (Carter and Rogers 2008)

1.1.1 Economic pillar

Each supply chain problem has some costs such as the installation of facilities, transportation and so forth that should be considered in designing the network. The economic dimension of sustainability represents the cost or the profit in net present value (Hugo and Pistikopoulos 2005). This side of sustainability is usually defined as an objective function that should be minimized as a cost or maximized as a profit. Customer service level and product quality are also other measures of performance which can be categorized in this sustainability pillar.

Meanwhile, different methods have been developed to measure the economic part of sustainability, including The Balanced Scorecard, Activity-Based Costing (ABC), and Economic Value Analysis (EVA).

1.1.2 Environmental pillar

Sustainability in the environmental side of the supply chain is the management of impacts, which supply chain activities, can have on the environment. Zsidisin and Siferd (2001) defined environmental supply chain management as *``the set of supply chain management policies held, actions taken, and relationships formed in response to concerns related to the natural environment with regard to the design, acquisition, production, distribution, use, reuse, and disposal of the firm`s goods and services``*. Energy use, water consumption, greenhouse gas emissions, and land use are only a few examples of environmental impacts from supply chain activities. There are many approaches which have been used and supported sustainability objectives, such as integrated chain management, industrial ecology, life cycle management as well as green/environmental/sustainable supply chain management (Seuring 2004). However, the environmental aspect of sustainability is mostly dominated by Life-cycle assessment and impact criteria.

1.1.2.1 Life Cycle Assessment

Environmental Life Cycle Assessment (E-LCA), generally denoted as Life Cycle Assessment (LCA), is a methodology which aims to address the environmental features of a product and their possible environmental impacts during its life cycle (Benoıt 2009). A product’s life cycle analysis includes the different steps from acquisition of raw material or production of natural resource to the disposal of the product at the end of its life, (i.e., cradle-to-grave) (Benoıt 2009).

LCA consist of (a) goal and scope definition, then (b) inventory analysis of all inputs and outputs, (c) impact assessment and, lastly, (d) evaluations. A comprehensive database for inventory analysis is available, and it is considered the least controversial part of this approach. The process of the impact assessment interpretation is typically very complex and time-consuming, and only an expert in environmental management can properly perform it (Chiu, Hsu, et al. 2008). However, some researchers in the Netherlands represented a methodology in order to overcome this complex task by using one index to represent the environmental impact of a manufacturing process or a product. The index is based on the concept of an “ecological footprint," and the current version is Eco-indicator 99 (Pishvae et al. 2014). The aforementioned index uses data from inventory analysis and converts these data into three categories in a unified way. These categories consist of ecological quality, resource consumption, and human health. Then a weight is considered for each quantity (40%, 20% and 40% for human ecological quality, resource consumption, and human health respectively) (Chiu, Hsu et al. 2008). The stages of LCA are shown in figure 1.2.

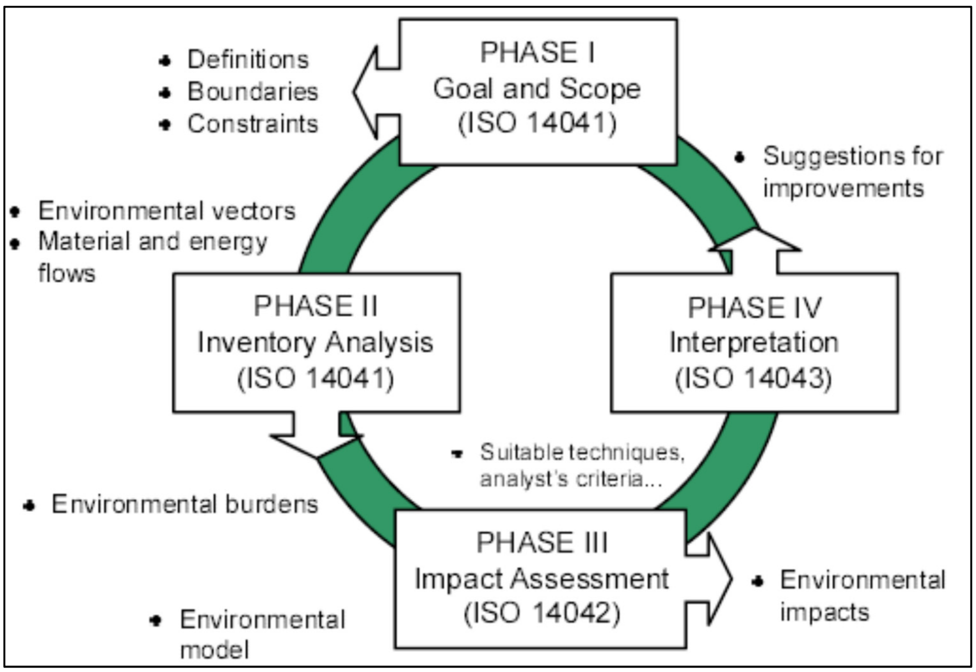


Figure 1.2 Phases of LCA (Guillén-Gosálbez and Grossmann 2009)

1.1.3 Social pillar

Social responsibility (SR) is defined as "*the continuing commitment by business to behave ethically and contribute to economic development while improving the quality of life of the workforce and their families as well as of the local community and society at large*" (WBCSD 1999). Despite technology advancements, supply chains are based on the interaction between individuals, which cause ethical issues at many levels of the process. (Clift 2003).

In recent years, the reputation of social responsibility has quickly increased (Beda 2004). One of the motivations is that consumers' attitudes have changed. Based on recent research, nowadays, many consumers preference is to buy products from and invest in shares of companies which care about the environment and keep good citizenship behavior (Maignan 2001). However, one of the benefits for socially responsible companies is to enhance corporate image and the possibility of gaining competitive advantage (Miles and Munilla 2004).

Due to complex nature and vast scope of social impact, measuring social sustainability in a supply chain is much related to the context of supply chain activity and the circumstances (Pishvaee, Razmi, et al. 2012). Most of the researchers in the subject of supply chain planning and also other fields like environmental management and supply chain management have not focused on the social side of sustainability (White and Lee 2009). Although different sorts of models have been applied, it is obvious that the social aspect of sustainability is addressed the least often in the related literature review.

Benoıt (2009) proposed a guideline for social life cycle assessment of products (GSLCAP). This guideline has the following benefits in comparison with other approaches: (1) GSLCAP is a product-oriented method to assess social impact which has designed on the foundation of life cycle assessment and consequently, it is suitably compatible with the logic of supply chain and simplify model design and formulation; (2) this approach is able to appropriately cover the social matters while does not consider environmental issues, therefore, it better complies with sustainability pattern and social considerations into the supply chain network; and (3) it has been benefited from the latest improvements in the area of social impact assessment, as it is one of the latest versions of developed frameworks (Pishvaee, Razmi et al. 2014).

The integration of all the three aspects plays an essential role, which is not considered that much in relevant literature. Investigation in previous works confirmed that the social side of sustainability requires being much better integrated with environmental and economic dimensions (Seuring 2013). This investigation represents a noticeable research gap concerning social performance and also the integration of the three dimensions of sustainability (Seuring 2013).

1.2 Sustainable supply chain planning

Mentzer et al. (2001) defined supply chain management as "*The systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole*".

Based on above definitions, sustainable supply chain management could be defined as the integration of economic, environmental and social goals in order to improve the long-term economic performance of the individual company and whole supply chain network (Carter and Rogers 2008).

Academic interests for sustainability in supply chain planning have considerably grown during the past years. Due to the growing concerns about social and environmental impacts on business processes, sustainability has absorbed more attention in supply chain network design. Management and design of supply chain play an essential role in the overall sustainability of a supply chain network (Pishvaee et al. 2014).

A comprehensive review of modeling approaches for sustainable supply chain planning and design is conducted by Seuring (2013). According to this study, there are mainly three approaches which are widely used in modeling of sustainable supply chain network: equilibrium models, analytical hierarchy process and multi-criteria decision making. Recently, some studies have also addressed simulation in order to model sustainable supply chains. Some researchers attempt to solve problems with exact methods using exact solvers such as Lingo, GAMS, and CPLEX which is complicated and limited to large-scale problems. On the other hand, some authors utilized heuristic methods and meta-heuristic algorithms like Simulated

Annealing (SA), Genetic Algorithm (GA), Tabu Search (TS), or Ant Colony (AC) for large-size problems.

Generally, most of the optimization models have focused on the economic side of the supply chain as the primary objective (Goetschalcks and Fleischmann 2008). However, environmental impacts have been recently received significant attention from researchers and several approaches have been developed to integrate such considerations at the plant level. The major disadvantage of these methods is that it might consequence in results that decrease the environmental impact somewhere in the supply chain while it will increase it elsewhere (Chaabane et al. 2012).

Hugo and Pistikopoulos (2005) developed a multi-objective mathematical programming-based methodology by considering the multiple environmental considerations together with the traditional economic criteria. Also, Guillén-Gosálbez and Grossmann (2009) presented a mixed integer non-linear programming model to design a supply chain network that maximizes the net present value and minimize negative environmental impact. Chaabane et al. (2012) introduced a mixed integer linear programming model to design a sustainable supply chain network of the aluminum industry to evaluate the trade-offs between economic and environmental objectives.

Multi-criteria decision-making approaches such as goal programming, ANP, AHP and TOPSIS are also applied by some researchers to solve problems related to sustainable supply chain network.

Nagurney and Toyasaki (2003) developed a framework for the formulation, analysis, and computation of solutions for the supply chain of electronic commerce with multi-criteria decision-makers and environmental considerations. Dehghanian and Mansour (2009) applied an AHP approach to handle the social side of sustainability in a recovery network of end-of-life products. They used AHP to get a single indicator that defines the social impact of different

end-of-life alternatives then; their indicator would be considered in calculating the social objective function.
Due to the randomness of some parameters, interaction among decision variables and the complexity of the sustainable supply chain network, simulation can be helpful for modeling and analyze the problem. Simulation techniques and software are very powerful methodologies to consider uncertainties in real situations (Govindan et al. 2015). Elhasia et al. (2013) applied a discrete event simulation model of sustainable supply chain using Arena simulation software in order to analyze a cement supply chain operations and find the best scenario that demonstrates the best economic, ecological and social performances in the cement industry. Van der Vorst et al. (2009), also, proposed a new integrated approach for supporting decision-making on sustainable design of food supply chain network using discrete event simulation.

Due to the complexity and dynamic nature of the supply chain, it is involved with a high degree of uncertainty that can affect the effectiveness of supply chain planning decisions, especially decisions at the strategic level (Klibi et al. 2010; Peidro et al. 2010). Uncertainty is one of the most critical factors in reverse supply chain problems. There is a high level of uncertainty associated with the quality, quantity, timing of the returned products (Fleischmann et al. 2001). At the same time, limited studies have addressed how to deal with sustainable supply chain management under uncertainty.

Researchers have utilized various methodologies to cope with uncertainties like different stochastic techniques (such as probability distributions, two-stage stochastic approaches, and chance constraints), interval programming approaches, fuzzy logic, chaos theory, and the combination of these (Govindan et al. 2015). In order to cope with uncertainty in the sustainable supply chain, some researchers have represented several stochastic programming models (e.g., Salema et al. 2007; El-Sayed et al. 2010). Meanwhile, due to the complexity and unavailability of adequate historical data, there are some disadvantages of using stochastic programming approaches. Consequently, some authors have applied other approaches to avoid this issue such as robust optimization (Pishvaee et al. 2011), probabilistic programming (e.g., Pishvaee and Torabi (2010); Qin and Ji (2010)) models for closed loop and reverse supply chain network design under uncertainty. Also, Pishvaee et al. (2014) proposed a multi-objective probabilistic programming model in order to design a sustainable medical supply chain network with consideration of conflicting economic, environmental and social performances. To deal with uncertainty in sustainable supply chain network, fuzzy programming (e.g., Pishvaee and Razmi (2012)) and Stochastic (e.g., Guillén-Gosálbez and Grossmann (2010)) models have also applied in the literature.

1.2.1 Strategic, tactical and operational planning

Sustainability issues in supply chain management can also be started at three decision-making levels; strategic, tactical and operational (Allaoui et al. 2016). Arampantzi and Minis (2017) proposed a multi-objective MILP to design an SC network over a long-term horizon, integrating three fundamental dimensions of sustainability namely economic, environmental and social. They considered a system from supplier to customer where products are aggregated into product families. To solve the proposed model both goal programming and ε-constraint methods are employed. A MILP model is also developed by Wang et al. (2011) to support decisions for the strategic planning of green supply chains. To achieve a trade-off between two conflicting objectives, a normalized normal constraint method is applied. Also, Chaabane et al. (2012) introduced a mixed integer linear programming to design a sustainable supply chain network of aluminum industry and to evaluate the trade-offs between economic and environmental objectives.

Bortolini et al. (2016) developed a decision support tool to tackle the tactical planning of distribution networks optimizing operational cost, environmental impacts and delivery time objectives. Also, to support tactical decisions of distribution networks Validi et al. (2015) presented a multi-objective optimization model based on Analytic Hierarchy Process (AHP) and 0-1 mixed integer-programming model. They also used genetic algorithms and Design of Experiments (DOE) to achieve a robust solution and find trade-offs between CO2 emissions and total cost. The model is implemented in a case study of the Irish dairy industry.

Few authors also focus merely on the decision making at the operational level with consideration of sustainability issues. Sabio et al. (2012) proposed a framework using an optimization model and a data analysis approach for minimization of the life cycle environmental impact of hydrogen infrastructures. Furthermore, Van der Vorst et al. (2009) proposed a new approach using discrete-event simulation to integrate logistics, product quality analysis, and environmental sustainability in a food supply chain network.

1.2.2 Sustainable food supply chain planning

1.2.2.1 Food Supply chain management

A food supply chain is composed of all the flows and activities from farmers to consumers (farm-to-fork). These activities consist of production, transportations, storages, packaging, distributions, and purchases. Figure 1.3 represents conceptually the main stages of Food supply chains which are described by Iakovou (2014).

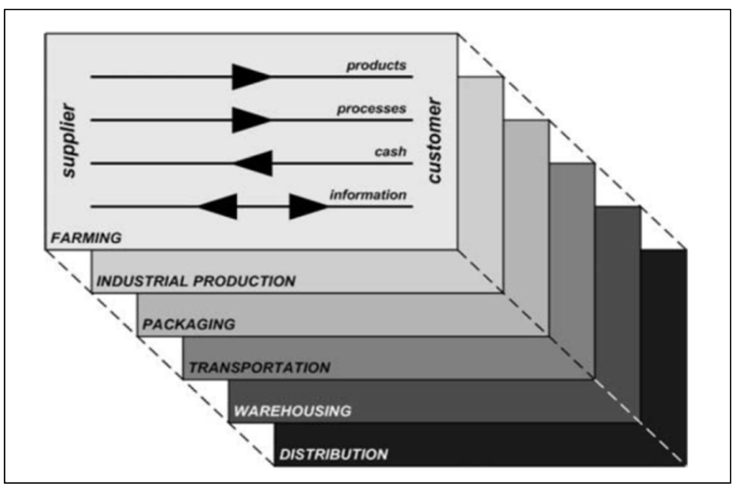


Figure 1.3 Food supply Chain management stages (Iakovou 2014)

Ahumada and Villalobos (2009) classified food supply chains into two main types: a) fresh foods include perishable products (fresh fruits and vegetables) which their keepability is only a few days, and b) Non-perishable products such as grains, nuts, and potatoes which can be kept for longer time.

According to Mercier et al. (2017), food supply chain can be separated into three categories depending on product characteristics of temperature system: frozen, chilled and ambient. Frozen products are usually kept at a temperature of -18^{o} or less, chilled products can be held at a temperature above freezing point to $+15^{o}$, and ambient products can be kept at room temperature. A special distribution solution is needed for food products because of the perishability of such products. This is why fast delivery and geographical location is of interest to food producers, especially for products, which are sensitive to distribution costs (Fredriksson and Liljestrand 2015). For instance, the importance of the warehouse location for frozen food products is described in the report of Levén and Segerstedt (2004). They claimed that warehouses in frozen food supply chain should be either close to manufacturing or customer location. Storage and transportation of frozen food supply chain fall into the “cold chains” classification, in which foods are retained at low temperature in order to prevent food products deterioration. To preserve products quality, and avoid spoilage of perishable products, energy should be properly used in such chains. The quality and nutritional values of foods could begin to deteriorate while harvesting or butchering. Thus, cold chains aim to avoid products value decrease and to preserve their quality over the entire supply chain network from farm to consumers (Zanoni and Zavanella 2012).

There are so many factors in the supply of food such as volatile prices of products, uncertainty in global food demand, various weather condition and so forth which make this chain quite a complex and challenging issue. Developing proper strategies, which can handle food products to satisfy customers’ demand, whereas replying to growing changes in dietary habits and lifestyle, has become a challenging and complicated matter.

A food supply chain network includes organizations, which have responsibilities for producing and distributing animal-based products and vegetables. Generally, two main types of food supply chain network (FSCN) are distinguished by van der Vorst et al. (2009):

1. FSCN for fresh products (like fresh fruits and vegetables). Generally, this type of FSCN comprises growers, wholesalers, retailers, importers, exporters, and shops. Main processes can

be named as handling, storage (conditioned), packaging, transportation, and trading. The product quality is related to the environmental conditions and it can either increase (e.g., ripening of fruits) or decrease during the time- if harvested at a mature stage.

2. FSCN for processed food products (like portioned meats, snacks, desserts, canned food products). This type of FSCN includes growers, processors, retailer, importer, and out-of-home segments. In general, in these chains, raw materials are agricultural products that are used to produce consumer products with higher added values.

van der Vorst (2000) and Van der Spiegel (2004) have summarized the following specific aspects of food supply chains that differentiate them from classical supply networks and demand particular managerial capabilities:

1. Shelf-life restrictions for raw materials.
2. Perishability of products.
3. Long production time.
4. Seasonality in harvesting and production.
5. Conditioned storage and transportation.
6. Variable process yield in quantity and quality due to biological variations, seasonality, factors connected with weather, pests and other biological hazards.
7. Storage-buffer capacity constraints, when materials or products can only be kept in special containers.
8. Governmental rules relating to environmental and consumer-related issues (CO2 emission, food-safety issues).
9. Physical product features like sensory properties such as taste, odor, appearance, color, size, and image.
10. The convenience of the ready-to-eat meal.
11. Perceived quality, also relevant for food applications: e.g., advertisement or brands (marketing) can have a considerable influence on quality perception.
12. Product safety: increased consumer attention concerning both product and method of production: no risks for the consumer of foods are allowed.

1.2.2.2 Decision making in the food supply chain

Managing and designing of a supply chain is associated with an integrated and complicated decision-making process, and this is even more complicated when a food supply chain deals with issues related to perishable, seasonable and fresh products (Tsolakis et al. 2014). More specifically, the planning and designing of food supply chain should cope with issues such as harvest planning, crops processing operations, transportation activities, food safety, environmental management and sustainability assurance (Tsolakis et al. 2014). Managing and planning of food supply chains are more complex due to perishability and seasonality of products (Tsolakis et al. 2014).

Four functional areas for food supply chain activities have been identified by Ahumada and Villalobos (2009) including production, harvest, storage, and distribution. They considered decisions made in each functional area as follows:

a) Production (cropping) – allocation of the land to each crop, scheduling of cultivation, and resource determination for growing the crops,

b) Harvest- scheduling of collecting the crops and determining the level of recourses for it, equipment and labor scheduling,

c) Storage – inventory control, the number of products to store and sell,
d) Distribution – transportation mode selection, vehicle routing, and shipping schedule.

Controlling the quality of the product throughout the supply chain is one of the most challenging tasks in the food sector. Complexity, the existence of randomness in parameters, numerous variables and constraints, and conflicting objectives make this problem have a potential to add some significant contributions to resolve the challenge. The different sources of uncertainty identified for food supply chain (by van der Vorst and Beulens (2002)) are the length of the order forecast horizon, data timeliness, and information availability, decision policies used, and supply, demand and process uncertainty. Moreover, Chaudhuri et al. (2014) claimed that size/weight of the product in fish and meat industry, and type of the product; typically, in the fish industry can be uncertain parameters. They also addressed supply uncertainty in dairy, processing fish, meat, and fruit and vegetables.

In many industries, supply as a source of uncertainty is predictable, but it is not always the case in food industry since the volume and the quality of the supply can be affected by the environment and long supply lead times (Dreyer and Grønhaug 2012 and van der Vorst and Beulens 2002).

Nevertheless, despite most of the chain members in the real world face with different uncertainties in food supply chains, almost all studies have focused on the deterministic environment (Soysal 2012). However, despite the importance of uncertainty in food supply chains only a few studies (such as Dabbene et al. 2008 and van der Vorst et al. 2009) have considered uncertainty in their model.

Food supply chain decisions based on timeframe and criticality can be categorized in strategic, tactical and operational level. Long-term decisions like; supplier selection, where to locate facilities, selection of farming technologies, etc., falls in the strategic level. Tactical planning is the connection between strategic direction and operational planning. The decisions in this level are medium-term and generally reviewed every month. Determining the optimal amount of inventory and production, harvest operations planning, transportation modes, etc., fall into this category. Short term decisions such as transportation and routing plans, delivery plans and supporting food safety via transparency and traceability are considered as operational decisions. In particular, Van Elzakker et al. (2014) optimize the tactical planning of the food supply chain, while considering product shelf life. García-Cáceres et al. (2015) proposed a MINLP to support tactical decisions of an oil palm harvest and extraction supply chain.

Nevertheless, according to the study conducted by Ahumada and Villalobos (2009), we categorized the decisions, which should be made in the food supply chain in three planning levels:

Strategic Level

- Supplier selection
- Vendor selection
- Facility location
- Determining the number of warehouses, its capacity, and location
- Selection of farming technologies
- Ensuring sustainability
- Risk management
- Quality management

Tactical Level

- Determining optimal amount of inventory level
- Determining the amounts of products in each flow
- Logistics operations planning
- Harvest operations planning
- Harvest and planting operation scheduling
- Determining farming machinery field routes

Operational Level

- Supporting food safety via transparency and traceability
- Demand planning and forecasting
- Vehicle routing problem and scheduling

1.2.2.3 Sustainability in the food supply chain

Obtaining sustainability in food sectors desires to deal with three different challenging issues known as 3P's: (a) Profit – stay competitive in food sector; (b) planet – attempting to reduce environmental concerns; and (c) people – promoting job opportunities and living standards. Nowadays, the food supply chain is not only about cultivation, warehousing, and transportation but also about preserving the environment and increasing social responsibilities. In comparison with other types of supply chain, food supply chain play an essential role in the social side of sustainability since it can act as an effective tool in favor of poverty relief. Also, as we all know these traditional supply chains are remarkably associated with social structures since many players and agents (i.e. costomers at one side and farmers at the other) are involved with this system.

The sustainability indicators put their impact on every stage of food supply chain such as from farm gate to market processing to wholesale to retail to catering. The indicators as described by Yakovleva and Flynn (2004) are presented in Fig 1.4.

A substantial proportion of the environmental impact and the total energy consumption in the food industry could be originated from activities such as harvesting with different kinds of equipment using fuels, products transportation in long distances, storage of perishable products for a long time and using more or less environmentally friendly technologies for final production. There are some methodologies for measuring the sustainability in food supply chain, such as labeling the `food miles`, which means the distance that a product travels to reach the customer (Akkerman et al. (2010); Saunders (2006)), and the total energy use during storage (Sim et al. 2007). Recent reviews discuss planning and optimization models proposed to deal with sustainability (Soysal et al. 2012, Seuring 2013, Eskandarpour et al. 2015, Govindan et al. 2015).

In recent years, due to the increasing attention to food supply chain management, the number of studies in this field has been increased. Soysal (2012) reviewed quantitative models related to sustainable food logistics management. Boudahri (2011) proposed a model for the redesign and optimization of the distribution network of the specific case of chicken meat. Hellweg et al. (2005) presented a methodology in order to evaluate the trade-off between economic and environmental impacts. However, the majority of researchers in the concept of the food supply chain have focused on the distribution part of the chain.

The unpredictability of weather conditions, the food perishability, and the complexity of food safety based on environmental regulations, the change of customers' lifestyle trends, and the environmental issues show key challenges to develop a robust food supply chain network (Tsolakis et al. 2014). Managing the food supply chain networks is a challenging and complex task, as it involves a high level of uncertainty, conflicts between objectives, numerous parameters, decision variables, and constraints. Thus, given the complexity of the food supply chain network, designing such a network needs a proper decision support tool.

Even though the food supply chain has received much attention in recent years, regarding methodologies developed it is in its infancy. The literature for sustainable food supply chains will be discussed in more details in chapter 2.

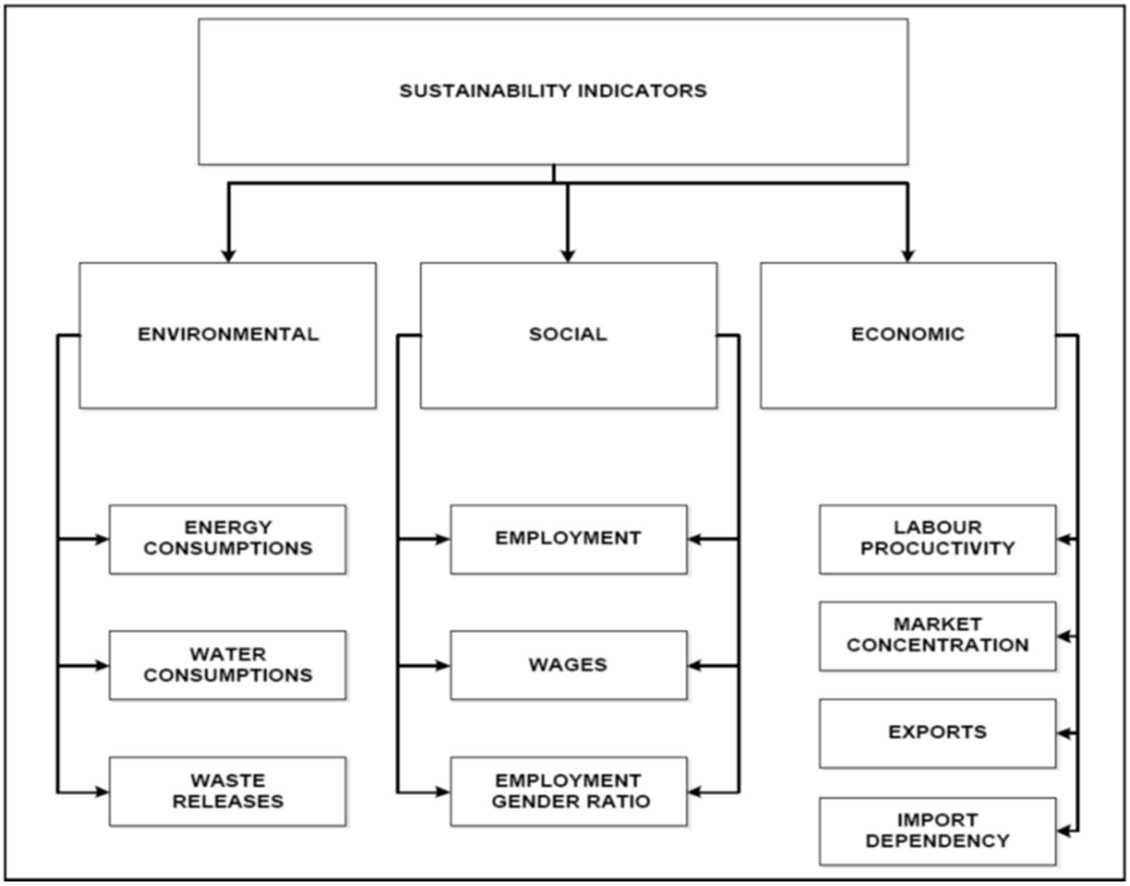


Figure 1.4 Sustainability indicators for food supply chain (Yakovleva and Flynn 2004)

1.3 Multi-criteria decision-making models

Integration of supply chain echelons naturally lead to large-scale and complex models that are hard to optimally solve in real-world problems (Selim et al., 2008). This integration typically deals with multi-objective problems including a large number of decision variables. Unlike the numerous researches on single-objective large-scale problems, few studies have been conducted on multi-objective large-scale problems. Selim et al., (2008) used an approach called Weighted Optimization Framework to solve a multi-objective optimization problem with a large number of decision variables. Altiparmak et al. (2006) considered different objectives in their model which is based on MILP and MOO using Genetic Algorithm which was the minimization of total SC cost, maximize service level, and maximize capacity utilization. Validi et al. (2015) presented a multi-objective optimization model based on

Analytic Hierarchy Process (AHP) and 0-1 mixed integers programming to support decision making in the distribution system of a case in the dairy industry. They also used genetic algorithms and Design of Experiments (DOE) in order to achieve a robust solution and find trade-offs between CO2 emissions and total cost. Metaheuristic algorithms in which the results are not expected to be optimal typically handle large-scale optimization models.

Goal programming (GP) is an important class of multi-criteria decision models widely used to analyze and solve applied problems involving conflicting objectives. GP is a well-known and very popular tool used to analyze multi-criteria problems. Over the last 50 years, the development and refinement of GP techniques have been impressive, leading GP to be one of the most preferred tools for dealing with multiple criteria decision analysis. Its range of applications is extremely large, including also engineering, management, and social sciences. Originally introduced in the 1950s by Charnes et al. (1955) the popularity and applications of GP have increased immensely due to the mathematical simplicity and modeling elegance. Over recent decades, algorithmic developments and computational improvements have significantly contributed to the diverse applications and several variants of GP models. Integration of GP with fuzzy set theory helps overcome vagueness of specifying the goals. FGP approach is suitable for models with flexible goals, multiple criteria, multi-objective and multiple strategies (Tsai and Hung 2009). Selim and Ozkarahan (2008) employ a fuzzy goal programming approach to study SC distributor network design model. Ghorbani et al. (2014) propose an FGP approach for a multi-objective model of reverse SC design. Comas Martí et al. (2015) proposed an SC network design model that simultaneously considers the emissions and costs related to both facility location and transport mode decisions while taking into account the innovative or functional nature of products through the explicit consideration of demand uncertainty and inventory costs.

1.4 Integrated sustainable supply chain planning

Strategic decisions address a long planning horizon for several years ahead, while tactical decisions deal with a shorter planning period with a focus on inventory, supply and demand planning. On the other hand, operational decisions are more about detail planning and demand fulfillment.

Zhang et al. (2014) present a holistic framework for sustainable supply chain by considering three decision levels. They proposed a multi-objective optimization framework, which considered three indicators, namely cost, GHG and lead-time. Amin and Zhang (2012) also proposed a MILP model for a closed loop supply chain network, which covers two decision levels (strategic and tactical). A fuzzy approach is also applied to evaluate suppliers based on qualitative criteria. Digiesi et al. (2016) developed an inventory management model called Sustainable Order Quantity (SOQ) to minimize logistics costs, which consider both economic and social-environmental costs. Shrouf et al., (2014) proposed a mathematical model to minimize energy consumption cost of production systems. Akhtari et al. (2017) developed an integrated model to support decisions at tactical and operational levels and analyzed the feasibility of strategic plans for forest-based biomass supply chains. Their results showed that variation in supply and demand at tactical level affect the feasibility of plans prescribed at the strategic level. A summary of papers in the context of sustainable supply chain based on decision planning levels is illustrated in table 1.1. Although the combination of simulation and optimization have been widely used to support decision making in supply chain management (Almeder et al. 2009), only one study attempted to integrate sustainability into supply chain planning levels using simulation-optimization approaches (e.g., Liotta et al. 2015).

A recent literature review conducted by a Barbosa-Povoa et al., (2017) has focused on a combination of decision levels (e.g., strategic-tactical and tactical-operational), with an attention to sustainable supply chain planning. A sample of 220 papers was reviewed in this study. The papers are categorized in strategic, tactical and operational levels, based on the decisions used in their study. The study shows that most of the papers have focused on the strategic aspects of a sustainable supply chain. Only six papers solely considered tactical decisions in sustainable supply chain management. Besides, only a few papers have exclusively focused on operational aspects. Combination of tactical and operational aspects have been studied in four papers (Chardine-Baumann & Botta-Genoulaz, 2014; Hsueh, 2015;

Mansoornejad et al., 2013; Ramos et al., 2014), and only two papers covered three decision levels in their studies (Liotta et al. 2015 and Zhang et al. 2014).

According to Povoa et al., (2017), most of the papers above only considered economic and environmental aspects together. The study also shows that operational decisions have seldom been studied when addressing sustainability. Furthermore, simultaneous consideration of economic, environmental and social aspects for the integrated models is still a missing link in literature. In additions, authors argued that consideration of three sustainability pillars when dealing with tactical and operational decisions is still an area, which needs further exploration.

The papers mentioned above either considered one decision planning level or ignored sustainability. Besides, decision levels are studied in a single timeframe, and coordination and consistency between decision levels are ignored. The integration of planning levels in sustainable supply chain management is a missing link in the literature. Decisions at lower planning levels might not be able to attain sustainability goals defined at upper decision level. Managing decision at several planning levels, while ensuring sustainability is challenging.

Table 1.1 Summary of papers based on supply chain planning levels

	Decisions								
	Strategic			Strategic/ tactical	Tactical			Operational	
	Supplier selection	Facility Location	Technolog y decisions	Capacity decisions	Workforce and production planning	Transportation Strategies	Inventory and Distributio n	Delivery Plans	Production scheduling
Wang et al. (2011)		*							
Chaabane et al. (2012)	*	*	*			*	*		
Validi et al. (2015)						*	*		
Soysol et al. (2014)							*	*	
Bortolini et al. (2016)		*				*	*		
Van der Vorst et al. (2009)						*			
Arampantzi and Minis (2017)		*		*	*	*	*		
Sabio et al., 2012								*	
Liotta et al. (2015)	*					*		*	
Amin and Zhang (2012)	*				*				
Zhang et al. (2014)	*			*	*			*	
Pishvaee et al. (2012)		*	*				*		
Varsei and Polyakovskiy (2016)	*	*				*	*		
Shrouf et al, 2014									*
Akhtari et al. (2017)			*				*		
Digiesi et al. (2016)						*	*		

1.5 Literature Summary

Table 1.2 summarizes the literature on sustainable supply chain design and planning. The purpose of these tables is to do a survey and to analyze them in order to find the gap in the research. Later in this chapter papers will be analyzed and discussed in details.

Table 1.2 Literature summary

No	Author(s)	year	Model Type	Solution Method	Main Decision(S)	Sustainability Dimensions			Multi-Objective	Descriptions
						Eco[1]	Env[2]	Soc[3]		
1	(Nagurney and Toyasaki)	2003	MCDM[4]	Euler Method	Equilibrium prices, product shipments, and emissions	●	●		●	
2	(Sheu et al.)	2005	MILP[5]	CPLEX	Material Flow- Inventory Management	●	●		●	Green Sc
3	(Hugo and Pistikopoulos)	2005	MILP	Heuristic Algorithm	Material Flow, Facility Location, Capacity expansion - Technology investment	●	●		●	
4	(Frota et al.)	2008	MILP	Multi-objective Programming and DEA[6]	Material Flow - Allocation - End-of –use	●	●		●	
5	(Dehghanian and Mansour)	2009	MILP	Genetic Algorithm	Material Flow - Facility Location	●	●	●	●	
6	(Cruz)	2009	Multi-Criteria Decision Making	Heuristic Algorithm	Determining social responsibility level	●	●	●	●	
7	(Chaabane et al.)	2012	MILP	LINGO	Material Flow- Facility Location- Technology Investment - inventory Management - Carbon Management	●	●		●	

[1] Economic
[2] Environmental
[3] Social
[4] Multi-Criteria Decision Making
[5] Mixed Integer Linear programming
[6] Data Envelopment Analysis

Table 1.2 Literature summary (continued)

No	Aut3333hor(s)	year	Model Type	Solution Method	Main Decision(S)	Sustainability Dimensions			Multi-Objective	Descriptions
						Eco	Env	Soc		
8	(Zhang et al.)	2014	MILP	Ɛ -constraint	Material Flow - Manufacturing - procurement - Capacity Expansion	•	•		•	
9	(Govindan et al.)	2014	MILP	MOPSO[7]+AMOVNS[8]	Material Flow - Facility Location - Vehicle Type - Technology Investment	•	•		•	
10	(Egilmez et al.)	2014	DEA and EIO-LCA[9]	Linear Programming	Optimal Efficiency for Manufacturing Sectors	•	•			
11	(Validi et al.)	2015	DOE[10]	MOGA[11]-II + TOPSIS	Distribution route - Vehicle Type	•	•		•	
12	(Boukherroub et al.)	2015	MILP	Weighted Goal Programming	Procurement - Material Flow - Inventory Management - Employment – Manufacturing	•	•	•	•	
13	(Pop et al.)	2015	MILP	Heuristic Algorithm	Material Flow - Facility Location	•	•			

[7] Multi-Objective Particle Swarm optimization
[8] Multi-objective Variable Neighbor-hood Search
[9] Economic Input Output Life cycle Assessment
[10] Design of Experiment
[11] Multi-Objective Genetic Algorithm

Table 1.2 Literature summary (continued)

No	Author(s)	year	Model Type	Solution Method	Main Decision(S)	Sustainability Dimensions			Multi-Objective	Descriptions
						Eco	Env	Soc		
14	(Fleischmann et al.)	2001	MILP	CPLEX	Facility Location - Material Flow	●	●			Reverse-Logistics
15	(Salema et al.)	2007	MILP	Branch & Bound	Facility Location-Customer Satisfaction	●	●			Reverse-Logistics
16	(van der Vorst et al.)	2009	Discrete-Event Simulation	ALADIN	Remaining Selling Time	●	●		●	Scenario-Based
17	(Guillén-Gosálbez and Grossmann)	2009	SMINLP[12]	Decomposition Method	Material Flow - Facility Location -Technology Investment - Production rate	●	●		●	
18	(Guillén-Gosálbez and Grossmann)	2010	MINLP	The Epsilon Constraint	Material Flows - Facility Location - Technology Investment	●	●		●	
19	(El-Sayed et al.)	2010	SMILP[13]	XpressSP 2006a	Facility Location - Material Flow - Inventory Management	●	●			Forward-Reverse logistics
20	(Qin and Ji)	2010	Fuzzy Programming	GA and Fuzzy Simulation	Customer Satisfaction - Facility Location	●	●			Reverse logistics

[12] Stochastic Mixed Integer non-Linear Programming
[13] Stochastic Mixed Integer Linear Programming

Table 1.2 Literature summary (continued)

No	Author(s)	year	Model Type	Solution Method	Main Decision(S)	Sustainability Dimensions			Multi-Objective	Descriptions
						Eco	Env	Soc		
21	(Pishvaee and Torabi)	2010	PMIP14	Interactive Fuzzy	Facility Location - Material Flow	●	●		●	Forward-Reverse logistics
22	(Pishvaee et al.)	2011	RMIP15	CPLEX	Material Flow - Facility Location	●	●			Closed-Loop
23	(Pishvaee and Razmi)	2012	PMIP	Interactive Fuzzy	Facility Location - Material Flow	●	●		●	Forward-Reverse logistics
24	(Pishvaee et al.)	2012	Robust Possibilistic Programming	Ɛ -constraint	Material Flow- Facility Location- Technology Investment	●		●	●	
25	(Cardoso et al.)	2013	MILP	CPLEX	Material Flow - Capacity Expansion - Inventory Management – Procurement	●	●			Reverse-Logistics
26	(Elhasia. T)	2013	Discrete-Event Simulation	Arena	Inventory Management - Costumer Service Levels	●	●			
27	(Pishvaee et al.)	2014	PMIP	Accelerated Benders Decomposition Algorithm	Material Flows - Facility Location - Technology Investment- Capacity of Facilities	●	●	●	●	Forward-Reverse logistics

14 Possibilistic MIP
15 Robust MIP

Table 1.2 Literature summary (continued)

No	Author(s)	year	Model Type	Solution Method	Main Decision(S)	Sustainability Dimensions			Multi-Objective	Descriptions
						Eco	Env	Soc		
28	Akkerman et al.,	2009	MILP	Unspecified	Production quantity, Packaging Type, Delivery structure	●	●		●	
29	Sutopo et al.,	2013	MILP	CPLEX	Determining the amount of supply, level of farmers training skills, Quality improvement target	●		●	●	
30	Validi et al,	2015	AHP + MIP	MOGA-II + DOE	Distribution route - Vehicle Type	●	●		●	
31	Chaabane and Geramianfar	2015	MILP	Ɛ -constraint	Production quantity, Inventory management, Service level	●	●		●	
32	Varsei and Polyakovskiy	2016	MILP	Augmented Ɛ -constraint	Supplier selection, production quantity, facility location transportation mode s	●	●	●	●	
33	Arampantzi, and Minis	2017	MILP	goal programming and the ε-constraint	Facility location, Inventory management, Transportation type	●	●	●	●	
34	Allaoui et al.,	2017	AHP+ OWA[16]+ MILP	Heuristic	Supplier selection, Facility location, Flow of material	●	●	●	●	

[16] Ordered Weighted Averaging

In this chapter, we have focused on exploring the existing literature review and relevant article related to ``*sustainable supply chain*``, ``*green supply chain*``, ``*reverse logistics*`` and ``*closed loop supply chain*``. The most important papers in the literature, which influence this research, were addressed in table 1.2. The whole sample includes 34 papers in total which covers published papers up to the end of 2017. Timely distribution of the 34 papers is highlighted in Figure 1.5. A small peak of published papers can be found in 2009, 2015 with 5 papers, but it seems to be accidental as there is no good reason to explain it.

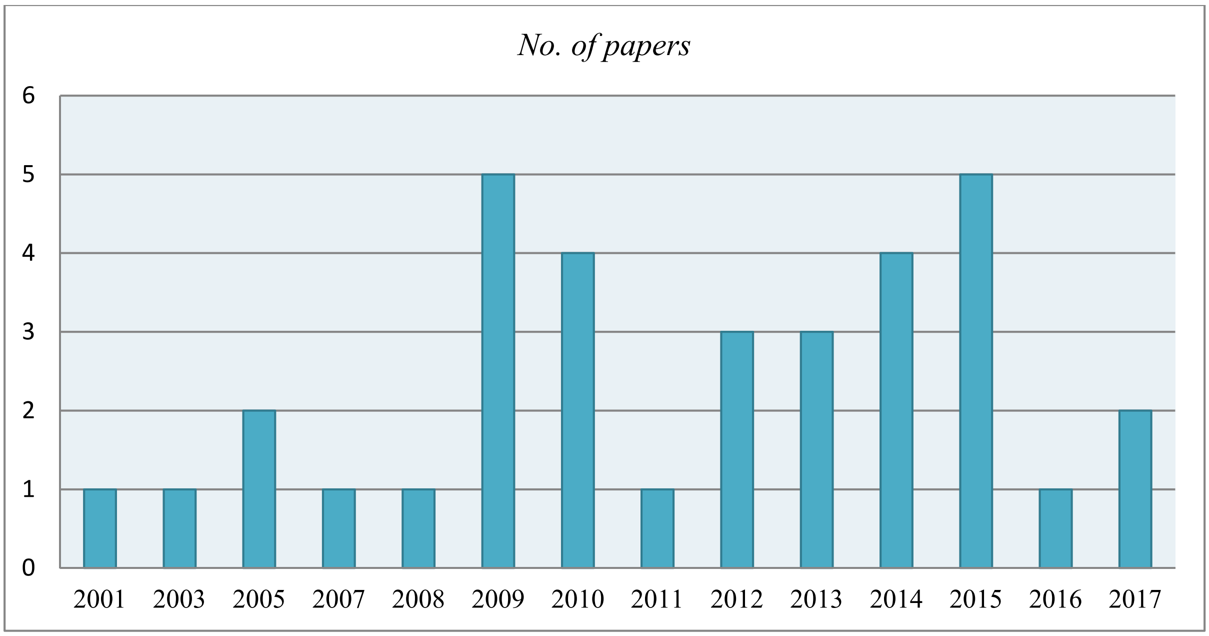


Figure 1.5 Time distribution of reviewed papers

Figure 1.6 shows the percentage of sustainability dimensions integrated into reviewed papers. As it can be seen in the chart, the numbers of papers considering the integration of three dimensions of sustainability are few. However, most of the related research focuses on the integration of environmental and economic aspects of sustainability, and the social pillar is almost completely missing (two last bars of the chart evidentially represent this fact). Modeling social impacts of a supply chain network is a difficult task, and there is a lack of research on this area in related literature.

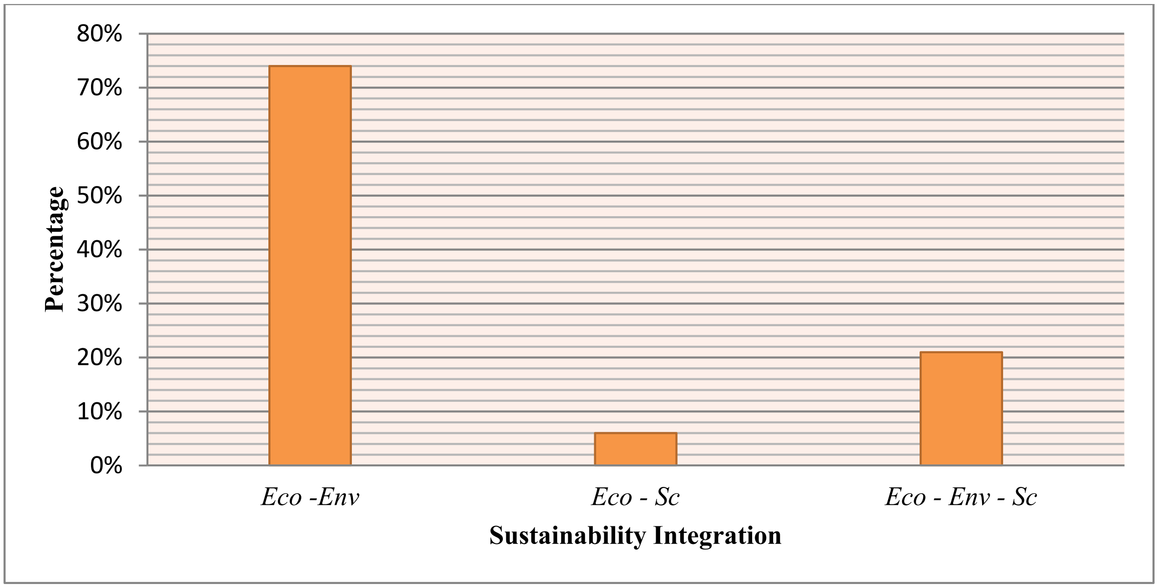


Figure 1.6 Percentage of sustainability integration in analyzed papers

1.6 Research gaps and opportunities

In this chapter, we have reviewed papers related to sustainable supply chain design and planning. Traditionally sustainability in supply chains has focused on environmental dimensions, while a few have attempted to focus on social and economic dimensions without really integrating them. Most of the papers considered deterministic and single-period models, which may reduce the complexity of the real-world problems. However, researchers need to take a deeper perspective of the integration of decision levels and its effect on sustainability aspects. Sustainability goals are typically set at upper decision levels, while the feasibility of these goals at lower levels has not been taken into consideration. Furthermore, to achieve adequate overall supply chain performance, supply chain planning should incorporate all long-term decisions and linked them with the decision criteria.

The research gaps found in the literature are listed as follows:

a. The literature lacks a proper methodology to incorporate the three sustainability concerns in the supply chain network design.

b. A proper methodology is required to deal with multiple conflicting objectives and decisions variables in reasonable computational time for sustainable supply chains planning.

c. Consideration of the three sustainability pillars when dealing with tactical and operational decisions is still an area, which needs further exploration. The effect of sustainability objectives at the integrated-operational planning has not yet been explored.

1.7 Conclusion

Based on sustainability definitions and what we reviewed of papers related to sustainability, sustainable supply chain management could be defined as the integration of economic, environmental and social goals in order to improve the long-term economic performance of the individual company and whole supply chain network (Carter and Rogers 2008). Sustainability in supply chain contains different objectives, which have to be met simultaneously. Also, these objectives are usually conflicting and increasing one objective result in decreasing another one. Accordingly, the concentration is dealing with trade-offs between conflicting objectives rather than getting an equilibrium situation.

The food sector has been considered as the second biggest emitter of greenhouse gases after energy, and it requires cutting the emissions from its growth (CDP 2015). However, studies, which attempt to optimize economic, environmental and social concerns at the same time, especially in food supply chain, are few. Besides, since social responsibility is becoming an emerging concern for food companies, social concerns have recently attracted great attention by researchers. However, due to the complex nature of social issues, measuring and assessing social impacts is a daunting task (Pishvaee et al. 2012).

Incorporating sustainability dimensions into the decision-making process and find a trade-off between sustainability sides are challenging. Besides, the perishability factor in food supply chain makes the problem more challenging (Soysal 2012). Therefore, a decision support tool, which can consider all these aspects, is required. In recent years, researchers have developed different methodologies to support decision-making in food logistics, but the research area still needs a comprehensive methodology to handle the current challenges of food companies in managing safety, quality, and sustainability.

This study aims to fill the research gap by 1) analyzing the effect of environmental and social factors in tactical planning of supply chains (chapter 2); 2) developing a solution methodology in order to cope with multiple objectives and decision variables in a reasonable computational time (chapter 3); 3) developing an integrated tactical-operational planning model for sustainable supply chains (chapter 4).

CHAPTER 2

A TRADE-OFF MODEL FOR SUSTAINABLE SUPPLY CHAIN OPTIMIZATION

This chapter introduces a supply chain optimization model that integrates the three dimensions of sustainability: economic, environmental and social objectives. We propose a mathematical formulation that allows supply chain decision makers to analyze the performance of the frozen food supply chain and identify actions to implement a sustainable supply chain strategy. Using a case study from a real medium-sized frozen food company located in Canada, the model is implemented to examine how the company should address sustainability challenges. The model is formulated as a multi-objective mixed integer nonlinear programming and solved using the weighted sum method by CPLEX. A trade-off between objectives shows how much cost to bear to reduce environmental impacts and increase social responsibilities. For practitioners, the contributions of this chapter provide a clear idea on how to transform the supply chain and implement a more sustainable logistic network.

2.1 Introduction

Sustainable Supply Chain Management (SSCM) has become a growing concern for numerous industries and companies of all sizes (Seuring 2013; Hsu et al. 2016). For many industrial sectors, sustainability is becoming more and more competitive advantage. Indeed, stringent environmental legislation puts prices on carbon emissions and waste to reduce the environmental impacts of manufacturing, distribution, and transportation. The concept of sustainability requires the use of a global approach to address the challenges related to environmental and social problems created by supply chain operations. Several criteria and metrics in performance evaluation should be used such as greenhouse gas emissions, customer service, profit, and social responsibilities. This will add more complexity not only for the modeling perspective but also for the solution approach (Zhang et al. 2014, Boukherroub et al. 2015, Validi et al. 2015). Therefore, supply chain managers should be able to choose and adopt the proper methodology at the organization level to maintain their competitive advantage (Balfaqih et al. 2016).

The food industry is one of the sectors where we observe more and more attention to sustainability during the last years in different regions: Europe, North America and Asia (Manzini and Accorsi 2013). The food industry is composed of a complex supply chain including many actors: suppliers of raw materials, manufacturers, distributors, shippers (transportation), and retailers. This sector consumes much energy, in particular for products that need conservation for a particular time such as refrigerated or frozen foods. The upward desire for convenience, affordable and nutritious food products has brought a tremendous opportunity for frozen products. According to data from Transparency Market Research (2013), the global frozen food revenue was valued at $224.74 billion in 2012, and it is expected to grow at a CAGR (the compound annual growth rate) of 3.9% from 2013 to 2019. In 2012, North America and Europe were the most significant market and accounted for 39.5% and 26.3% share in the frozen food market respectively. Frozen food industry's total employment impact to the U.S economy was 670,000 jobs in 2012 (AFFI 2015). Therefore, the frozen food industry contribution in the economy and society is significant. However, increasing and more volatile energy costs raise prices for transportation and cold storage. Besides, concerns about the increasing earth temperature, as a result of this energy consumption, have been emerged (Adekomaya et al. 2016). Rising costs and environmental impacts put manufacturers under pressure to look for new strategies.

The cold chains aim to avoid products value decrease and to preserve their quality over the entire supply chain network from farm to consumers (Zanoni and Zavanella 2012). The demand for many frozen food products, such as ice cream, presents a highly seasonal pattern, which makes the production and distribution planning a daunting task. To manage the demand variation, some companies match the production plan with demand by hiring and laying off workers. In particular, Takey and Mesquita (2006) mentioned seasonal workers to deal with high seasonal demand in production planning of a Brazilian ice cream manufacturer. This helps to avoid the significant levels of inventory in low demand periods. However, under this plan, the company offers to hire those who are ready and willing to work while there is no employment guarantee. Flexibility in employment contracts leaves workers with little hope for job security. Workers dealing with a risk of job loss are in a vulnerable position, mainly in countries with less social safety nets. Martin (1991) mentioned temporary and seasonal workers as a labor social responsibility issue in the food industry. Moreover, the study of Bardasi and Fansesconi (2003) reports a low level of job satisfaction and ill mental health among seasonal workers. Zeytinoglu et al. (2004) also indicated that job insecurity contributes to stress, high turnover, and workplace conflicts.

Developing proper strategies, which can lead food companies to satisfy customers' demand, whereas ensuring sustainability, becomes a challenging and complicated matter. The existence of numerous variables and constraints with different conflicting objectives make this problem more complex and in need of a sophisticated decision-making process and tools. Thus, this study makes contributions at different levels. First, we provide a supply chain model to support the tactical planning that integrates the three objectives of sustainability: total cost, GHG emissions, and social responsibilities. Since the contribution of social dimension is usually missing in the literature, we pay close attention to it. Second, we propose a mathematical formulation that allows supply chain decision makers to analyze the performance of the frozen food supply chain and identify actions to implement a sustainable supply chain strategy. Third, a case study is proposed to show the applicability of the model in a real industry setting.

The remaining of the chapter is as follows. After a brief introduction to the problem, section 2.2 gives an overview of recent literature on food and sustainable supply chains. Section 2.3 presents the multi-objective optimization model for sustainable frozen food supply chain optimization. Section 2.4 describes the case study and problem data. In section 2.5, numerical results are conducted using a case study from the "Frozen Food" industry to demonstrate how to manage sustainable supply chains based on the proposed methodology. Finally, future research and possible extensions are discussed.

2.2 Existing Sustainable Food Supply Chain Models

We have conducted a literature review of quantitative models concerning sustainable food supply chains. The research on sustainable supply chain planning models which covers all three pillars of sustainability (i.e., economic, environmental and social criteria) in the food sector is scarce. Only limited empirical research related to sustainable food logistics management has been done. Mathematical optimization is the most common approach to design a sustainable food supply chain in the literature. Akkerman et al. (2009) developed a MILP formulation to support production and distribution planning for prepared meals. Their formulation allows evaluating the supply chain performances and the trade-off between economic and environmental objectives.

Moreover, a multi-objective MILP model is developed by Govindan et al. (2014) to integrate sustainability in the distribution of a perishable food supply chain. This paper considers environmental impacts related to opening facilities, transportation, and operational activities including the most damaging GHG emissions, e.g., CO2, CFC, and NOx. Chaabane and Geramianfar (2015) formulated a multi-objective MILP to evaluate sustainability based on three performances; cost, GHG emissions, and service level. Since social responsibility is becoming an emerging concern for food companies, social concerns have recently attracted considerable attention by researchers. However, due to the complex nature of social issues, measuring and assessing social impacts is a daunting task (Pishvaee et al. 2012). Sutopo et al. (2012) proposed a multi-objective mathematical optimization model to improve the quality of a vegetable distribution network while discussing social aspects. Also, Varsei and Polyakovskiy (2016) represented a generic model for sustainable wine supply chains design. This study is limited to consider GHG emissions emitted from transportation activities. Further, unemployment rates and regional gross domestic product (regional GDP) are used as indicators to measure social impacts of company's supply chain network.

Some authors employed other methodologies to study similar problems. Van der Vorst et al. (2009) used discrete-event simulation to redesign the distribution network of a pineapple supply chain in an uncertain environment. In this paper, the calculation of energy consumption for transportation and inventory is considered to measure environmental impacts. Validi et al. (2015) presented a multi-objective optimization model based on Analytic Hierarchy Process (AHP) which is linked to the optimization model to support decision-making in the distribution system of a case in dairy industry. They also used genetic algorithms and Design of Experiments (DOE) to achieve a robust solution and find trade-offs between CO2 emissions and total cost. Miret et al. (2016) developed a multi-objective optimization model to integrate the three dimensions of sustainable development for a bioethanol supply chain. They applied the goal programming approach to reach a trade-off between the three dimensions. Banasik et al. (2017) also developed a bi-objective model for a closed loop mushroom supply chain in order to optimize decisions at strategic and tactical levels.

The numbers of papers on the design of a sustainable supply chain in the food sector are few, and most of them have only emphasized the distribution part of the network. Furthermore, only very few studies incorporated social aspects in the supply chain network design, and integration of the three sustainability concerns is still missing in the literature. Moreover, the research is conducted in some limited application areas which are hard to adapt to other food supply chains. Table 2.1 gives a summary of the critical features of the reviewed papers.

Table 2.1 A review of papers related to sustainable supply chain planning/design

Publication	Planning scope			Model Type	Main Decisions	Sustainability			Solution Approach	Application Area
	S	T	O			Eco	Env	Soc		
Akkerman et al., (2009)		✓	✓	MILP	Production quantity, Packaging Type, Delivery structure	✓	✓		Unspecified	Prepared meals
Van der Vorst et al., (2009)			✓	Simulation	Remaining selling time	✓	✓		ALADIN	Pineapple
Sutopo et al., (2013)		✓		MILP	Determining the amount of supply, level of farmers training skills, Quality improvement target	✓		✓	CPLEX	Vegetables
Govindan et al., (2014)	✓	✓		MILP	Material Flow - Facility Location - Vehicle Type - Technology Investment	✓	✓		MOPSO+AMOVNS	Perishable foods
Validi et al., (2015)		✓		AHP + MIP	Distribution route - Vehicle Type	✓	✓		MOGA-II + DoE	Dairy Industry
Chaabane and Geramianfar (2015)		✓		MILP	Production quantity, the flow of materials, Inventory management, Service level	✓	✓		Ɛ -constraint	Frozen food
Varsei and Polyakovskiy (2016)	✓	✓		MILP	Supplier selection, production quantity, facility location, the flow of material, transportation mode selection	✓	✓	✓	Augmented Ɛ -constraint	Wine industry
Miret et al. (2016)	✓			MILP	Technology Investment, production quantity, the flow of materials, facility location	✓	✓	✓	Goal programming	Bioethanol
Banasik et al. (2017)	✓	✓		MILP	The flow of materials, the quantity of mushrooms and substrates	✓	✓		ε-constraint method	Mushroom
Current study		✓		MINLP	Number of workforces, Production quantity, flow of materials, Distribution center selection, Transportation type selection, Inventory management, Service level	✓	✓	✓	Weighted sum method	Frozen food

2.3 Problem statements

We consider the planning of a two-echelon multi-commodity supply chain. A set of products is manufactured and shipped from plants to distribution centers and retailers to fulfill customer demands. Plants, distribution centers, and customer locations are known. Production and warehousing capacities and costs, delivery lead times, variable costs as well as GHG emissions factors related to supply chain operations are also known. Transportation links, transportation distances, and transportation capacities are known. The demand of each retailer at each period is aggregated into product family groups to increase data accuracy.

The formulation of the model is emphasized on production/distribution activities. The proposed model supports the decisions in tactical planning level. Several plants manufactured the products and delivered to customer sites directly or through DCs (distribution centers), depending on customer location and quantity of demand. We suppose that there are potential 3PL (third-party logistics) companies, and a contract will be established with selected 3PLs for the planning horizon. The primary aim of 3PL companies is to provide frozen food logistics and storage to food manufacturers, maximizing products quality whereas keeping the costs low. The 3PL companies offer refrigerated trucks with different load capacities. The variable cost of a truck with a large capacity is usually cheaper compared to the smaller trucks. However, transportation with large trucks might also increase inventory levels at DCs and retailers. Therefore, the model should be able to make a trade-off between transportation and inventory costs. Manufacturing plants have an initial number of workers. Production capacity can change by hiring and laying-off workers at each plant during the planning horizon. A reception capacity is considered as a buffer at distribution centers and customer sites to receive the products, which are just delivered from the plants and have not yet stored. Products are first stored in the temporary storage (reception), and then will be transferred to other stores where they can be kept for a longer period. However, no inventory at DCs is allowed at the end of the planning horizon. Inventory capacities are also enforced for each product and at each plant.DC, and retailer during the planning horizon. Moreover, we assume that the shelf life of frozen products is very high so products can be stored for the whole planning horizon, and the quality will not change, and products remain acceptable. To control the supply chain agility, a maximum amount of surplus and backorders is restricted.

Due to the enormous amount of GHG emissions emitted from this industry, companies are willing to identify the main environmental impacts and potential strategies to reduce these impacts. One of the environmental challenges of such enterprises is to reduce the impacts of the facilities' energy consumption coming from freezing storages in distribution centers and retailers. Distribution centers in various regions might use a different energy mix, due to the energy source, producing different amounts of GHG emissions. For instance, Ontario electricity generation is from a mix of energy sources – nuclear, hydro, gas, coal, wind, and others. Therefore, to calculate the environmental impacts associated with freezing storage, per unit energy requirement at storages are multiplied by the GHG emission produced from the corresponding energy sources.
Furthermore, transportation of frozen food products by road also requires high energy-intensive refrigeration systems with more energy consumption and environmental impacts than non-refrigerated transports. In this study, the distance-based method is used to calculate CO_2 emissions from transportation activities. Given that the products have the same characteristics regarding weight, emission factors do not depend on products. Thus, the distance estimate can be converted to CO_2 emission by multiplying the distance-traveled data by distance based emission factor.

Problem decisions can directly or indirectly influence the social impacts of the SC network. In this study, production quantity as a decision variable affects the social impact of the problem by hiring and laying-off workers. Although many companies benefit from hiring seasonal workers, it has negative social effects. An organization should use an active workforce planning to avoid using the work performed on a temporary or casual basis and recognize the value of secure employment for both the society and the individual workers (ISO, 2010). Companies must provide conditions for stable employment to be sustainable (SAO 2013). To the best of our knowledge, there have been no attempts to reduce the impacts of job insecurity within the SC network. In this work, however, we are going to minimize the number of workers hired or laid-off in the planning horizon. To this aim, we minimize the deviation from the average number of workers at manufacturing sites. Using an average number of workers in each period helps to build stable production rates, while the demand satisfaction is guaranteed.

The main objective is to optimize the supply chain based on the proposed framework. Thus, different decision variables are considered here, and have a direct influence on the supply chain performance:

- Number of workforces at each plant during each period,
- Amount of products manufactured at each plant during each period,
- Amount of products shipped between different nodes during each period,
- Amount of surplus of products delivered to the retailer during each period.

2.4 Mathematical model formulation

2.4.1 Model Assumptions

In this section, we propose an optimization model for the problem. Several plants produce products. Products are delivered to customers (retailers) in a direct way or indirect; transportation to retailers through DCs (see figure 2.1). Locations of DCs controlled by 3PLs are also known. A pre-assigned capacity for each product at each plant is defined, and consequently, lead times between plants, distribution centers, and retailers are known. For each plant, distribution center, and retailer, a separate warehousing capacity for each product is known.

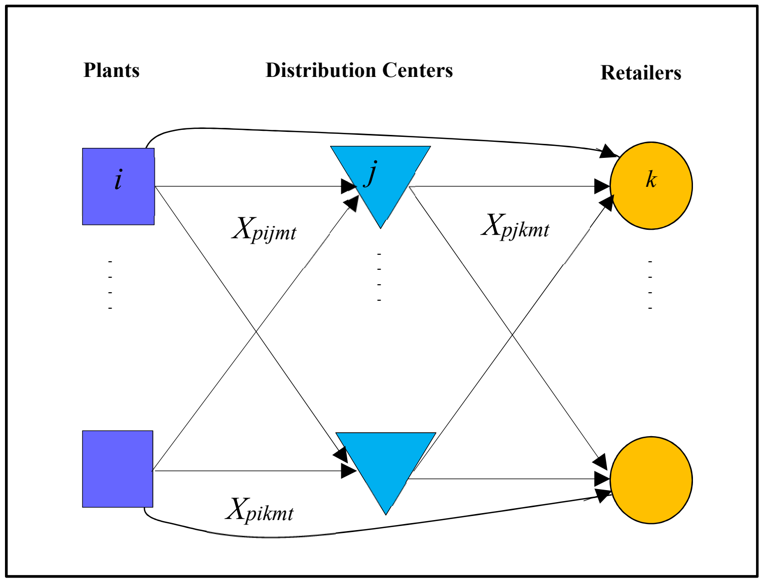


Figure 2.1 Supply chain network under study

Different sets, indices, and parameters are used for the problem formulation (Table 2.2).

Table 2.2 Summary of notation

Indices	Description
p	Set of products: $p \in \{1,2,...,P\}$
i	Set of plants: $i \in \{1,2,...,I\}$
j	Set of distribution centers: $j \in \{1,2,...,J\}$
k	Set of retailers: $k \in \{1,2,...,K\}$
t	Set of time-periods: $t \in \{1,2,...,T\}$
m	Set of truck types: $m \in \{1,2,...,M\}$
n,n'	Set of all nodes: $n,n' \in \{i,j,k\}$
e_j	Set of energy mix at DC j: $e_j \in \{1,2,...,E_j\}$
e_k	Set of energy mix at retailer k: $e_k \in \{1,2,...,E_k\}$

2.4.2 Parameters

The input parameters include the following:

- Sw_{it}: number of working hours at plant *i* during period *t*
- Wr_{it}: hourly wage rate of each worker at plant *i* during period *t [$/hour]*
- Hc_i: the cost of hiring a worker at plant *i*
- Fc_i: the cost of laying off a worker at plant *i*
- Ldc_j: fixed cost of establishing contracts with DC *j*
- *Dpkt:* demand of product *p* from retailer *k* during period *t*
- Pc_{pit}: per unit production cost of product *p* at plant *i* during period *t*
- $TFc_{nn'mt}$: the Fixed cost of using truck type *m* between node *n* and *n'* during period *t*
- $Tc_{nn'mt}$: per unit transportation cost of truck type *m* from node *n* to node *n'* during period *t*
- $Cap_{nn'mt}$: transportation capacity using truck type *m* between node *n* and *n'* during period *t*
- Bc_{pkt}: per unit backorder cost of product *p* at retailer *k* during period *t*
- U_{pit}: per unit holding cost of product *p* at plant *i* from period t to period *t+1*
- V_{pjt}: per unit holding cost of product *p* at DC *j* from period *t* to period *t+1*
- W_{pkt}: per unit holding cost of product *p* at retailer *k* from period *t* to period *t+1*
- B_{ikp}: delivery lead time of product *p* from plant *i* to retailer *k*
- C_{jkp}: delivery lead time of product *p* from DC *j* to retailer *k*
- FW_{it}: minimum number of workers at plant *i* during period *t*
- K_{it}: number of products that each worker can produce at plant *i* during period *t*

- KK_{pit} : warehousing capacity for product p at plant i during period t
- WW_{pkt} : warehousing capacity for product p at retailer k during period t
- VV_{pjt} : warehousing capacity for product p at DC j during period t
- LC_{jt} : global reception capacity for DC j during period t
- LD_{kt} : global reception capacity for retailer k during period t
- $F_{nn'}$: distance between node n and n' [in km]
- M_{kpt} : the maximum amount of permitted backorders of product p at retailer k during period t
- ρ : Coefficient for transformation between planning horizon and lead time unit
- EF_{pi} : GHG emission factor due to the production of one unit product p in plant i [kg CO_2e]
- $EF_{nn'm}$: GHG emission factor for transportation of one unit of product using truck type m between node n and n'[kg CO2e/(t km)]
- EM_{e_j}: Percentage share of energy source e in the energy mix of the region where DC j is located ($\sum_{e_j=1}^{E_j} EM_{e_j} = 1 \quad \forall j$)
  - ER_j: Energy requirement for storing one unit of product at DC j [kWh/ period]
- EF_{e_j}: GHG emission factor for energy source e_j [kg CO2e/kWh]
- EM_{e_k}: Percentage share of energy source e in the energy mix of the region where retailer k is located ($\sum_{e_k=1}^{E_k} EM_{ek} = 1 \quad \forall k$)
  - ER_k: Energy requirement for storing one unit of product at retailer k [kWh/ period]
- EF_{e_k}: GHG emission factor for energy source e_k [kg CO2e/kWh]

2.4.3 Decisions variables

- *Continuous variables*

Q_{pit} : Quantity of product p manufactured at plant i during period t

$X_{pnn'mt}$: Quantity of product p shipped from node n to node n' using truck type m during period t

IP_{pit}: Inventory level of product p at plant i at the end of period t

ID_{pjt}: Inventory level of product p at DC j at the end of period t

R_{pkt} : Quantity of product p backordered at retailer k during period t

S_{pkt} : Quantity of surplus of product p delivered to retailer k during period t

- *Integer variables*

NW_{it} : Number of workers at plant i during period t

NH_{it}: Number of employees hired at plant i during period t

NL_{it}: Number of employees laid off at plant i during period t

- *Binary variables*

$$I_{pkt} : \begin{cases} 1 \text{ ; if there is a suplus for product } p \text{ at retailer } k \text{ during period } t \\ 0\text{; if there are backorders for product } p \text{ at retailer } k \text{ during period } t \end{cases}$$

$$L_j\text{:} \begin{cases} 1 \text{ ; if distribution center } j \text{ is selected} \\ 0\text{; otherwise} \end{cases}$$

$$Z_{nnt'mt}\text{:} \quad \begin{cases} 1 \text{ ; if truck type } m \text{ is selected between node } n \text{ and } n\text{` during period } t \\ 0\text{; otherwise} \end{cases}$$

2.4.4 Objective functions

Using the parameters and decision variables defined in Appendix, the cost objective function (Z1) is formulated in Eq. (1). It includes production costs, inventory holding costs in manufacturing plants and warehouses, transportation costs, penalty/shortage costs of backordered demand, and labor costs.

$$Min\ Z_1 = Z_a + Z_b + Z_c + Z_d + Z_e + Z_f + Z_g + Z_h + Z_i + Z_j + Z_k \quad (2.1)$$

Production cost at plants

$$Z_a = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{p=1}^{P} Pc_{pit}Q_{pit} \quad (2.2)$$

Fixed transportation cost of trucks

$$Z_b = \sum_{t=1}^{T}\sum_{n}\sum_{n'}\sum_{m}^{M} TFc_{nn'mt}Z_{nn'mt} \quad (2.3)$$

Variable transportation cost

$$Z_c = \sum_{t=1}^{T}\sum_{n}\sum_{n'}\sum_{m}^{M} Tc_{nn'mt}X_{nn'mt} \quad (2.4)$$

Inventory cost at plants

$$Z_d = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{p=1}^{P} U_{pit}IP_{pit} \quad (2.5)$$

Inventory cost at DCs

$$Z_e = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{p=1}^{P} V_{pjt}ID_{pjt} \quad (2.6)$$

Inventory cost at retailers

$$Z_f = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{p=1}^{P} W_{pkt}S_{pkt} \quad (2.7)$$

Fixed cost for establishing contracts with DCs

$$Z_g = \sum_{j=1}^{J} Ldc_j L_j \quad (2.8)$$

Backorders cost

$$Z_h = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{p=1}^{P} Bc_{pkt}R_{pkt} \quad (2.9)$$

Labour cost at plants

$$Z_i = \sum_{i=1}^{I}\sum_{t=1}^{T} Sw_{it} wr_{it} NW_{it} \tag{2.10}$$

Hiring cost at plants

$$Z_j = \sum_{i=1}^{I}\sum_{t=1}^{T} Hc_{it} NH_{it} \tag{2.11}$$

Laying off cost at plants

$$Z_k = \sum_{i=1}^{I}\sum_{t=1}^{T} Lc_{it} NL_{it} \tag{2.12}$$

The environmental performance of the supply chain is measured by the total GHG emissions (Z2). GHG emissions are related to production activities at each plant, energy consumption at DC and retailers (inventory and warehousing), and transportation between nodes.

$$Min\ Z_2 = Z_l + Z_m + Z_n + Z_o + Z_p \tag{2.13}$$

Production emission

$$Z_l = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{p=1}^{P} EF_{pi} Q_{pit} \tag{2.14}$$

Transportation emission

$$Z_m = \sum_{t=1}^{T}\sum_{n}\sum_{n'}\sum_{m}^{M}\sum_{p=1}^{P} EF_{nn`m} F_{nn'} X_{pnn`mt} \tag{2.15}$$

DC emission

$$Z_o = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{p=1}^{P}\left[\sum_{e_j}^{E_j} EM_{e_j} EF_{e_j}\right] ER_j ID_{pjt} \tag{2.16}$$

Retailer emission

$$Z_p = \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{p=1}^{P}\left[\sum_{e_k}^{E_k} EM_{e_k} EF_{e_k}\right] ER_k S_{pkt} \tag{2.17}$$

In the third objective, we aim to promote the social responsibility of the network by minimizing the deviation from the average number of workers, increasing the job stability at manufacturing sites. Let μ_i be the average number of workers at plant *i*. The average number of workers can be calculated based on the total demand at each plant.

$$Min\ Z_3 = Z_q \tag{2.18}$$

Job stability at plants

$$Z_q = \sum_{t=1}^{T} \sum_{i=1}^{I} \left| NW_{it} - \mu_i \right| \tag{2.19}$$

2.4.5 Constraints

The model is subject to the following constraints:

The workforce size of plants

$$NW_{it} = NW_{i(t-1)} + NH_{it} - NL_{it} \quad \forall i \forall t \tag{2.20}$$

The number of workers at each plant cannot be less than the fixed capacity

$$NW_{it} \geq FW_{it} \quad \forall i \forall t \tag{2.21}$$

Demand satisfaction during the planning horizon

$$\sum_{i=1}^{I} \sum_{t=1}^{T} Q_{pit} = \sum_{k=1}^{K} \sum_{t=1}^{T} d_{pkt} \quad \forall \mathrm{p} \tag{2.22}$$

Production capacity for plants

$$\sum_{p=1}^{P} Q_{pit} \leq K_{it} \mathrm{NW}_{it} \quad \forall i \forall t \tag{2.23}$$

Demand satisfaction for each retailer during the planning horizon

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{pikmt} + \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{pjkmt} = \sum_{t=1}^{T} d_{pkt} \quad \forall k \forall p \tag{2.24}$$

Inventory of plants

$$IP_{pit} = \sum_{\tau=1}^{t} Q_{pi\tau} - \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pijm\tau} - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pikm\tau} \quad \forall i \forall p \forall t \tag{2.25}$$

Inventory capacity at plants

$$IP_{pit} \le KK_{pit} \quad \forall i \forall p \forall t \tag{2.26}$$

Conservation of flow at plants

$$\sum_{j=1}^{J}\sum_{m=1}^{M} X_{pijmt} + \sum_{k=1}^{K}\sum_{m=1}^{M} X_{pikmt} \le Q_{pit} + IP_{pi(t-1)} \quad \forall i \forall p \forall t \tag{2.27}$$

Inventory at DCs

$$ID_{pjt} = \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pijm\tau} - \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pjkm\tau} \quad \forall j \forall p \forall t \tag{2.28}$$

Warehousing capacity at DCs

$$ID_{pjt} \le VV_{\mathrm{pjt}} L_j \quad \forall j \forall p \forall t \tag{2.29}$$

Conservation of flow at DCs

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pijm\tau} \ge \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pjkm\tau} \quad \forall j \forall p \forall t \tag{2.30}$$

No inventory at DCs at the end of the planning horizon

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{pijmt} = \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{t=1}^{T} X_{pjkmt} \quad \forall j \forall p \tag{2.31}$$

Amount of product delivered in advance or backordered

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pjkm\tau} + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{\tau=1}^{t} X_{pikm\tau} - \sum_{\tau=1}^{t} d_{pk\tau} = S_{pkt} - R_{pkt} \quad \forall k \forall p \forall t \tag{2.32}$$

Global reception capacity at DCs

$$\sum_{i=1}^{I}\sum_{p=1}^{P}\sum_{m=1}^{M} X_{pijmt} \le LC_{jt} L_j \quad \forall j \forall t \tag{2.33}$$

Global reception capacity at retailers

$$\sum_{j=1}^{J}\sum_{p=1}^{P}\sum_{m=1}^{M} X_{pjkmt} + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{p=1}^{P} X_{pikmt} \le LD_{kt} \quad \forall k \forall t \tag{2.34}$$

Transportation capacity

$$\sum_{p=1}^{P} X_{pnn`mt} \le Cap_{nn`mt} Z_{nn`mt} \quad \forall n \in i, j, \forall n' \in j, k, \forall m \forall t \tag{2.35}$$

Maximum of permitted products delivered in advance

$$S_{pkt} \le WW_{pkt} \cdot I_{pkt} \quad \forall k \forall p \forall t \tag{2.36}$$

Maximum of permitted backordered products

$$R_{pkt} \le M_{pkt} \cdot (1 - I_{pkt}) \quad \forall k \forall p \forall t \tag{2.37}$$

No shipment to retailers if products are delivered after the planning horizon

$$X_{pjkmt} = 0 \quad \forall p \forall j \forall k \forall m \forall t \mid \left\{ \text{t}.\rho + \text{C}_{\text{jkp}} > \text{T}.\rho \right\} \tag{2.38}$$

$$X_{pikmt} = 0 \; \forall p \forall i \forall k \forall m \forall t \mid \left\{ t.\rho + B_{ikp} > T.\rho \right\} \tag{2.39}$$

Non-negativity, binary restrictions

$$Q_{pit}, X_{pnn'mt}, R_{pkt}, S_{pkt}, IP_{pit}, ID_{pjt}, NW_{it}, NH_{it}, NL_{it} \geq 0 \tag{2.40}$$

$$I_{pkt} \in \{0,1\}, \; L_j \in \{0,1\} \quad , Z_{nn`mt} \in \{0,1\} \tag{2.41}$$

Due to the absolute value presented in the third objective function (Z_3), the model introduced above in nonlinear. To linearize the objective function, a new variable (JID_{it}) is introduced and let

$$JID_{it} = \left| NW_{it} - \mu_i \right| \quad \forall i,t$$

Therefore;

$$JID_{it} = max\left\{ NW_{it} - \mu_i, \mu_i - NW_{it} \right\} \quad \forall i,t$$

Thus, the social objective function (Z_3) can be linearized by introducing two additional constraints into the model.

$$min \quad z_3 = \sum_{i=1}^{I} \sum_{t=1}^{T} JID_{it} \tag{2.42}$$

$$JID_{it} \geq NW_{it} - \mu_i \qquad \forall i,t \tag{2.43}$$

$$JID_{it} \geq \mu_i - NW_{it} \qquad \forall i,t \tag{2.44}$$

2.5 Case study and data gathering

To illustrate the application of the model for sustainable supply chain design, the mathematical formulation has been validated and applied in a preliminary study of a case in the frozen food industry. We attempt to illustrate the production and distribution situations of the case study

(PDC), but due to the massive data scale, we are unable to provide the detailed data used for the experiment. PDC is involved with the production and distribution of frozen food products in North America (Canada and United States (US)). PDC offers more than four hundred products. However, we regroup the products into four families: Breakfasts, Meals, Snacks, and Raw Doughs.

Products are produced by passing through different machine centers at one of the two production plants sited in Quebec and Ontario. Breakfast and meals are produced in Ontario and Snacks and Raw doughs in Quebec. Due to less efficient machinery used, more carbon emissions are created in Quebec, but production costs are considerably lower. The plant in Ontario is the greenest due to the recent investments in new machines. Manufacturing plants supply six (6) customer areas in six various regions containing Canada East, Canada Central, Canada West, US East, US Central and US West. The distribution between manufacturing plants to retailers can be carried out either directly or indirectly through thirty established distribution centers. These distribution centers are controlled by third-party logistics (3PLs). The potential 3PL companies in this case study are selected from those who have already established business with the company. The available transport options might be different from one direction to another. Sometimes, the flow of products between some nodes is not big enough to be carried out using big trucks. Also, there might be some restrictions on big trucks traveling to residential areas. The 3PL companies offer storage rates and transportation costs for each direction and transportation type. The planning horizon at PDC is considered to be one year including twelve one-month periods. The pallet is defined as the product unit in production, transportation, and storage. The company is facing more stringent environmental policies under implementation in Quebec and Ontario.
Moreover, cooling inventory at distribution centers and retailers requires much energy. Due to the strong competition in this sector, the company has to minimize production and distribution (inventory and transportation) costs while offering a good service level and guarantee fresh products for final customers. Samples of some parameters are reported in tables 2.3 to 2.5. Note that for this research, the parameters associated with emission factors are estimated based on the best information available.

2.5.1 Data of the Case study

Table 2.3 lists the aggregated demand of retailers for all product families through the planning horizon. There seems to be higher seasonality in some product families such as breakfast, meals and raw doughs. Consumers prefer to buy these products when the weather is cold, and there is less demand from April to August. In fact, the consumption pattern of all product families somehow follows a similar trend.

Noteworthy, there is a high demand for the products in December, but fewer working hours are available due to Christmas holidays. Per pallet inventory holding costs of products at each period in distribution centers are reported in table 2.4.

Table 2.3 Aggregated demands (per pallet)

Month / *Product Family*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*	*Feb*	*Mar*	*Total Demand*
Breakfasts	281	366	242	208	491	793	1202	1792	971	1698	1565	1567	**11177**
Meals	515	430	463	398	388	638	955	878	1251	1840	2325	1669	**11750**
Snacks	82	118	110	88	85	98	90	147	111	161	162	249	**1500**
Raw Doughs	734	529	540	496	679	1278	1423	3159	2819	3414	3171	3461	**21702**

Table 2.4 Holding cost at DCs in each period

	Country	Province	City	Holding cost ($)
DC location	Canada	British-Columbia	Delta	18.425
		British-Columbia	Surrey	34
		Alberta	Calgary	16.75
		Ontario	Kitchener	16.5
		Ontario	Concord (1)	9.5
		Ontario	Concord (2)	9.5
		Ontario	Concord (3)	9.5
		Ontario	Vaughan	19.98
		Ontario	Concord (4)	9.5
		Ontario	Mississauga	16.5
		Quebec	Dorval	18.425
		Quebec	Saint-Laurent (1)	34
		Quebec	Lachine	14.25
		Quebec	Montreal	11
		Quebec	Saint-Laurent (2)	14.25
		Quebec	Anjou	13.75
	United-States	California	Riverside	18.425
		California	Anaheim	17.17
		Illinois	Belvidere	17
		Illinois	Rochelle	18.425
		Washington	Fife	3.696
		Texas	Forth Worth	15.675
		Georgia	Atlanta	15.13
		Maryland	Elkton	12.04875
		Florida	Orlando	5.4026
		Pennsylvania	Fogelsville	13.65
		Missouri	Carthage	14.69
		Massachusetts	Tewksbury	8.8776
		Connecticut	Rocky Hill	4.1004

The 3PL companies typically offer two types of refrigerated trucks with average truckloads of 16 and 40 tonnes. Emission factors of transportation are reported in table 2.5. GHG emission factors for refrigerated trucks are estimated from the data provided by Food Cold Chain Council ("GFCCC") (2015). To keep the products safe, warehouses are equipped with cooling storage area, which is highly energy-intensive. We used the data provided by Adekomaya et al. (2016) in measuring the energy requirements at storage. Table 2.6 represents the per pallet energy consumption for cooling storages in each period.

Table 2.5 Emission factors of refrigerated trucks

Truck type	Emission factor (per pallet km)
16 Tonnes	0.0604
40 Tonnes	0.024

Table 2.6 Energy consumption by cooling storages

Storage size	Energy requirement (kW h/pallet month)
Distribution centers (10,000 m^3)	25
Retailers (1000 m3)	50

2.6 Results and analysis

The model is implemented in GAMS 24.7.1 and solved using CPLEX solver 12.5. With four product families (P=4), two manufacturing plants (I=2), thirty distribution centers (J=30), five hundred and ninety-four retailers (K=594) and twelve time periods (T=12), the proposed MILP model has approximately 1,348,473 variables and 580,447 constraints.

2.6.1 Single objective optimization

The model is first optimized with one objective at a time to study the best economic, environmental and social solutions, and also to examine the differences between obtained solutions from different objectives. For the sake of this study, we assume that backorder is not allowed in any scenario.

2.6.1.1 Economic objective minimization

We solve the proposed model from an economic perspective to get the optimal arrangements which reduce the network costs. The company is equipped with the fixed number of workers, 148 in Ontario site and 143 in Quebec site. The potential 3PL providers offer storage with limited capacities. Besides, some distribution centers are located far from plants and customers locations which might impose an additional cost on the transportation side. Therefore, to absorb the demand variations and keep down the inventory and transportation costs, the company hires temporary workers in some periods. This scenario of the problem, optimizing economic objective, is referred to as the "Eco-optimal." After solving the optimization model, we came up with the optimal number of distribution centers (22 DCs). Figure 2.2 represents the location of potential distribution centers and the flow of products from plants to selected DCs. The number of DCs selected in each state/province is also reported in table 2.7

Table 2.7 Number of DCs in Eco-optimal scenario

Country	***State/Province***	***Number of DCs***	
		Potential	***Selected***
Canada	Quebec	6	6
	Ontario	7	5
	British Columbia	2	1
	Alberta	1	1
United-states	California	2	1
	Washington	1	1
	Georgia	1	-
	Massachusetts	1	1
	Illinois	2	-
	Texas	1	1
	Florida	1	1
	Maryland	1	1
	Pennsylvania	1	1
	Missouri	1	1
	Connecticut	1	1
	Indiana	1	-
	Total number of DCs	**30**	**22**

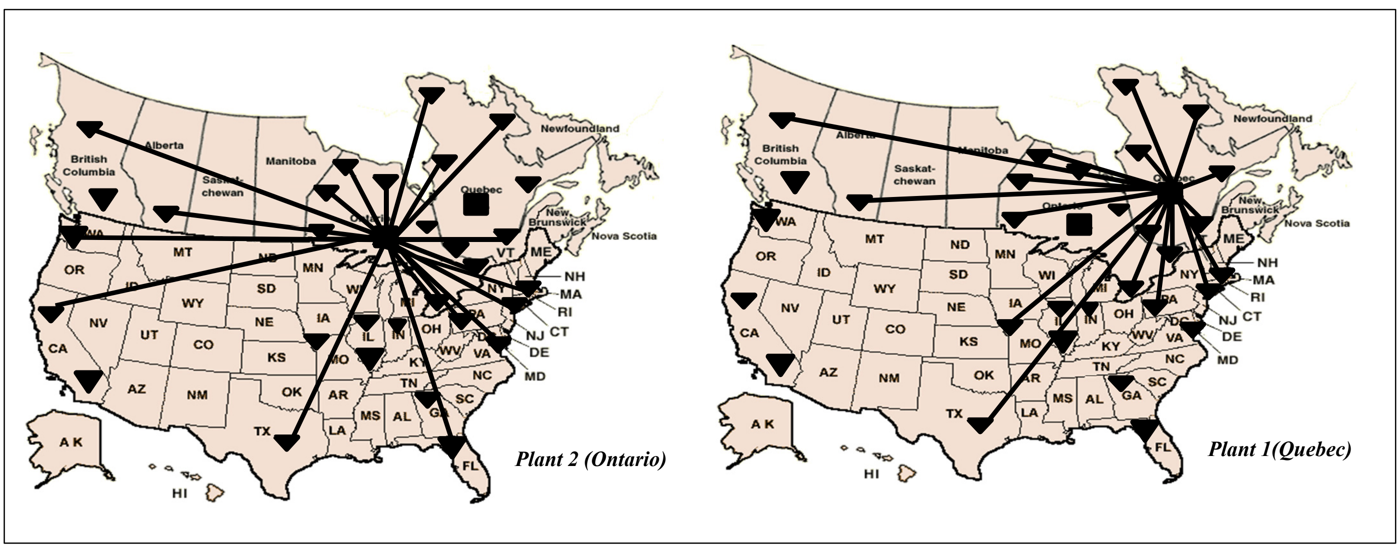


Figure 2.2 Supply chain configuration

Figure 2.3 Number of workers at manufacturing sites

As shown in Figure 2.3, the production is set at a fixed rate using a fixed workforce in some periods. However, additional workers are required to match the production plan to the demand variations and cut off the inventory and transportation costs. Following the production plans provided by the proposed model, the company can minimize the inventory and transportation costs, with an increase in hiring and firing costs. A summary of SC network costs is listed in table 2.8. More than half of the shipments from plants to DCs are carried out using big trucks (see Figure 2.4), which could increase the transportation efficiency of the network by increasing the shipment volumes and decreasing the number of shipments. Since the number of shipments between DCs to retailers is usually small, only 12% of products are transported using big trucks. Figure 2.6 illustrates the production, inventory and demand levels for Eco-optimal scenario during the planning horizon. As shown, the products are produced and stocked in DCs using an increased number of workers in some periods in order to be used for the high demand periods.

In the next sections, we analyze how the environmental and social impacts might affect the economic performance and network configuration.

Table 2.8 Supply chain cost in Eco-optimal scenario

scenario	**Warehousing cost (Thousand dollar)**	**Transportation cost (Thousand dollar)**	**Production Cost (Thousand dollar)**	**Total Cost (Thousand dollar)**
Eco-optimal	792 $	11,517 $	11,549 $	**23,858 $**

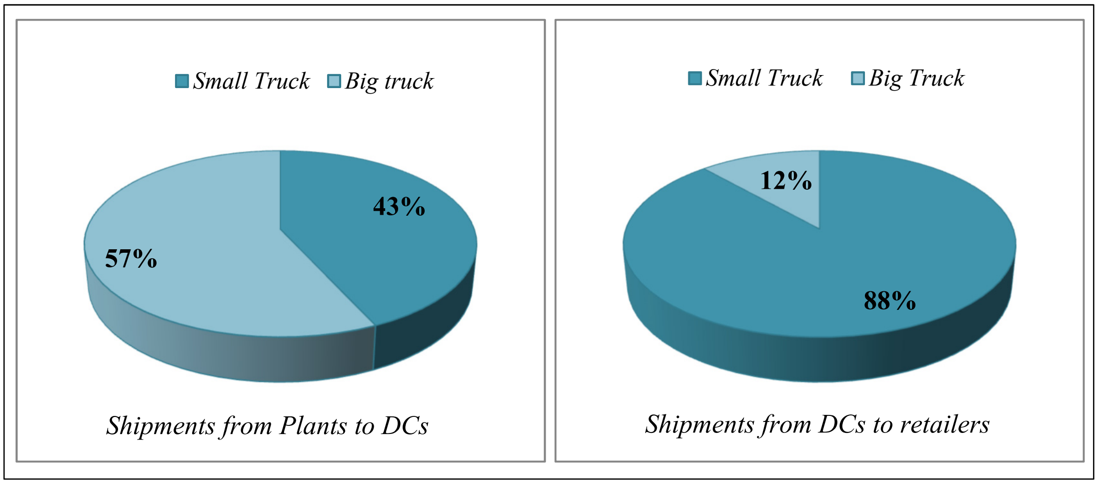


Figure 2.4 Transportation using small and big trucks (Eco-optimal scenario)

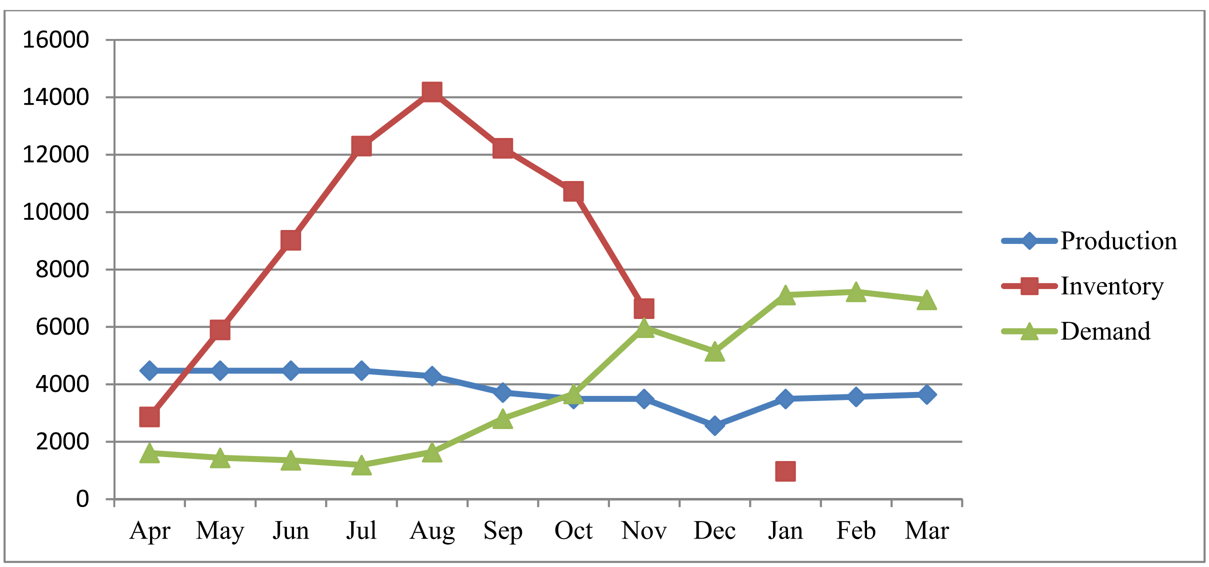
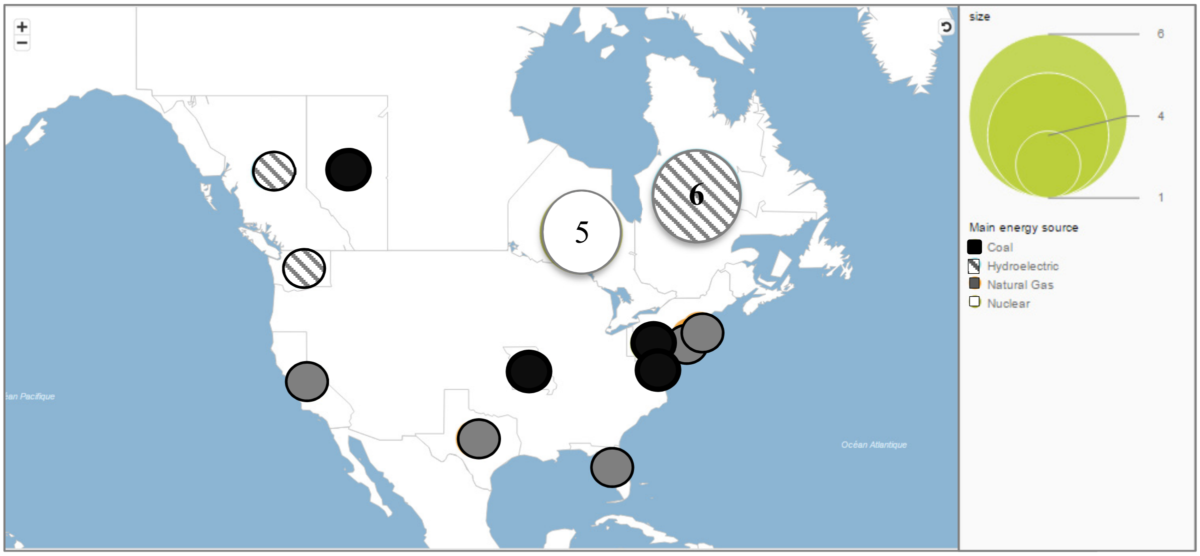


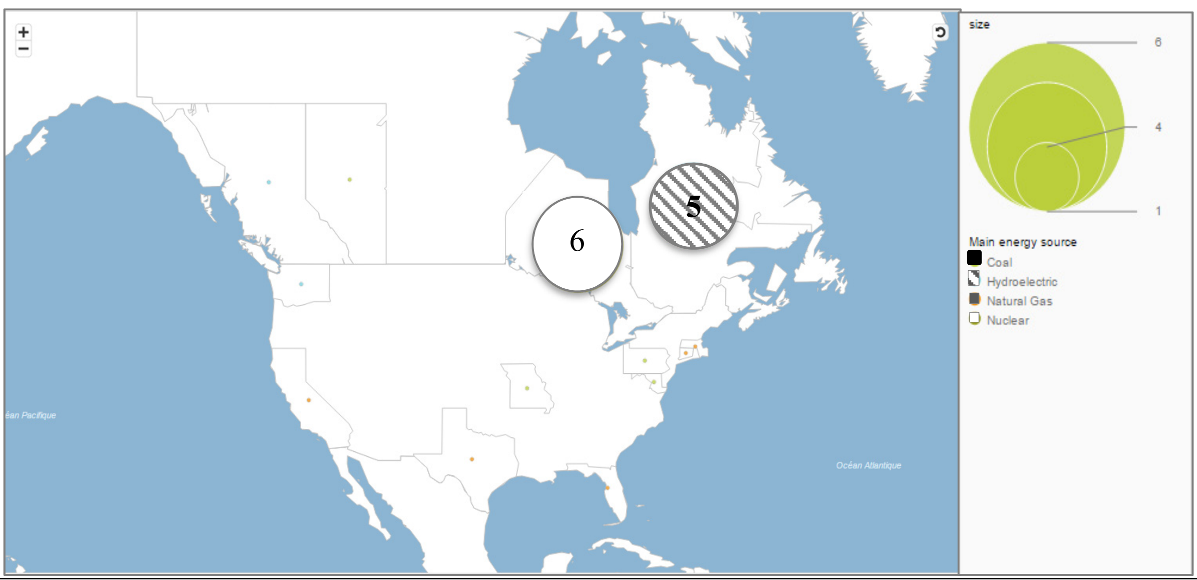
Figure 2.5 Production, Inventory and demand levels (Eco-optimal scenario)

2.6.1.2 Environmental objective minimization

About half of the products are sold in the US, using the US grid mix with the main combustion of fossil fuels. The other half of the products sold use the Canadian grid mix which uses more clean energy sources such as hydroelectric. The data for the province’s energy mix can be found in EIA (U.S Energy Information Administration) and CEA (Canadian Electricity Association) database. For instance, Ontario’s energy mix is composed of 24% hydroelectricity, 42% nuclear, 30% natural gas and 4% coal. Furthermore, emission factors of energy sources are provided based on a literature review conducted by IPCC (2011). In this section, we will get some insights on how the supply chain configurations will change in “Env-optimal” scenario, optimizing the environmental impacts.



a) Eco-optimal



b) Env-optimal

Figure 2.6 Location of DCs in the optimized network and Green scenarios

Figure 2.6a and 2.6b show locations of the distribution centers, number of distribution centers in each province, and their corresponding main energy source in the Eco-optimal and the Env-optimal scenarios. As shown in Figure 2.6b, only 11 DCs are selected in the Env-optimal scenario. The GHG emissions emitted from warehousing activities are substantially reduced, compared to the Eco-optimal scenario. GHG emissions in the Eco-optimal scenario are calculated by substituting the values of decision variables obtained from this scenario in the environmental objective function. The same method is also used to derive the Env-optimal costs reported in table 2.9. In this scenario, DCs use more environmentally friendly energy sources. In particular, the DCs are selected in two Canadian provinces where the primary sources of energy are hydroelectric (Quebec) and nuclear (Ontario). However, the holding costs for some of the DCs located in these provinces are higher than other DCs, which explain the increased cost of warehousing in this scenario (see table 2.9). Also, reducing the inventory levels helps to keep down the warehousing emissions. Figure 2.9 shows the inventory levels in comparison with production and demand levels for the Env-optimal scenario. The total inventory in this scenario is reduced by about 45%, compared to the Eco-optimal scenario. As a result of this reduction, workers are hired and laid-off in different periods to absorb the variation in demand and match the production plans to the demand pattern. However, since job instability is higher in this scenario, the associated production costs would slightly rise. In the Env-optimal scenario, the DCs are located closer to the plants to reduce GHG emissions emitted from transportation activities.

Furthermore, using big trucks for carrying out about 96 percent of shipments is another reason for the considerable reduction of GHG emissions for transportation activities. However, because retailers are located far from DC locations, the cost associated with transportation activities is significantly increased. The distribution of trucks is shown in Figure 2.7.

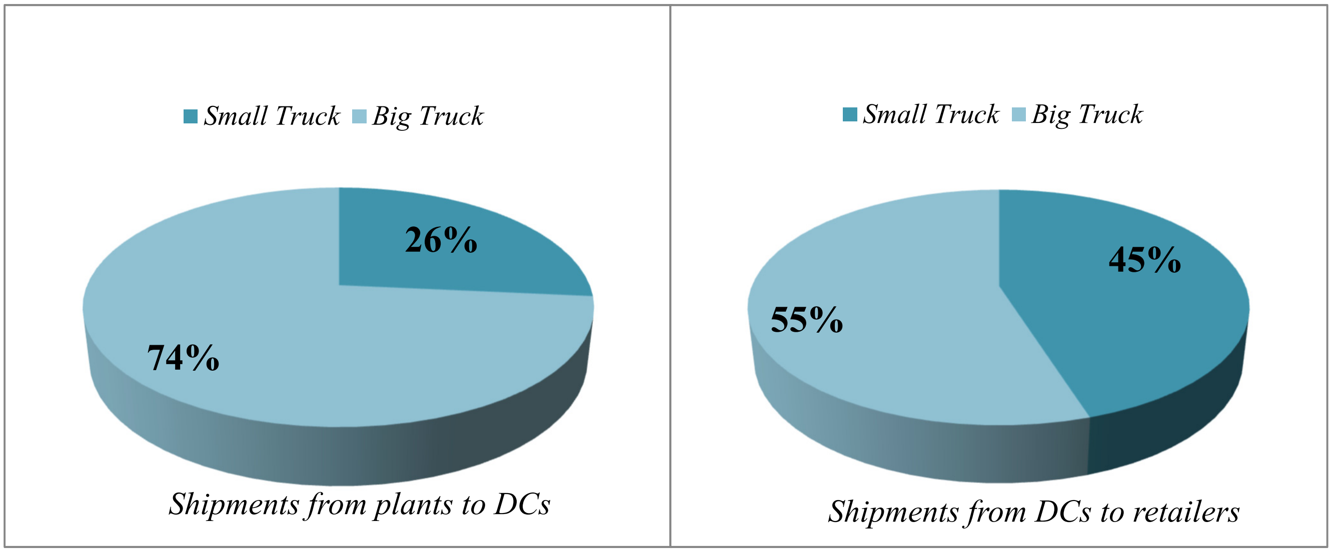


Figure 2.7 Transportation using small and big trucks (Env-optimal scenario)

Table 2.9 Env-optimal versus Eco-optimal scenario (thousand dollars)

Network costs	**Env-optimal**	**Eco-optimal**	**Difference**
Production	11,554 $	11,549 $*	0.043 %
Warehousing	1,724 $	792 $*	117 %
Transportation	19,179 $	11,517 $*	67 %
Total	**32,457 $**	**23,858 $***	**36 %**

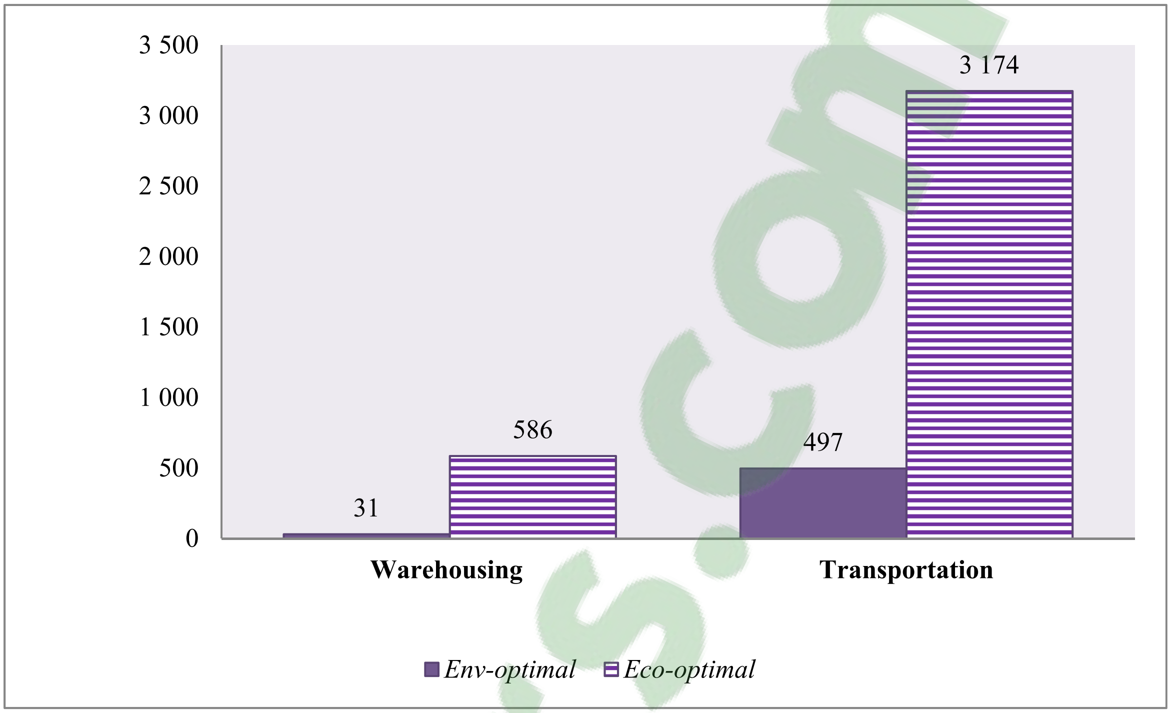


Figure 2.8 GHG emissions from warehousing and transportation activities (Ton CO_2)

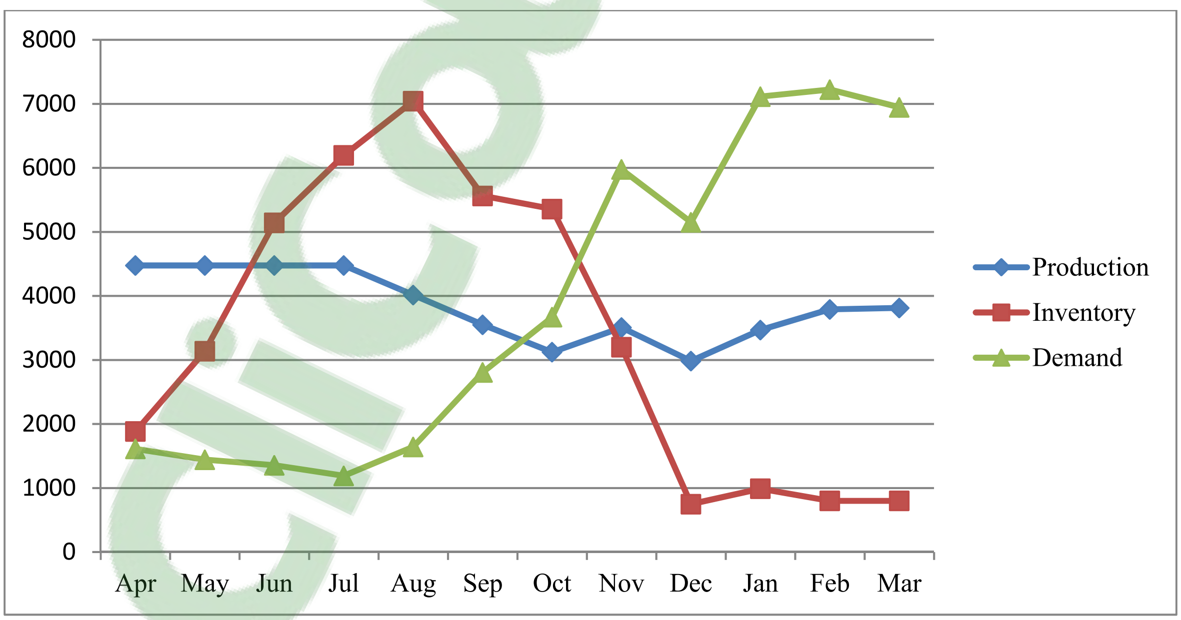


Figure 2.9 Production, Inventory and demand levels (Env-optimal scenario)

2.6.1.3 Social objective minimization

In this section, the model is optimized based on the social objective. This objective is going to minimize the job instability, referred to as “Sc-optimal" at manufacturing sites. As a result of this optimization, thirty DCs are selected. Also, the production rates are fixed using a fixed number of workers during the planning horizon, 164 and 166 in Quebec and Ontario sites respectively. Since these values are also the average number of workers at plants (μi), the optimal value of the objective function would be zero. The results of this scenario are compared with the Eco-optimal scenario. Network costs for the Sc-optimal scenario are calculated by substituting the values of decision variables obtained from this scenario in the economic objective function. As indicated in table 2.10, the production cost is slightly lower in the Sc-optimal scenario, because hiring and firing costs are cut off in this scenario. However, 61 and 74 percent increases the network costs associated with warehousing and transportation activities, respectively. Figure 2.10 shows the inventory levels at DCs in both scenarios during the planning horizon. As represented, the inventory levels are increased in low demand periods using stable production rates in the Sc-optimal scenario. Figure 2.11 also illustrated the inventory, production and demand levels in this scenario. The total inventory in this scenario is increased by about 16% and 54%, compared to Eco-optimal and Env-optimal scenarios respectively. As a result, the cost and emission associated with warehousing activities are considerably increased. Transportation is mostly carried out using big trucks (figure 2.12). However, transportation cost is increased, which is mainly because of the locations of selected DCs and their distance from plants and retailers’ locations.

Table 2.10 Sc-optimal versus Eco optimal scenario (thousand dollars)

Network costs	**Sc-optimal**	**Eco-optimal**	**Difference**
Production	11,521$	11,549 $*	-0. 24 %
Warehousing	2,018 $	792 $*	154 %
Transportation	19,513 $	11,517 $*	69.43 %
Total	**33,052 $**	**23,858 $***	**38.54 %**

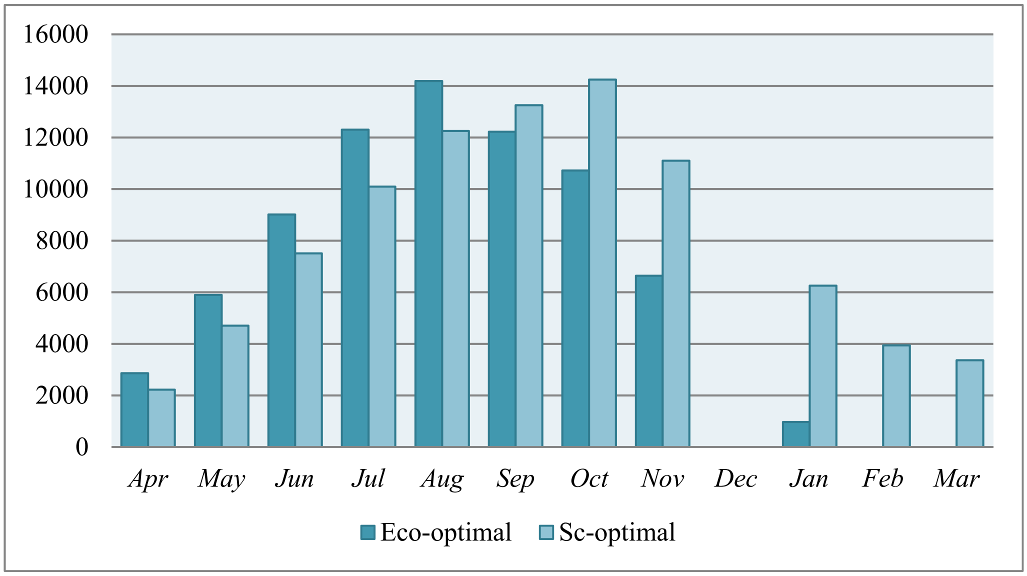


Figure 2.10 Inventory level at DCs (Eco and Sc scenarios)

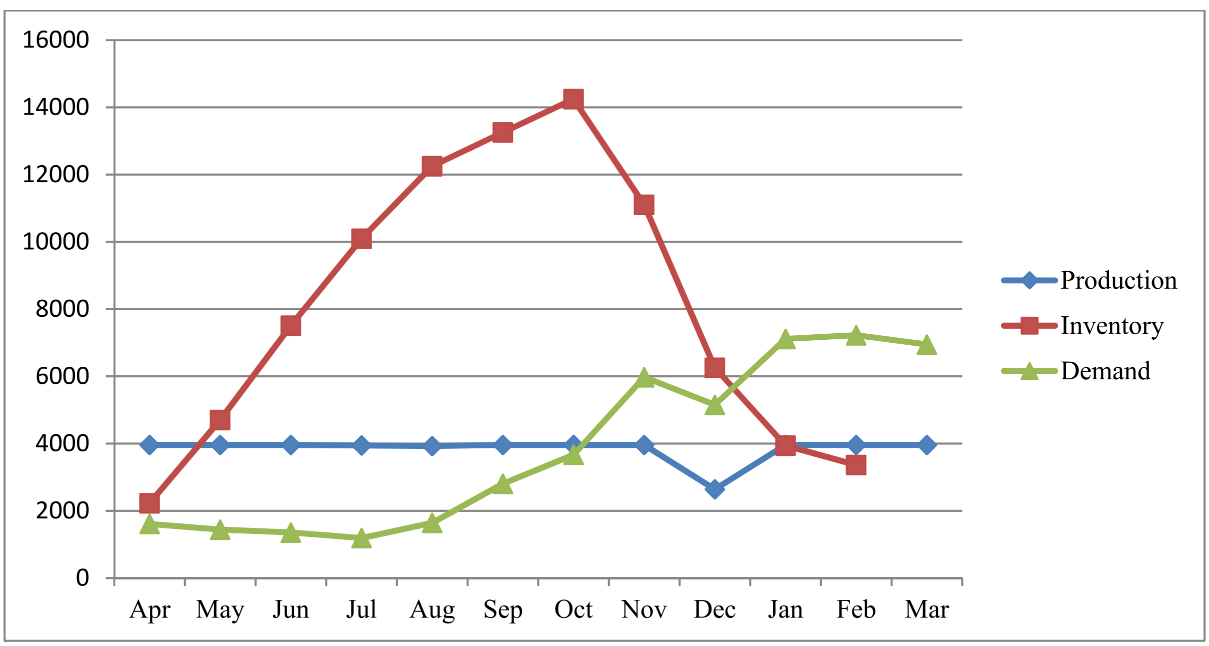


Figure 2.11 Production, Inventory and demand levels (Env-optimal scenario)

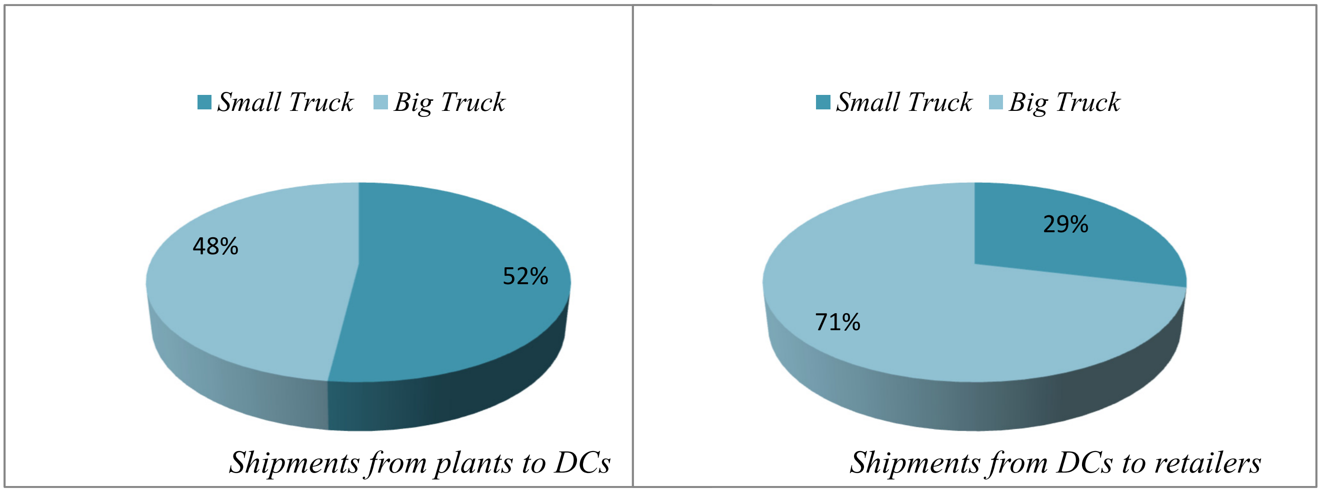


Figure 2.12 Transportation using small and big trucks (SC-optimal scenario)

2.6.2 Optimization based on the three objectives

In this section, the mathematical model is evaluated through numerical experimentation to determine the trade-off between the conflicting objectives. To this end, solving every single objective separately to determine the nadir values and generate the range of objective functions creates the payoff table, illustrated in table 2.11.

Table 2.11 Payoff table

	Eco performance (Thousand dollar)	**Env Performance** (Ton CO_2)	**Sc Performance**
Eco performance (Thousand dollar)	23,858 $*	3,760	406
Env Performance (Ton CO_2)	32,457 $	527*	413
Sc Performance	33,052 $	6,021	0*

In this study, multi-objective optimization of the mathematical formulation is performed through the weighted sum method. This method is the most widely used approach to solve multi-objective problems (Santoro 1992). In this approach, the multi-objective problem is converted to a single objective problem by multiplying each objective with a defined weight. Since interaction with decision makers in sustainable supply chain design is important, the weighted sum method can help them decide how much cost to bear to reduce emissions and increase social responsibilities of the network. For the sake of this study, some scenarios have been designed using different weights to find a trade-off between economic, environmental and social objectives.

The mathematical formulation for weighted sum method is as follows:

$$\textit{Minimize} \quad w_1Z_1+w_2Z_2+w_3Z_3$$

$$\textit{S.t} \quad \textit{Equation}\ (2.20)\ \textit{to}\ (2.44)$$

In which $w_1, w_2, w_3 > 0$ and $w_1+w_2+w_3 = 1$

However, to obtain a unidimensional numerical form, the multi-objective functions have to be normalized. A normalized vector objective function of the following form, suggested by Koski (1984), has been applied:

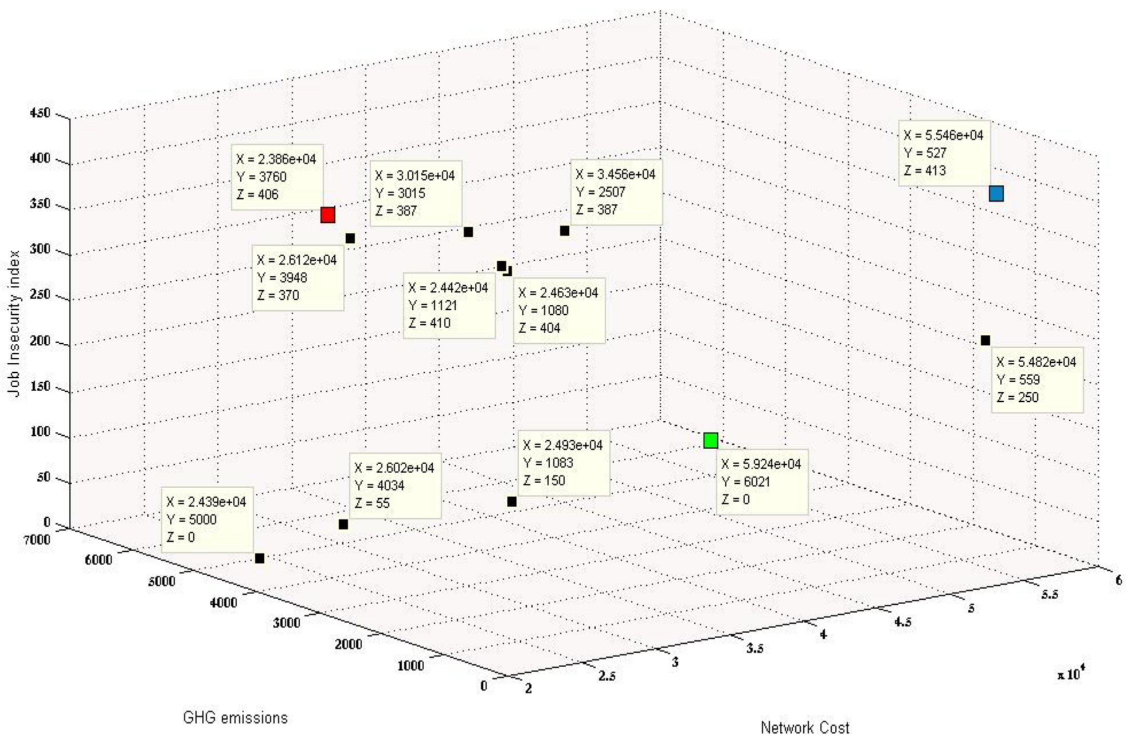
$$Z_i = \frac{Z_i - \min Z_i}{\max Z_i - \min Z_i} \qquad i \in 1,2,3 \tag{2.45}$$

The trade-offs between economic, environmental and social objectives using various weights are represented in table 2.12 and figure 2.13. The weights are randomly generated to examine how different network configurations impact the supply chain performance. It can be concluded from the trade-off relationship that improvement in one objective could not be achieved without degrading the performance of another objective.

Table 2.12 Trade-off between economic, environmental and social objectives

Scenario	Weights			Eco Objective	Δ vs. Eco-optimal	Env Objective	Δ vs. Env-optimal	Sc Objective	Δ vs. Sc-optimal
	w_1	w_2	w_3						
1	1	0	0	23,858 $	-	3,760	86%	406	406
2	0	1	0	32,457 $	36%	527	-	413	413
3	0	0	1	33,052 $	39%	6,021	91%	0	-
4	0.7	0.3	0	24,416 $	2%	1,121	52%	410	410
5	0.6	0.2	0.2	26,450 $	8%	1,123	53%	55	55
6	0.5	0.5	0	30,146 $	20%	1,015	82%	387	387
7	0.33	0.33	0.33	24,925 $	4%	1,083	51%	150	150
8	0.5	0.25	0.25	24,633 $	3%	1,080	51%	404	404
9	0.6	0.3	0.1	26,116 $	9%	3,948	86%	370	370
10	0.5	0	0.5	24,394 $	2%	5,000	89%	0	-
11	0.3	0.7	0	30,555 $	31%	2,507	78%	387	387
12	0	0.8	0.2	32,015 $	34%	559	6%	250	250

The proposed model could also be applied to other food supply chain networks. Although high seasonality is not the case in our study, it could be the case for other food supply chain networks. Moreover, in the case study introduced in section 5, if the company is not able to meet the demand in the right period, the sales will be lost (backorder is not allowed). Shortage in the form of backorder can be an alternative for food companies at some periods when there is insufficient inventory to fulfill an order. Therefore, the impacts of demand variation and backorder options on economic, environmental and social objectives can be investigated through the proposed model.



X-axis: Network cost, Y-axis: GHG emissions, Z-axis: Job insecurity index.
Red square: Eco-optimal solution; Blue square: Env-optimal solution; Green square: Sc-optimal solution.

Figure 2.13 Results from trade-offs analysis using different weights

2.7 Conclusion

In this chapter, a planning model for managing "sustainable" supply chain planning was presented. The multi-objective optimization problem is solved with the weighted sum method which reveals that improvement in one objective could not be achieved without degrading the performance of another objective. From an organizational perspective, it was shown in this chapter that there are certain areas of the SC where investments can be made to reduce emissions and increase social responsibilities. However, there are also business goals that need to be met. However, there are several objectives to be considered when managing "sustainable" supply chains. Also, in this model, we ignored sourcing and procurement activities. These extensions will be discussed in the next chapter, with more experimentation on significant supply chains reflecting the industrial reality. Given the complexities of the problem, a solution methodology with reasonable computational time is needed.

CHAPTER 3

MULTI-OBJECTIVE SUPPLY CHAIN PLANNING MODEL FOR LONG-TERM DECISION-MAKING

To evaluate SC performance, we have to consider many different criteria throughout the network. In contrast to traditional SC design, which typically relies on economic performance, recent studies focus on the integration of sustainability and utilization aspects along with economic criteria. However, SC network planning with multiple conflicting objectives is complex and often contains incommensurable goals. The goal programming (GP) approach ensures to cope with multiple objectives at a reasonable computational time, while incommensurable goals are treated in a practical way. In this chapter, a SC network planning framework and a methodology based on GP are proposed, which is then applied to a case in the context of Frozen Food industry in order to illustrate the applicability of the model and methodology.

3.1 Introduction

With increasing globalization, organizations must implement an effective and integrated sustainable supply chain management in order to improve their economic performance while minimizing environmental impacts and maintain their social reputation. In order to compete in today's business environment, supply chains are confronted to eliminate current inefficiency and increase productivity (Banasik et al. 2016). Improving productivity and designing a sustainable supply chain is linked with the calculation of trade-offs among economic and environmental and social indicators, which lead to the eco-efficiency concept (Dekker et al. 2012). Applying eco-efficiency in sustainable supply chains requires the inclusion of multiple criteria and typically trade-offs between different conflicting objectives (Wang et al. 2011). To support decision making for sustainable supply chains, a set of eco-efficiency indicators must be considered (Banasik et al. 2016).

Eco-efficiency is influenced by decision making at different supply chain stages: supplier selection, production planning, and inventory and distribution management. Supplier selection can affect the performance of supply chains by decisions concerning the location and number of suppliers. These decisions can determine the total travel distance, which not only affects the operational costs, but also energy use and quality of raw materials. The supply chain performance is also affected by production planning. The decisions related to production activities affect eco-efficiency as they determine of the technology to use, the location of plants, utilization of capacity and amount of waste produced. The decisions concerning inventory and distribution include two main aspects: transportation and facility location. Decisions related to transportation activities such as transportation mode and size of shipments can have a substantial impact on operational costs, energy consumption, and delivery performance, which is an important factor about products, which degrade in quality over time (Banasik et al. 2016). The location of facilities can affect holding costs and energy consumption, as they use different energy grid mix.

Additionally, the amount of inventory at distribution centers is associated with capacity utilization, energy use and operation costs. Inventory management is an important aspect in relation to products with limited shelf life (Dekker et al. 2012). Aggregation of important indicators to account for eco-efficiency leads to a sustainable supply chain planning.

Due to the multiple inputs and outputs in supply chain systems, selecting suitable supply chain performance indicators are complicated. The choice of performance indicators depends on the strategy of a company. There is no single set of globally agreed on key performance indicators (KPIs) to assess the sustainability of supply chain systems (Bloemhof et al. 2015). Tang and Zhou (2012) suggest that there is a need to incorporate sustainability aspects into traditional supply chain performance indicators such as cost, product quality, and responsiveness. Lusine et al. (2014) proposed a conceptual framework for measuring the performance of Agri-food supply chains containing financial and non-financial indicators. They identified four main categories of performance measurements, namely efficiency, flexibility, responsiveness, and food quality. Bloemhof et al. (2015) developed a framework to assess sustainability issues for food supply chains. They identified some internal and external drivers such as costs, efficiency, product quality, and brand reputation to improve sustainability performances. Yakovleva and Flynn (2004) introduced sustainability indicators to measure food supply chains performance. Lia et al. (2002) identified four performance indicators as responsiveness, reliability, costs, and assets. Van der Vorst (2000) also divided performance indicators into three primary levels: the supply chain level including responsiveness, quality delivery, reliability, and total costs; the organization level including inventory level, delivery reliability, responsiveness, and total organizational costs; and the process level including throughput time, responsiveness and process costs.

The need to incorporate social and environmental concerns in SC planning has increased the use of multi-criteria approaches. Multi-criteria decisions making (MCDM) is a well-known method of decision making which deals with decision problems in the presence of multiple objectives. The objectives (quantifiable or non-quantifiable) are typically conflicting. Therefore, the solution is hugely dependent on the decision makers' preferences. There are usually a group of decision-makers with a different point of view involved in the decision-making process. Multi-objective problems typically involve many decisions variables and conflicting objectives. Even though real-world problems may involve a large number of decision variables and objectives, most of the studies on multi-objective optimization are limited to small-scale problems. Goal programming (GP) is a useful method for decision-makers to consider multiple objectives simultaneously in order to find a set of acceptable solutions (Chen and Tsai 2000). However, it is difficult for decision-makers to precisely determine the goal value of each objective function. Narasimhan (1980) introduced fuzzy goal programming (FGP) approach using membership function to specify imprecise aspiration levels of the goals.

In this chapter, the aim is to incorporate all criteria required for SC network planning from suppliers to costumers where sustainability issues are also involved. However, solving an optimization model with conflicting objectives is computationally intensive, especially for large-scale problems (Grodzevich and Romanko 2006). Traditional multi-objective optimization approaches such as e-constraint and weighted-sum method are barely capable of solving a model with more than two or three objective functions. These methods above are less popular because of their computational effort (Mavrotas 2009). The motivation behind the proposed methodology is to solve the problem with several conflicting objectives at a reasonable computational time. The main benefit of this method is its computational efficiency and simplicity. Also, most of the papers in literature have merely considered an economic objective along with one sustainability or utilization criterion. Equal consideration of criteria, which are required in SC design, is a missing link. The proposed methodology, however, can give managers insights on how to make a trade-off between several criteria including sustainability and utilization criteria simultaneously.

3.2 Multi-objective model for supply chain design

3.2.1 Problem description and assumptions

To design the SC, we will consider the same functions as mentioned in figure 3.1 below.

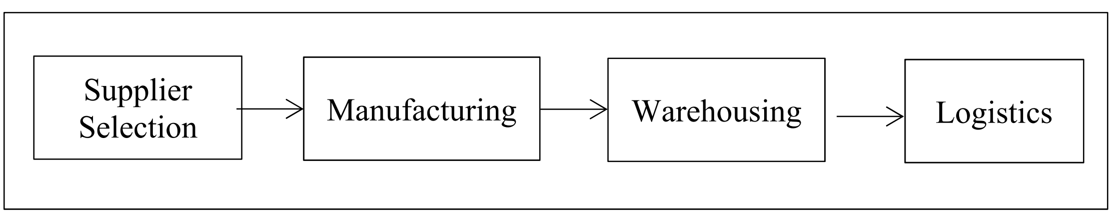


Figure 3.1 Considered SC functions for designing/redesigning

We present a generic mathematical model for a multi-objective supply chain planning. Some major long-term SC decisions that are essential for SC design are (1) Outsourcing decisions, (2) production and warehouse location decisions, (3) warehouse and production facility capacity decisions, (4) logistics service provider selection, and (5) location of distribution center decisions. We extend the model proposed in the previous chapter and give more precision using long-term SC criteria introduced in this chapter. This model will be used as an example to illustrate the performance of the proposed methodology to solve a large scale multi-objective sustainable supply chain planning model.

3.2.2 Set and Indices

In this study following set and indices are used:

r	set of raw materials: $r \in \{1,2,...,R\}$
p	set of products: $p \in \{1,2,...,P\}$
h	set of manufacturing technology: $h \in \{1,2,...,H\}$
m	set of transportation modes: $m \in \{1,2,...,M\}$
s	set of suppliers: $s \in \{1,2,...,S\}$
i	set of manufacturing sites: $i \in \{1,2,...,I\}$
j	set of distribution centers: $j \in \{1,2,...,J\}$
k	set of retailers: $k \in \{1,2,...,K\}$
t	set of time-periods: $t \in \{1,2,...,T\}$
e_j	Set of energy mix at DC j: $e_j \in \{1,2,...,E_j\}$
e_k	Set of energy mix at retailer k: $e_k \in \{1,2,...,E_k\}$

3.2.3 Parameters

The mathematical model requires the following parameters:

FC_s	the fixed cost of establishing a business with supplier s
FC_j	the fixed cost of establishing a business with DC j
FC_{ih}	fixed establishing the cost of plant i with technology h
PC_{rst}	purchasing cost of raw material r from supplier s during period t

MC_{piht}	the manufacturing cost of product *p* at plant *i* with technology *h* during period *t*
TC_{simt}	per unit transportation cost of transportation mode *m* from supplier *s* to plant *i* during period *t*
TC_{ijmt}	per unit transportation cost of transportation mode *m* from plant *i* to DC *j* during period *t*
TC_{jkmt}	per unit transportation cost of transportation mode *m* from DC *j* to retailer *k* during period *t*
BC_{pkt}	per unit backorder cost of product *p* at retailer *k* during period *t*
BC_{rit}	per unit backorder cost of raw material *r* at plant *i* during period *t*
HC_{pit}	per unit holding cost for product *p* at plant *i* from period *t* to period *t+1*
HC_{rit}	per unit holding cost for raw material *r* at plant *i* from period *t* to period *t+1*
HC_{pjt}	per unit holding cost for product *p* at DC *j* from period *t* to period *t+1*
HC_{pkt}	per unit holding cost for product *p* at retailer *k* from period *t* to period *t+1*
Dem_{pkt}	the demand of retailer *k* for product *p* during period *t*
$TCap_{simt}$	the capacity of transportation mode *m* between supplier *s* and plant *i* during period *t*
$TCap_{ijmt}$	the capacity of transportation mode *m* between plant *i* and DC *j* during period *t*
$TCap_{jkmt}$	the capacity of transportation mode *m* between DC *j* and retailer *k* during period *t*
$MCap_{piht}$	manufacturing capacity of plant *i* with technology *h* for product *p* during period *t*
$SCap_{rst}$	the reserved capacity of supplier *s* for raw material *r* during period *t*
$WCap_{rit}$	warehousing capacity of plant *i* for raw material *r* during period *t*
$WCap_{pit}$	warehousing capacity of plant *i* for product *p* during period *t*
$WCap_{pjt}$	warehousing capacity of DC *j* for product *p* during period *t*
$WCap_{pkt}$	warehousing capacity of retailer *k* for product *p* during period *t*
LT_{jkp}	delivery lead time for product *p* from DC *j* to retailer *k*
Dis_{si}	the distance between supplier *s* and plant *I* [*in km*]

Dis_{ij}	distance between plant *i* and DC *j* [*in km*]
Dis_{jk}	distance between DC *j* and retailer *k* [*in km*]
Max_{pkt}	the maximum permitted backorders for product *p* at retailer *k* during period *t*
α_{piht}	Percentage of waste for product *p* manufactured at plant *i* with technology *h* during period *t*
R_{rp}	unit requirement for raw material *r* to manufacture one unit of product *p*
ρ	the coefficient for transformation between planning horizon and lead time unit
EIS_{rs}	per unit environmental impacts associated with raw material *r* at supplier *s*
EIM_{pih}	per unit environmental impacts of producing product *p* at plant *i* with technology *h*[kg CO2e]
EIT_{sim}	per unit environmental impacts of transportation using transportation mode *m* from supplier *s* to plant *i* [kg CO2e/(t km)]
EIT_{ijm}	per unit environmental impacts of transportation using transportation mode *m* from plant *i* to DC *j* [kg CO2e/(t km)]
EIT_{jkm}	per unit environmental impacts of transportation using transportation mode *m* from DC *j* to retailer *k* [kg CO2e/(t km)]
EM_{ej}	the percentage share of energy source *e* in the energy mix of the region where DC *j* is located ($\sum_{e_j=1}^{E_j} EM_{e_j} = 1 \quad \forall j$)
ER_j	the energy requirement for storing one unit of product at DC *j* [kWh/ period]
EF_{ej}	GHG emission factor for energy source *ej* [kg CO2e/kWh]
EM_{ek}	the percentage share of energy source *e* in the energy mix of the region where retailer *k* is located ($\sum_{e_k=1}^{E_k} EM_{ek} = 1 \quad \forall k$)
ER_k	the energy requirement for storing one unit of product at retailer *k* [kWh/ period]
EF_{ek}	GHG emission factor for energy source e_k [kg CO2e/kWh]

3.2.4 Decision Variables

This will include continuous, binary variables:

- *Continuous variables*

p_{rst}: Amount of raw material r to be purchased from supplier s

q_{piht}: Amount of product p manufactured at plant i with technology h during period t

g_{pit}: Amount of good product p manufactured at plant i during period t

x_{rsimt}: Flow of raw material r from a supplier s to plant i using transportation mode m during period t

x_{pijmt}: Flow of product p from plant i to DC j using transportation mode m during period t

x_{pjkmt}: Flow of product p from DC j to retailer k using transportation mode m during period t

ip_{rit}: Inventory level of raw material r at plant i at the end of period t

ip_{pit}: Inventory level of product p at plant i at the end of period t

id_{pjt}: Inventory level of product p at DC j during period t

b_{pkt}: Amount of product p backordered at retailer k during period t

b_{rit}: Amount of raw material r backordered at plant i during period t

s_{pkt}: Amount of surplus for product p delivered at retailer k during period t

- *Binary variables*

y_{rs}: 1 if raw material r provided by supplier s, 0 otherwise

z_{ih}: 1 if plant i with technology h is opened, 0 otherwise

u_j: 1 if DC j is selected, 0 otherwise

w_{pkt}: 1 if there is a surplus for product p at retailer k during period t, 0 if there are backorders for product p at retailer k during period t

l_{simt}: 1 if transportation mode m is selected between supplier s and plant i during period t, 0 otherwise

l_{ijmt}**:** 1 if transportation mode *m* is selected between plant *i* and DC *j* during period *t*, 0 otherwise

l_{jkmt}**:** 1 if transportation mode *m* is selected between DC *j* and retailer *k* during period *t*, 0 otherwise

3.2.5 Assumptions

The following assumptions are considered in developing the model:

a) The demand of retailers, the price of raw materials, cost and other considered parameters are known a priori.
b) The demand for retailers must be satisfied.
c) The capacity of suppliers, plants, DCs, and retailers are limited.
d) The flow between facilities of the same echelon is not allowed.
e) The products cannot be sent directly from plants to retailers.
f) Only good products would be shipped to DCs (e.g., 100 percent inspection at plants).

3.2.6 Objective Functions

As mentioned earlier, the proposed model consists of three objective functions. We start the mathematical formulation by introducing the economic objective:

- Economic Objective

Procurement, manufacturing, transportation and warehousing costs mainly evaluate the economic objective. This objective function minimizes the total fixed and variables costs of the network. The economic objective consists of the following sub-functions:

- *Procurement function*

This function includes the variable cost of purchasing raw material from suppliers which are introduced as a monetary value in table 1.3 and backorder cost at manufacturing sites.

$$MV = \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{S} PC_{rst} p_{rst} + \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{i=1}^{I} BC_{rit} b_{rit} \tag{3.1}$$

- *Geographical location cost*

This function addresses the fixed cost of establishing a business with suppliers.

$$GLC = \sum_{s=1}^{S}\sum_{r=1}^{R} FC_{s} y_{rs} \tag{3.2}$$

- *Manufacturing cost function*

This function is the fixed cost of establishing plants with manufacturing technologies, production and backorder costs. Since products are clustered into families by manufacturing technologies, it is possible to have a plant with more than one technology. The equation (3) represents the fixed and variable manufacturing cost at plants.

$$MC = \sum_{i=1}^{I}\sum_{h=1}^{H} FC_{ih} z_{ih} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{h=1}^{H}\sum_{i=1}^{I} MC_{piht} q_{piht} + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{p=1}^{P} BC_{pkt} b_{pkt} \tag{3.3}$$

- *Plants Inventory cost function*

This function calculates the inventory costs at manufacturing sites.

$$IC = \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{i=1}^{I} HC_{rit} ip_{rit} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I} HC_{pit} ip_{pit} \tag{3.4}$$

- *Transportation cost function*

This function represents the cost associated with transportation activities. This three-term represent the variable transportation cost of raw materials and products carried out using various modes of transportation.

$$TC = \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{m=1}^{M} TC_{simt} x_{rsimt} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} TC_{ijmt} x_{pijmt} + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M} TC_{jkmt} x_{pjkmt} \quad (3.5)$$

- *Inventory cost function*

The first term in this function is the fixed cost of establishing a business with DCs. The next two summations represent the variable costs of holding raw materials and products at plants, distribution centers, and retailers, respectively.

$$ILC = \sum_{j=1}^{J} FC_j u_j + \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{J} HC_{pjt} id_{pjt} + \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{p=1}^{P} HC_{pkt} s_{pkt} \quad (3.6)$$

- *Utilization objective*

The second objective function aims to maximize the utilization of the network. This objective consists of the following sub-functions:

- *Supplier delivery performance function*

The first term of this function represents the delivery performance of suppliers which is defined as the ratio of the number of purchase orders fulfilled by suppliers without backorder to the total amount of required raw materials at manufacturing sites. This term is the fraction of in full and on-time delivery of raw materials by suppliers during the planning horizon.

$$SDP = \left[\frac{\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{i=1}^{I}\sum_{s=1}^{S}\sum_{m=1}^{M} x_{rsimt} - \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{i=1}^{I} b_{rit}}{\sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{p=1}^{P}\left(\sum_{k=1}^{K} Dem_{pkt} R_{rp}\right)} \right] \quad (3.7)$$

- *Overall equipment effectiveness Function*

The overall equipment effectiveness (OEE) is also addressed in the second summation, which reports the overall utilization of manufacturing operations at plants. In this work, OEE is measured by dividing the quantity of good products (e.g., production quantity minus waste) at manufacturing sites by the total amount of products, which are planned to produce (the total demand).

$$OEE = \left[\frac{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{i=1}^{I} g_{pit}}{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{k=1}^{K} Dem_{pkt}} \right] \tag{3.8}$$

- *Manufacturing capacity utilization function*

The capacity utilization at manufacturing sites is calculated by dividing the total production quantity by the total production capacity of plants.

$$CU = \left[\frac{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{i=1}^{I} q_{pimt}}{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{i=1}^{I} MCap_{pimt}} \right] \tag{3.9}$$

- *Storage utilization function*

In order to measure how well the storage capacities at plants, DCs and retailers are being utilized, the ratio of the number of products and raw materials stored to the maximum capacity of storages is calculated.

$$SU = \left[\frac{\sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{i=1}^{I} ip_{rit}}{\sum_{t=1}^{T} \sum_{r=1}^{R} \sum_{i=1}^{I} WCap_{rit}} \right] + \left[\frac{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{i=1}^{I} ip_{pit}}{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{i=1}^{I} WCap_{pit}} \right] + \left[\frac{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{J} id_{pjt}}{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{j=1}^{J} WCap_{pjt}} \right] + \left[\frac{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{k=1}^{K} s_{pkt}}{\sum_{t=1}^{T} \sum_{p=1}^{P} \sum_{k=1}^{K} WCap_{pkt}} \right] \tag{3.10}$$

- *Delivery reliability function*

Delivery reliability is also the fraction of on-time and in full delivery shipments of products to retailers. This is calculated as the ratio of the amount of product delivered at retailers without backorder to the total demand of the product at retailers per period.

$$DR = \left[\frac{\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{k=1}^{K} x_{pjkt} - \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{i=1}^{I} b_{pkt}}{\sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{k=1}^{K} Dem_{pkt}} \right] \tag{3.11}$$

- *Transportation flexibility function*

The function represents the number and type (capacity) of fleet available for delivery. The function is calculated as the ratio of available transportation capacity using selected transportation modes to the total transportation capacity.

$$F = \left[\frac{\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{m=1}^{M} TCap_{simt}\, l_{simt}}{\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{m=1}^{M} TCap_{simt}} \right] + \left[\frac{\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} TCap_{ijmt}\, l_{ijmt}}{\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M} TCap_{ijmt}} \right] + \left[\frac{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M} TCap_{jkmt}\, l_{jkmt}}{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M} TCap_{jkmt}} \right] \tag{3.12}$$

- *Environmental Objective*

The third objective function aims to minimize the environmental impacts of SC network which contains the following sub-functions:

- *Environmentally friendly supplier function*

This function represents the environmental impacts associated with purchasing raw materials from suppliers. Indeed, green procurement is necessary for a company in determining the suitability of a supplier in the sustainable SC.

$$EFS = \sum_{t=1}^{T}\sum_{r=1}^{R}\sum_{s=1}^{S} EIS_{rs}\, p_{rst} \tag{3.13}$$

- *Environmentally friendly operations function*

GHG emissions emitted due to manufacturing products at plants are calculated in this function.

$$EFO = \sum_{t=1}^{T}\sum_{p=1}^{P}\sum_{h=1}^{H}\sum_{i=1}^{I} EIM_{pih} q_{piht} \tag{3.14}$$

- *Environmentally friendly transportation function*

To calculate the environmental impacts of transportation activities, the distance-based method is used. The estimated distance would be converted to CO_2 emission by multiplying the distance traveled by the distance-based emission factor.

$$EFT = \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{r=1}^{R} EIT_{sim} Dis_{si} x_{rsimt} + \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{p=1}^{P} EIT_{ijm} Dis_{ij} x_{pijmt} + \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{K=1}^{K}\sum_{m=1}^{M}\sum_{p=1}^{P} EIT_{jkm} Dis_{jk} x_{pjkmt} \tag{3.15}$$

- **Environmentally friendly warehousing function**

Distribution centers and retailers in various regions might use different energy mix producing the dissimilar amount of GHG emissions. Energy mix is referred to the range of energy sources of a region. For instance, Ontario electricity generation is from a mix of energy sources – nuclear, hydro, gas, coal, wind, and others. However, to calculate the environmental impacts associated with storages, per unit energy requirement at storages are multiplied by the GHG emission produced from the corresponding energy sources.

$$EFW = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{p=1}^{P}\left[\sum_{e_j}^{E_j} EM_{e_j} EF_{e_j}\right] ER_j ID_{pjt} + \sum_{t=1}^{T}\sum_{k=1}^{k}\sum_{p=1}^{P}\left[\sum_{e_k}^{E_k} EM_{e_k} EF_{e_k}\right] ER_k S_{pkt} \tag{3.16}$$

The model also includes constraints (2.17) to (2.39)

3.2.7 Constraints

$$\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{i=1}^{I} R_{rp} q_{pimt} = \sum_{s=1}^{S} p_{rst} \quad \forall r,t \tag{3.17}$$

$$p_{rst} \le SCap_{rst}\, y_{rs} \quad \forall r,s,t \tag{3.18}$$

$$q_{pimt} \le MCap_{pimt}\, z_{im} \quad \forall p,i,m,t \tag{3.19}$$

$$g_{pit} = (1-\sum_{m=1}^{M} \alpha_{pimt}) \sum_{m=1}^{M} q_{pimt} \quad \forall p,i,t \tag{3.20}$$

$$\sum_{i=1}^{I}\sum_{t=1}^{T} g_{pit} = \sum_{k=1}^{K}\sum_{t=1}^{T} Dem_{pkt} \quad \forall p \tag{3.21}$$

$$\sum_{j=1}^{J}\sum_{t=1}^{T} x_{pjkt} = \sum_{t=1}^{T} Dem_{pkt} \quad \forall k,p \tag{3.22}$$

$$\sum_{i=1}^{I} x_{rsit} \le \sum_{\tau=1}^{t} p_{rs\tau} - \sum_{i=1}^{I}\sum_{\tau=1}^{t-1} x_{rsi\tau} \quad \forall s,r,t \tag{3.23}$$

$$\sum_{j=1}^{J} x_{pijt} \le \sum_{\tau=1}^{t} g_{pit} - \sum_{j=1}^{J}\sum_{\tau=1}^{t-1} x_{pij\tau} \quad \forall p,i,t \tag{3.24}$$

$$\sum_{i=1}^{I}\sum_{\tau=1}^{t} x_{pij\tau} \ge \sum_{k=1}^{K}\sum_{\tau=1}^{t} x_{pjk\tau} \quad \forall j,p,t \tag{3.25}$$

$$\sum_{i=1}^{I}\sum_{t=1}^{T} x_{pijt} = \sum_{k=1}^{K}\sum_{t=1}^{T} x_{pjkt} \quad \forall j,p \tag{3.26}$$

$$\sum_{\tau=1}^{t}\sum_{s=1}^{S} x_{rist} - \sum_{\tau=1}^{t}\sum_{p=1}^{P}\sum_{m=1}^{M} R_{rp}\, q_{pimt} \le WCap_{rit} \quad \forall r,i,t \tag{3.27}$$

$$\sum_{\tau=1}^{t} g_{pi\tau} - \sum_{j=1}^{J}\sum_{\tau=1}^{t} x_{pij\tau} \le WCap_{pit} \quad \forall i,p,t \tag{3.28}$$

$$\sum_{i=1}^{I}\sum_{\tau=1}^{t} x_{pij\tau} - \sum_{k=1}^{K}\sum_{\tau=1}^{t} x_{pjk\tau} \le WCap_{pjt}\, u_{j} \quad \forall j,p,t \tag{3.29}$$

$$\sum_{j=1}^{J}\sum_{\tau=1}^{t} x_{pjk\tau} - \sum_{\tau=1}^{t} Dem_{pk\tau} = s_{pkt} - b_{pkt} \quad \forall k,p,t \tag{3.30}$$

$$\sum_{r=1}^{R} X_{rsimt} \le T\mathrm{Cap}_{simt}\, \mathrm{l}_{simt} \quad \forall s,i,m,t \tag{3.31}$$

$$\sum_{p=1}^{P} X_{pijmt} \le T\mathrm{Cap}_{ijmt}\, \mathrm{l}_{ijmt} \quad \forall i,j,m,t \tag{3.32}$$

$$\sum_{p=1}^{P} X_{pjkmt} \le T\mathrm{Cap}_{jkmt}\, \mathrm{l}_{jkmt} \quad \forall j,k,m,t \tag{3.33}$$

$$s_{pkt} \le WCap_{pkt}\, w_{pkt} \quad \forall k,p,t \tag{3.34}$$

$$b_{pkt} \leq Max_{pkt}(1-w_{pkt}) \quad \forall k, p, t \tag{3.35}$$

$$\alpha_{pimt} \leq Max_{pimt} \tag{3.36}$$

$$x_{pjkt} = 0 \quad \forall p, j, k, t \mid \{t.\rho + LT_{jkp} > T.\rho\} \tag{3.37}$$

$$p_{rst}, q_{pimt}, g_{pit}, \alpha_{pimt}, x_{rsit}, x_{pijt}, x_{pjkt}, b_{pkt}, s_{pkt} \geq 0 \tag{3.38}$$

$$y_{rs} \in \{0,1\},\ z_{im} \in \{0,1\}, u_j \in \{0,1\}, w_{pkt} \in \{0,1\}, l_{simt} \in \{0,1\}, l_{ijmt} \in \{0,1\}, l_{jkmt} \in \{0,1\} \tag{3.39}$$

- Constraint (3.17) ensures that the amount of required raw materials purchased from suppliers is equal to the production quantity at plants.
- Constraint (3.18) represents that the number of purchased raw material must be less than the capacity of the supplier.
- Constraint (3.19) states the maximum production capacity at plants with selected technology.
- Constraint (3.20) is the fraction of good products to the total amount of products produced at plants.
- Constraint (3.21) guarantee that the quantity of good products is equal to the product demands at retailers during the planning horizon.
- Constraint (3.22) ensures that the demand of each retailer is satisfied by DCs.
- Flow conservations at suppliers, plants, and DCs are also stated in constraints (3.23), (3.24) and (3.25), respectively.
- Constraint (3.26) guarantees that there would be no inventory at DCs at the end of the planning horizon.
- Constraint (3.27) - (3.29) represents the capacity limitation for storages at plants and DCs.

3.3 Solution Methodology

Goal programming approaches are widely used for dealing with multi-criteria decision-making problems, as well as solving real-world problems (Selim and Ozkarahan (2008a), Ghrobani et al. (2014)). Supply chain planning problems are complex and mostly involved multiple objectives and incommensurable goals. Incommensurability in goal programming problems occurs when deviational variables in different units are directly summed up. To overcome this problem, a normalization constant is required. Given the complexity of the problem and having multiple conflicting objectives, it might be suitable to use GP approaches. A numerical example is illustrated to show the strengths and validity of the proposed methodology.

As mentioned in table 3.2, we have different attributes (criteria) for each function of SC, and we have different objectives to improve overall SC performance. To formulate such kind of problem in which we have different objectives and goals, different weights of different attributes, and different degree of satisfaction, Selim et al. (2008) proposed to use Tiwari et al. (1987) weighted additive approach, which is defined as follows:

$$\begin{aligned} & \max \sum_{k=1}^{n} W_k . \mu_k (\mathrm{X}) \\ & \mathrm{s.t} \\ & 0 \le \mu_k (\mathrm{X}) \le 1 \\ & \mathrm{G(X)} <= 0 \\ & X \ge 0 \end{aligned} \tag{3.42}$$

In this approach, W_k and μ_k represent the weights and the satisfaction degree of the k^{th} goal and objective respectively. This transformation will allow the decision makers (experts) in considered SC functions to assign different weights to the individual goals or objectives or attributes. Five steps are essential to follow to solve the problem. Firstly, optimize each criterion individually; secondly, create payoff table to find a range of objective function, thirdly, develop membership function of each objective function between (0,1); fourthly, convert mathematical formulation to GP model; and finally, solve the model with expert's importance weights of each objective function. This model also considered all the constraints mentioned in the previous section.

3.4 Experimental study

3.4.1 Model implementation

In this section, the same case study introduced in chapter 2 will be used to demonstrate the strength and validity of the proposed approach. The mathematical formulation is implemented in GAMS 24.7.1 and solved using CPLEX solver. Problem decisions can directly or indirectly influence SC criteria defined in mathematical formulation. For the sake of this study, only six criteria related to the case study are selected. The company under study is involved with the production and distribution of frozen food products in North America. Therefore, only those criteria associated with production and distribution planning are selected. These criteria are as follows: transportation cost, inventory cost, storage utilization, flexibility, environmentally friendly transportation, and environmentally friendly warehousing.

First, the model is optimized for the economic, environmental and social objectives introduced in the previous chapter and compared with the results obtained from the weighted sum method. The results of this comparison are addressed in Table 3.1. The weights are considered to be equals for both approaches. As indicated, the solution obtained from the weighted sum method for the economic and environmental objectives are slightly improved, compared to the proposed GP approach.

Table 3.2 below shows the upper and lower bound of objectives and their % change with total cost minimization. To obtain the nadir values (optimum) and generate the range of criteria, the payoff table is also illustrated in table 3.3. Solving each criterion individually and substituting the values of decision variables in objective functions accordingly create the payoff table

Table 3.1 Solution obtained by weighted sum method and GP approach

	Weighted sum method	**GP**	**change**
Eco performance **(Thousand dollar)**	24,925	26,600	-6.7 %
Env Performance **(Ton CO_2)**	1,083	1,106	-2.12 %
Sc Performance	150	0	+150

Table 3.2 Upper and lower bound of objective function with total cost minimization

Criteria	**Objective**	**Upper / Lower Bound optimization**	**Total Cost optimization**	**% Change**
C1 (Min)	Transportation cost (TC) $	11,224,669	11,549,000	+2.81%
C2 (Min)	Inventory cost (IC) $	623,411	792,000	+21%
C3 (Max)	Storage Utilization (SU) %	58	51	-12.07%
C4 (Max)	Flexibility (F) (%)	20	5	-75.00%
C5 (Min)	Environmentally Friendly Transportation (EFT) (tCO_2)	487	3,174	+86%
C6 (Min)	Environmentally Friendly Warehousing (EFW) (tCO_2)	16	586	+97%

Table 3.3 Pay off Table

	Optimization criteria					
Results for	**TC***	**IC***	**SU***	**F***	**EFT***	**EFW***
TC (1000$)	11,224 *	83,995	85,072	86,562	80,075	83,222
IC (1000$)	3,922	623*	1,627	4,098	3,673	2,421
SU (%)	18	52	58 *	18	17	51
F (%)	4.7	13	12.8	20 *	10	11
EFT (tCO_2)	2,916	3,300	3,613	2,975	487*	3,305
EFW (tCO_2)	162	135	157	189	132	16*

3.4.2 Computational time

The weighted sum method and e-constraint are the most widely used approaches to solve multi-objective problems (Mavrotas 2009). The e-constraint method copes with multi-objective problems by solving the sole objective subproblems. In this method, one objective is set as the objective function, and other objectives are transformed into constraints. However, the weighted-sum method turns a multi-objective problem into a single objective problem using weights, which represent the importance of each objective. Both methods have a limitation on the number of criteria they can handle. The proposed formulation is solved using both approaches, and the results are compared regarding computational time. For the sake of comparison, the weights are considered to be equals for all scenarios. The model is implemented in GAMS 24.7.1 and solved with CPLEX solver on PCs with 2.30 GHz and 64.0 GB RAM. The solution time for all scenarios is limited to 20,000 seconds (~ 5.6 hours). The time required by the proposed model to provide a solution is better and more efficient than that by weighted sum and e-constraint methods. The result of these comparisons is represented in Figure 3.2.

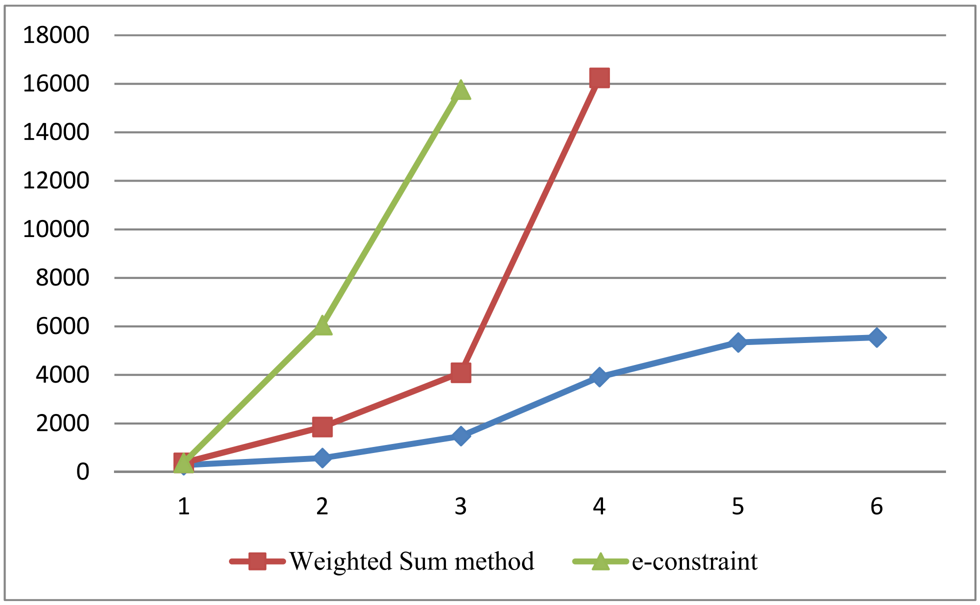


Figure 3.2 Computational time for GP, e-constraint and weighted sum approaches

In instances with more than three criteria, no precise solution was found by the e-constraint method. Besides, the weighted sum method was not able to provide a solution to the problem with more than four criteria.

According to the findings, the proposed GP method is efficient for solving multi-criteria problems in large dimensions. The proposed method can provide acceptable results at a reasonable computational time. The main advantage of GP approach against the weighted sum method and e-constraint is the ability of this approach in providing a solution when multiple conflicting objectives are involved. To determine if there is a significant change in the performance of the three approaches, solutions obtained by optimization of different criteria are compared. As illustrated in Table 3.4 and Figure 3.3, the weighted sum method provides a better solution than those from the e-constraint and GP approaches. However, solving the model with more than four criteria using the weighted sum method is not possible.

Table 3.4 Solutions obtained by optimization of different criteria

Criteria	e-Constraint						Weighted Sum Method						GP					
	No. of Criteria						No. of Criteria						No. of Criteria					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
TC	11,227	14,346	25,358	-	-	-	11,227	11,771	18,481	18,247	-	-	11,227	13,946	20,452	20,262	20,383	27,320
ILC	4,073	624	695	-	-	-	4,073	671	727	852	-	-	4,073	673	730	857	857	964
EFT	2,935	2,963	599	-	-	-	2,935	3,301	734	725	-	-	2,935	3,005	733	722	723	777
EFW	1,555	1,341	945	-	-	-	1,555	838	894	47	-	-	1,555	869	895	46	46	60
SU	0.14	0.52	0.51	-	-	-	0.14	0.51	0.51	0.52	-	-	0.14	0.52	0.51	0.52	0.55	0.55
FL	0.0019	0.0048	0.0056	-	-	-	0.0019	0.0045	0.0054	0.0054	-	-	0.0019	0.051	0.049	0.049	0.051	0.19

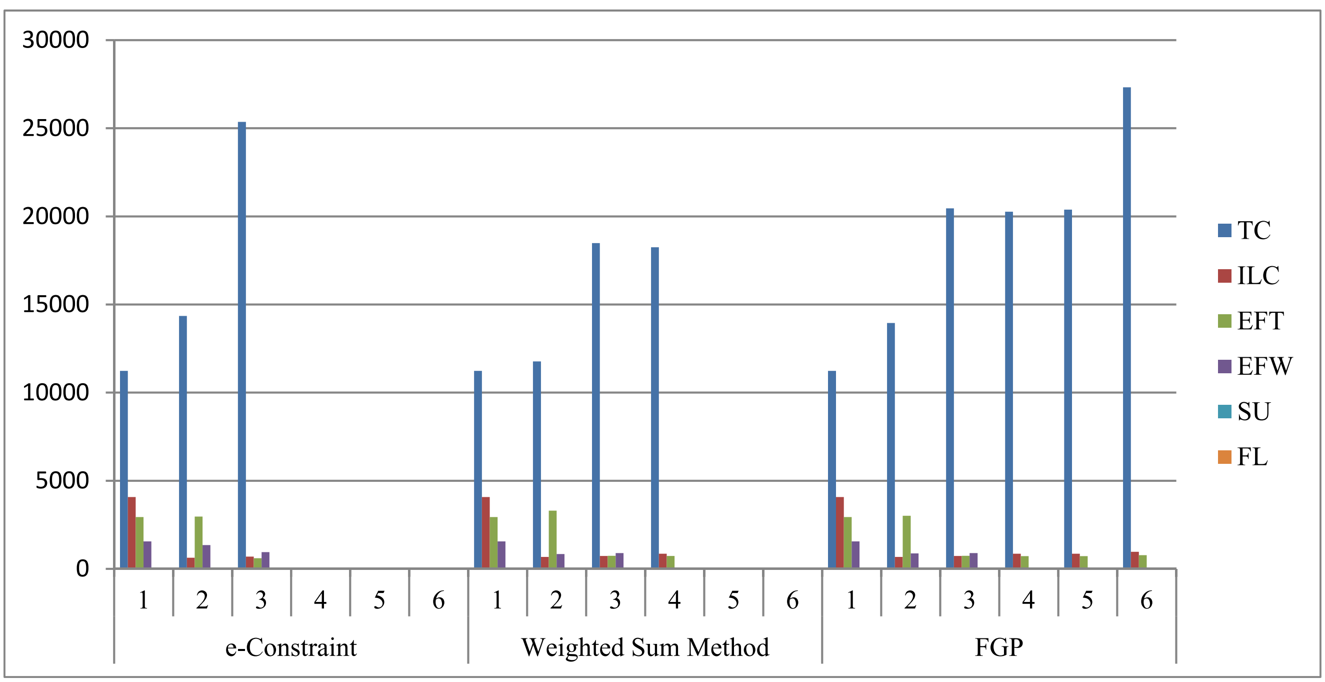


Figure 3.3 Solutions obtained by optimization of different criteria

3.5 Conclusion

In this chapter, a model is proposed in which decision-makers can see the impact of their decisions on different objective functions. As the results indicate, the proposed GP approach is considerably more time efficient compared to the weighted sum method and e-constraint approaches.

In this chapter, a general model is presented by considering the most appropriate decisions criteria (attributes) from literature and aligned with the overall SC performance evaluation system. The results show that the proposed methodology can cope with multiple conflicting objectives at a reasonable solution time. In this chapter, first, a general SC design framework is developed by considering all long-term decision criteria (attributes). A case from a frozen food company was considered because of the availability of data. However, we considered six (6) objective functions (long-term decision criteria) that were related to our case study.

Future studies might focus on different criteria such as social aspects of SC network design. Moreover, Complexity and dynamic nature of supply chain impose a high degree of uncertainty throughout the SC network. Future research might also consider uncertainty in parameters such as price, demand, capacity and so forth using a fuzzy approach.

CHAPTER 4

A MULTI-OBJECTIVE OPTIMIZATION-SIMULATION APPROACH FOR INTEGRATED TACTICAL AND OPERATIONAL PLANNING IN SUSTAINABLE SUPPLY CHAIN

To address the sustainability in the supply chain (SC) planning, the decision makers should integrate the three sustainability dimensions (Economic, Environmental and social) simultaneously into the decision-making process. Sustainability targets are typically defined at long-term planning levels. Decision makers should ensure that sustainability targets are also respected at lower planning levels, achieving decisions at short-term. One of the problems that might arise when SC planning is divided into levels is that solutions at one level may not be consistent with the results of another level. This may affect sustainability goals, leading to the infeasibility of SC plan and a failure to fulfill the demand. To solve this issue, an integrated methodology for sustainable supply chain (SC) planning is developed that includes medium and short-term decisions simultaneously. In the first step, the main decisions related to the tactical planning level are optimized using a mixed integer linear programming (MILP) model to the total cost and environmental impact, as well as to maximize social responsibility within the network. In the second step, from an operational perspective, the operation of the SC network is simulated using a discrete-event simulation model to analyze the feasibility of tactical plans. The tactical optimization model can get insights on the best network configuration which combined with the operational simulation model helps realize the practicability of a given configuration and sustainable strategy. The results from a case study from North American Frozen Food SC showed that prescribed plans from tactical model might be infeasible at the operational level. The integrated approach can help decision makers prevent infeasibility issues. The numerical results can provide managerial and practical insights on a) the impact of economic, environmental and social sustainability on the tactical and operational planning of SC; b) the trade-off analysis among environmental, social implications and associated costs in order to make more informed sustainable SC planning decisions.

4.1 Introduction

According to Anthony (1965), SC planning is carried out at strategic or long-term, tactical or medium-term, and operational control levels. The SC planning levels differ in terms of decisions to be made and the planning horizons. Long-term decisions like supplier selection, facilities location, and technology selection fall into the strategic category. Tactical planning is the connection between strategic direction and operational planning. The decisions in this level are medium-term and generally reviewed every month. Determining the optimal amount of inventory and production, harvest operations planning, and transportation modes fall into this category. The short-term decisions such as transportation, routing plans, and delivery plans are considered as operational decisions. The SC plans also differ in terms of degree of aggregation. Strategic and tactical decisions are associated with aggregated information which helps in better forecasting and is also adequate for decision-making at this level, while operational decisions are the outcome of detailed and disaggregation plans which are based on more accurate information (Kanyalkar and Adil 2005). Aggregation is commonly used for product, capacity, time, and location (Wijngaard 1982).

Integration of SC planning levels has become gradually more important. Besides, sustainability considerations are recognized as a critical matter in SC planning (Seuring 2013). Sustainable SC management focuses on every stage of the SC from suppliers to customers and has an impact on many decisions related to SC planning levels (Reefke and Sundaram 2018, Validi et al., 2015, Varsei and Polyakovskiy 2016, Soysal et al., 2014). With the rapid change and the inherent uncertainty in the SC environment, SC agility becomes a challenge for tactical and operational planning (Esmaeilikia et al., 2016). Thus, the importance of the integration of strategic, tactical and operational level decisions to minimize costs and emissions and maximize social responsibilities cannot be undervalued (Barbosa-Povoa et al., 2017).

To avoid infeasibility and conflicting decisions, the interaction between long-term and short-term SC decisions is crucial. To obtain a feasible SC plan, the integration of SC planning levels are required (Amaro and Barbosa-Povoa 2008, Maravelias and Sung 2009). However, the integration of all planning levels into a monolithic model has received many critics in the literature (Vogel et al. 2017). In fact, since SC planning levels have different degrees of aggregation (e.g., product aggregation, period, costumer zone) and the importance of decisions at every SC level varies, monolithic models are less useful in practice (Fleischmann and Meyr 2003). Furthermore, To reduce the problem complexity, the SC planning can be divided into sub-problems which are solved individually in a hierarchical manner. To avoid infeasibility and inconsistency, interdependency between planning levels should be taken into consideration (Vogel et al. 2017).

Aligning SC decision levels in a daunting task, due to the multi-structural nature of SCs (Ivanov 2010). This is more challenging when sustainability is involved in SC planning. Although sustainability targets are typically defined at long-term planning levels, managers should ensure that these targets are respected at lower levels, achieving decisions at short-term. Ensuring sustainability goals set at top levels impose constraints on the lower planning level. Increasing level of detail (from top to bottom) and degrees of aggregation (e.g., time, products, resources) might affect sustainability goals such as the amount of GHG emitted from transportation and warehousing activities, leading to the infeasibility of SC plan and a failure to fulfill the demand. For instance, the plan set at a strategic level for the reduction of GHG emissions by 20% might not be achievable at the operational level. This could occur due to the uncertainty of the collected data or due to disaggregation mechanism used to link the two planning levels. This problem may lead to infeasibility in some cases and failure to achieve the targets defined at the strategic level.

Recent studies have mostly focused on the improvement of sustainability on individual decision planning levels rather than designing an entire SC (Bhattacharjee and Cruz 2015). Although substantial effort has been put into studying sustainable SC planning and design, there is no research available concerning the development of a comprehensive model that addresses integrated SC planning while sustainability criteria are included. Indeed, must of the literature related to integrated models has focused on traditional economic metrics optimization such as cost minimization or revenue generation. The literature lacks such modeling, not due to the insignificance of the research but due to the complexities involved in integrated sustainable SC planning models.

This study attempts to addressing this gap. This chapter studies an integrated tactical and operational planning for sustainable SC management with an illustration in a case study form the food sector. Management of sustainable food SCs deals with seasonality, perishability, high energy consumption of transportation and warehousing activities, etc., which make this problem even more complicated (Tsolakis et al. 2014, Balaji and Arshinder 2016, Egilmez et al. 2014). Similar to other industry, integration and coordination of SC decision levels in food SC planning are necessary.

In this study, an integrated tactical and operational decision-making model is developed and solved iteratively. A hybrid simulation optimization approach is adopted to address the combined decision planning model. We proposed a framework consisting of two stages. The integrated SC planning model is divided into two sub-problems: long-term model (first stage) and short-term model (second stage). The first stage planning model is related to the decisions required to the tactical planning of SC network in long-term planning horizon, and a detailed short-term planning model is developed to assess the feasibility of the proposed SC design. The decisions variables obtained in the first stage are used as input parameters in the second stage detailed model. Indeed the goal of the short-term model is to ensure that the criteria set by the long-term decision model are satisfied.

The main contribution of this study is to develop an integrated tactical-operational model to prevent the infeasibility of decisions and sustainability goals from separate models. The proposed model combines tactical decisions including location, transportation and warehousing activities together with operational decisions related to delivery and inventory. Considering environmental impacts related to energy grid mix in different locations and social issues related to workers are another aspects of the proposed model in this work. The proposed solution methodology allows the simultaneous consideration of the sustainability dimensions in tactical and operational planning levels. The model could help decision makers make decisions based on SC performance level (including sustainability criteria) they want to achieve and ensure the feasibility of decisions and applicability of sustainable SC strategies. The numerical results can provide managerial and practical insights into the trade-off analysis between environmental, social implications and associated costs in order to make decisions which are feasible in both planning levels.

The remaining of the chapter is as follows. After a brief introduction to the problem, section 2 gives an overview of recent literature in integrated planning and sustainable supply chains. The problem characteristics are identified in section 3. Section 4 presents the two-stage modeling approach developed using simulation and optimization. Section 5 describes the model validation with initial experimentation where the problem data are presented. In section 6, numerical results are conducted using a case study from the "Frozen Food" industry to demonstrate how to manage sustainable supply chains based on the proposed methodology. Finally, future research and possible extensions are discussed.

4.2 Integrated SC planning models

Integration of SC levels has received great attention from researchers in the last decades. This integration can be done either in the form of a monolithic (Weintraub and Navon, 1976) or hierarchical model with one or several iterations (Weintraub et al., 1986). The main benefit of the hierarchical planning procedure is to reduce the complexity and uncertainty of the problem (Stadtler and Fleischmann, 2012). However, the interaction between the decision levels to avoid inconsistency and infeasibility is challenging (Vogel et al., 2017). The solution of the upper decision level (aggregated) might not gain a feasible solution to the detailed (disaggregated) problem. Bitran and Tirupati (1989) used some aggregation and disaggregation techniques to resolve infeasibility in the hierarchical planning approach; however, these techniques cannot guarantee feasibility. The monolithic approach attempts at formulating various planning levels simultaneously in a single integrated model. In this method, the optimal solution is guaranteed for a given problem. However, this method has received many critics in the literature due to the high computational effort required for obtaining a solution (Vogel et al., 2017).

Kanyalkar and Adil (2005) developed a mixed-integer linear programming model for aggregated and detailed production planning of multi-site production facilities. They used different timescales and planning horizon in a single formulation. The aggregation is done over manufacturing capacity and demand based on time and location. Weintraub and Cholaky (1991) introduced a hierarchical approach for forest planning problem, considering two SC decision levels to make the problem in a reasonable size. Sabri and Beamon (2000) developed a multi-objective approach to design SC at strategic and operational levels simultaneously. They used an iterative approach to integrate two sub-models that include cost, customer service levels and flexibility as three performance measurement. Also, a MILP model is developed by Badri et al. (2013) to support strategic and tactical decisions at SC network design. This model helps decision makers make decisions of a four echelon SC about supplier selection, production and distribution as well as expansion planning in a long-term horizon, where strategic and tactical decisions are made in different time resolutions. Bouchard et al. (2017) employed an integrated planning model based on an iterative approach which simulates the interaction between strategic and tactical planning decisions in forestry. This integrated model is solved using column generation decomposition which resulted in an increase of 13% in profit compared to the non-integrated approach. In order to cope with the complexity of this problem, some studies used a Lagrangian decomposition approach to divide the problem into a set of subproblems (Munoz et al. 2015).

Martins et al. (2017) proposed a non-iterative hybrid optimization-simulation approach to obtain the best network configuration for pharmaceutical wholesalers. The optimization model used aggregated data to make the main strategic decisions such as warehouse locations and customer allocation, optimizing operational costs. The simulation model, however, is used to evaluate the network design through operational indicators, such as order waiting times and vehicle delays. As mentioned earlier, the complexity of integrated problems causes computational burden. According to the literature, mathematical formulations are the most widely used approach to deal with multi-criteria decision-making problems. The downside of optimization models is that it is difficult to develop detailed and accurate model which represents the complexity of SC design while having a simple model to solve (Ivanov 2010). Simulation, however, is a powerful tool to analyze the performance of proposed configuration further and evaluate the SC strategy resulted from the optimization model. Simulation-based optimization can integrate optimization approaches into simulation analysis (Martins et al. 2017). Therefore, a more detailed representation of complex SCs is obtained, which allows larger optimization problems to be solved in reasonable times.

The vast literature in quantitative SC models did not focus on the importance of integrated models to achieve sustainability. While substantial effort has been put into studying sustainable SC planning and design, there is no research available concerning the development of a comprehensive model that addresses integrated SC planning while sustainability criteria are included. Therefore, an integrated approach which can assess the feasibility of the decisions at different levels and ensure the applicability of sustainable SC strategies is investigated in this chapter. The tactical optimization model can get insights on the best network configuration which combined with the operational simulation model helps realize the practicability of a given configuration and sustainable strategy.

4.3 Problem Description

The studied supply chain network composed of manufacturing sites, distribution centers, and retailers, as well as transportation links between these nodes (Figure 4.1). Products are manufactured at plants and sent to retailers through distribution centers to satisfy their demand. At the tactical level, products are aggregated into periods. Production capacity is determined by the number of workers at each period. The company produces multiple products, employs various transportation types, and aims to meet the demand over multiple time periods. Transportation between nodes is carried out using trucks with different capacities. Cost of transportation with small trucks is typically higher than bigger trucks.

This model helps managers to make decisions at tactical and operational levels when sustainability concerns are involved. To this end, a two-stage iterative approach is proposed using simulation and optimization tools to avoid sub-optimality and make coordination between two decision levels. An MILP model is developed to make tactical decisions in the SC network, such as production and distribution planning on a midterm horizon. This multi-objective model makes decisions in a sustainable manner, considering three pillars of sustainability. The objective of the tactical optimization model is to optimize the SC configuration and flow of materials. The operational simulation model is integrated to validate the decisions achieved on the upper level and give insight into the trade-off between three conflicting objectives namely economic, environmental and social optimization. The connection between two models is made by constraints which impose in the operational model the objectives set by the tactical model. The planning decisions are identical at both levels, only the degree of aggregation is different. For instance, production quantities and inventory levels are calculated in aggregated forms in the optimization model but disaggregated in the simulation model. The aggregated planning which is the output of the optimization model is passed to the simulation model. The simulation model records the actual delivery to the market which is affected by uncertainty in actual demand to be satisfied based on the plan and depending on production quantity, transportation modes and inventory levels. The production quantity is determined by the number of workers selected for each planning period. Seasonality in demand can affect the number of workers selected at manufacturing sites. Location of distribution centers is also dependent on energy mix and holding cost.

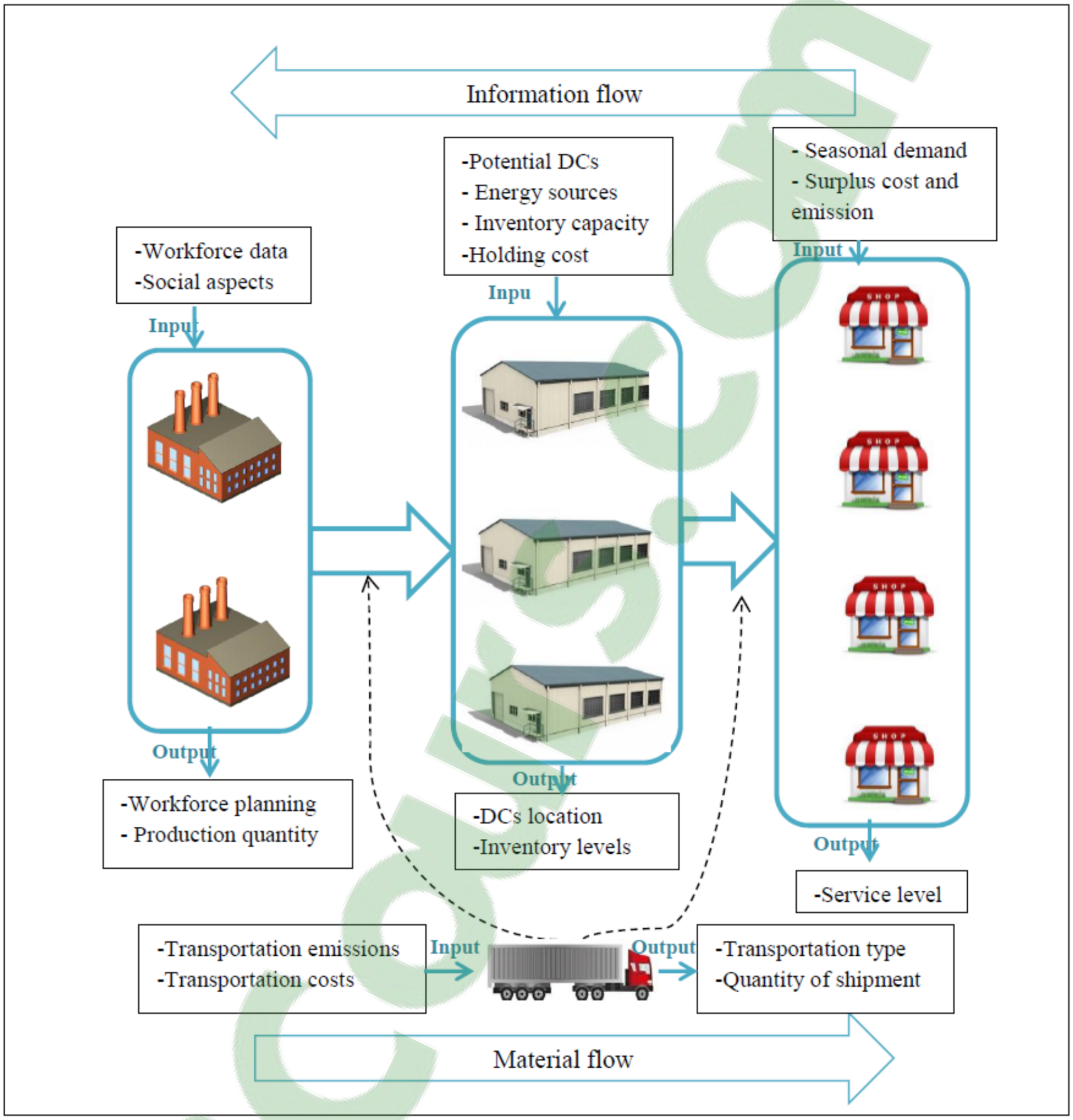


Figure 4.1 Supply chain network

The disaggregation process at the lower decision level may incur infeasibility. Also, sustainability targets defined in upper decision levels might not be achievable in lower decision levels. The purpose of using optimization-simulation in this work is to enhance the solution and redesign the network if necessary.

To formulate the planning models that are relevant to the supply chain in the food sector, the tactical and operational models are developed based on the following assumptions:

- The location of distribution centers (3 PL) is predetermined.
- A pre-assigned capacity for each product at each plant is defined.
- Lead times between plants, distribution centers, and retailers are known.
- Each tactical period is equal to a set of equal operational time periods.
- The planning horizon of both models has the same length.
- The time representation of both tactical and operational models is discrete.

We consider the problem in which the company has set a target in terms of sustainability objectives, and they are looking to identify the following decisions. At the tactical level, the objective is to identify the DC locations (3PL) and sign mid-term contracts for transportation and inventory management and the necessary resources (number of workers) for production activities. At the operational level, the company has to decide on weekly production planning.

4.4 Tactical and Operational planning models: development and implementation

In this section, we will describe the overall computational framework developed and implemented for this study. First, we present the logic of each planning model (decomposed models) and then detail the integration of the two computational models.

4.4.1 Tactical planning model

The tactical optimization model is formulated as a mathematical MILP model, where main tactical decisions regarding supply chain network design are optimized. These decisions include the number of workers at manufacturing sites, aggregated production quantity, the location of distribution centers, inventory levels, the flow of materials, selection of transportation modes and amount of surplus and backorder. This model focuses on economic, environmental and social aspects of a supply chain network, aiming to minimize network costs, as well as environmental impacts and maximize social responsibilities. Cost minimization in this network considers production, transportation and warehousing costs. Production cost relates to workers' salary, as well as hiring and laying-off costs. A second key objective is introduced in this model to capture the environmental impacts associated with transportation and warehousing activities. As mentioned earlier, transportation and warehousing activities are the most significant contributors to produce GHG in supply chain networks, especially for products which need temperature-control systems. Therefore, CO_2 emissions emitted from transportation and warehousing activities are considered as the most important factors to measure the environmental impacts for the optimization model. The distance-based method is used to calculate CO_2 emissions from transportation activities. Since distribution centers and retailers are located in different regions, they might use different energy mix producing the different amount of GHG emissions. Integration of this issue in the formulation allows the model to select those distribution centers which use more environmentally friendly energy sources.

Furthermore, the social aspect of the problem is associated with hiring and laying-off workers at manufacturing sites, aiming to minimize job instability in the network. Some companies use dynamic production rates to match the production with demand and avoid overstock inventory at distribution centers. However, that can have a negative impact on society. To this aim, we minimize the deviation from the average number of workers at manufacturing sites. Using the average number of workers in each period helps to build stable production rates, while the demand satisfaction is guaranteed. The production quantity is indirectly affected by the social objective of the optimization model. However, there is no guarantee that production quantities obtained in the tactical planning model can satisfy the disaggregated demand at the lower decision level model. To integrate these objectives into one single function, a weight is associated with each objective showing the importance of the corresponding objective. Some of the decision variables such as production quantity and inventory levels in this stage are used as instruction for the next stage.

The mathematical formulation based on the multi-objective optimization introduced in chapter 2 is used for this stage. The first objective minimizes the total logistics costs. The second objective minimizes the carbon footprint of the production-distribution system. The third objective considers the minimization of job instability at manufacturing sites.

4.4.2 The operational discrete-event simulation model

The simulation model helps to analyze the model, make decisions at operational planning, and make sure the goals set in tactical level are satisfied. This model aims to replicate the supply chain network activities in detail. Thus, the activities performed by the supply chain network are depicted in the simulation model, from product manufacturing, distribution, and transportation in disaggregated form. Simulating operational planning makes it possible to understand the impact of new supply chain configurations on operational activities and how it will affect the sustainability goals and customer service level. To determine the production quantity in an operational time scale, an optimizer is introduced in the simulation model. Production quantities obtained at the tactical level is used as capacities to constraint the production rates at the operational level. The values for the production quantities at this level are generated by the optimizer and set in the simulation model at each iteration. The optimizer will find the best set of production quantities which minimizes the objective function of the operational model. Transportation and warehousing costs are defined as an objective function in the optimizer. Besides, the amount of unmet demand is considered in the objective function with an associated cost. Environmental impact, however, is integrated as a constraint in optimizer model. The simulation model is further discussed in detail. A baseline scenario can be defined by managers based on the importance of objectives and change the weights accordingly until a feasible configuration is achieved. The manager may also wish to change the weights if the configuration is feasible, but the associated costs are far from what is expected. The detail of the simulation model is described in appendix.

4.4.3 An integrated optimization-simulation approach

We propose a framework consisting of two stages. A multi-objective mixed integer linear programming model is developed to measure the supply chain performance and decisions on a long-term horizon. The decisions and performance criteria obtained in the first stage can be used as instruction for the second-stage model. A solution methodology is developed using simulation to validate the decisions in the upper level and come up with a detail planning model. The model could help decision makers to make decisions based on supply chain performance level (including sustainability criteria) they want to achieve and ensure the feasibility of decisions and applicability of supply chain strategy. The interaction between the two planning models is illustrated in Figure 4.2.

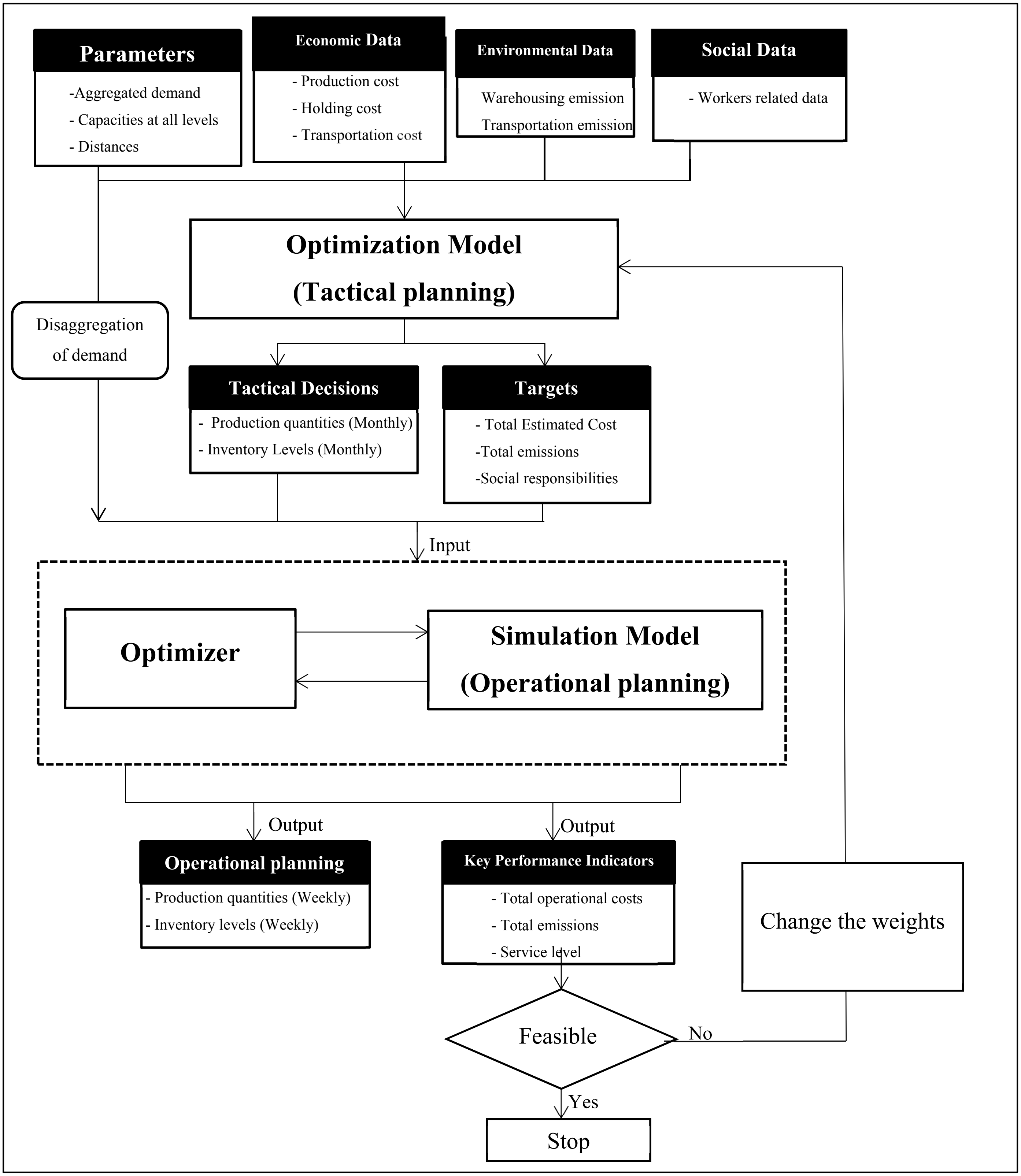


Figure 4.2 Iterative procedure for hybrid optimization-simulation of sustainable SC

4.5 Model Validation and data gathering

In this chapter, we use the case study introduced in chapter 2 for computational analysis. Summary of parameters is reported in Tables 4.1 and 4.2. The aggregated demand of retailers for all product families is also illustrated in Table 4.2.

The data are collected based on the best information available provided by the company. To verify the accuracy of the model and the collected data, the models are validated against the current scenario of the SC. We compared the real cost of each category to the ones given by optimization and simulation models when the current network design of the SC is applied. To this end, we run the models by fixing all the binary variables of the proposed models. The results of this model demonstrate that the model indicators have a good fit to the real-world value. The tactical indicators of each activity, such as production, warehousing, and transportation costs were compared, and the deviation of around 1% was obtained. Furthermore, the operational indicators are compared with real values, and the deviation obtained is about 5%.

The tactical optimization model is implemented in GAMS 24.7.1 and solved using CPLEX solver. With four product families (P=4), two manufacturing plants (I=2), thirty distribution centers (J=30), five hundred and ninety-four retailers (K=594) and twelve time periods (T=12), the proposed MILP model has approximately 1,348,473 variables and 580,447 constraints.

The operational simulation model is validated using approaches suggested by Sargent (2014), such as model behavior analysis and conceptual model validation. The connections and flows among the various processes of the company were examined. Besides, the conceptual model of the simulation model was validated by the company's coordinators. The model behavior was also analyzed using the system input/output data, where real input data was used.

To validate the model and demonstrate the problem, we use the case study data to run the model without sustainability considerations. Section 5.1 and 5.2 illustrate the results obtained from the optimization and simulation model while sustainability is not considered.

Table 4.1 Distribution centers data

Data	Details	Description	Sources
Transportation between plants and DCs	- There are thirty potential 3PLs across united-states and Canada. - Percent of the mass of products sold to: **USA: 52%** ✓ East: 12.95% ✓ Mid-West: 28.64% ✓ North East: 14.34% ✓ North West: 3.11% ✓ South East: 10.60% ✓ South West: 2.41% ✓ West: 27.95% **Canada: 48%** ✓ Eastern: 65% ✓ Western: 35%		Collected data
	The average distance between plants and DCs:		GoogleMaps.com
	Transportation between plants and DCs is done by freezer 53' truck with an average load of 16 tonnes.	Assumption	
	Emission factor for transportation: 1.29 kg CO2 eq./km	Assumption	GFCCC (2015)
Freezing storage in DCs	Average energy consumed for storage: 40 kWh/m3/year	Assumption	Duiven (2002)
	Average product volume: 2.8 L		Collected data

Table 4.2 Retailers' data

Data	Details	Description	Sources
Demand	- Total demand for product families is as follows : ▪ Breakfast: 11177/pallet ▪ Meals: 11750/pallet ▪ Snacks: 1500/pallet ▪ Raw doughs: 21702/pallet - The total mass of products sold: 13,758 tones		Collected data
Transportation between DCs and retail stores	The average distance between DCs and retail stores: 720 km		
	Transportation between DCs and retailers is done by 53' freezer truck with an average load of 16 tonnes.	Assumption	
	Emission factor for transportation: 1.29 kg CO2 eq./km	Assumption	GFCCC (2015)
Freezing storage in retail stores	Average energy consumed for storage: 2,700 kWh/m3/year	Assumption	IEA, 2012
	Average product volume: 2.8 L ▪ Based on the main seller's average volumes		Collected data

4.5.1 Supply chain configuration (tactical planning)

To examine the optimal network configuration which minimizes the cost, the model is first optimized using the economic objective in the optimization model. The result will be used as input for the simulation model to analyze the operational cost associated with the optimal configuration.

A summary of the results from the optimization model is illustrated in Table 4.3. As a result, 22 distribution centers out of 30 are selected in the optimal network. Thirteen distribution centers in Canada and nine in United-states are selected, among sixteen and fourteen distribution centers in Canada and united-states respectively. As mentioned before, the company hires temporary workers to match the production with demand pattern and cut off inventory and transportation costs. This cost reduction results in job insecurity which has a negative social impact on workers. The number of fixed and temporary workers of manufacturing sites in the optimal network is represented in Figure 4.3. As shown, the proposed model uses a fixed number of workforce in some period. However, additional workers are required to matches the production plan to the demand variations. This increases the production cost, while costs associated with warehousing and transportation are decreased.

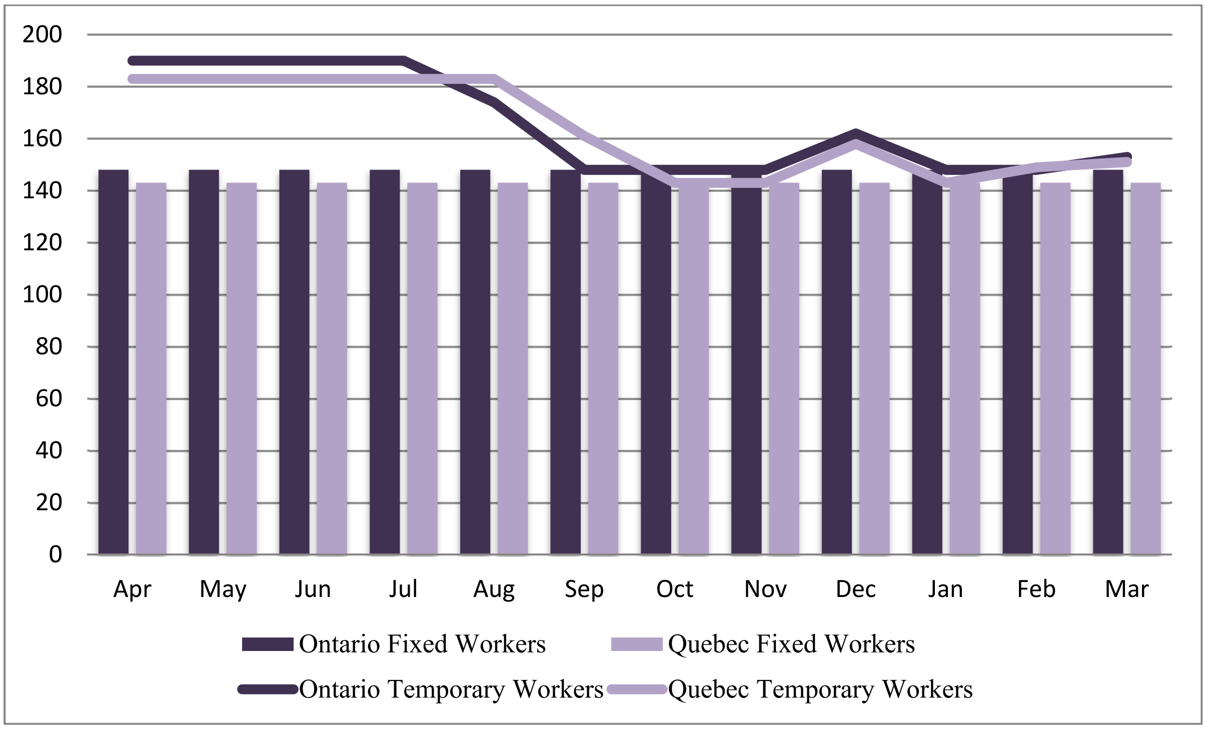


Figure 4.3 Number of fixed and temporary workers at manufacturing sites (traditional supply chain)

Table 4.3 Optimal supply chain network cost

Scenario	Number of DCs	Warehousing cost (Thousand dollar)	Transportation cost (Thousand dollar)	Production Cost (Thousand dollar)	Total Cost (Thousand dollar)
Optimal network	22	792 $	11,517 $	11,549 $	**23,858 $**

4.5.2 Operational supply chain decisions (without sustainability considerations)

This tactical planning is evaluated by the simulation model to examine the feasibility of the network and operational costs related to this configuration. The optimizer finds the optimal set of weekly production quantities which minimize the warehousing and transportation costs, and the amount of unmet demand in the network. Figure 4.6 represents the improvements of the operational costs over simulation runs. As suggested by OptQuest User's guide, to find high-quality solutions for a model with 20-50 variables, a minimum number of simulations is set to 2000. The networks costs of operational planning model compared to tactical planning costs are addressed in Figure 4.4.

As observed in Figure 4.4, the cost of transportation in the operational model is slightly increased. To transfer the disaggregated production quantities from manufacturing sites to costumer's location, the majority of shipments are carried out using small trucks. Ninety-three percentages of the shipments are transported using small trucks in the operational planning model. This is because the shipments are in smaller quantities for the weekly planning, compared to the aggregated planning. This is the reason why operational costs associated with transportation activities have increased. The percentage share of trucks in both models is depicted in Figure 4.5. However, the operational cost of warehousing is decreased, compared to the warehousing cost at tactical planning model. According to the strategy defined in the operational model, the products would be stored for a shorter period at distribution centers. Also, the amount of surplus at retailers is significantly decreased in operational planning model. Figure 4.4 clearly shows that transportation cost has increased in operational planning model. This is because meeting disaggregated demands increase the frequency of shipments which increases transportation cost.

Conversely, warehousing cost is significantly decreased. Overall, the operational cost of the network is increased by about 5%, compared to the estimated cost at tactical planning network. Compared with tactical planning, the number of small trucks has considerably increased in operational planning. Under this configuration, the service level is 100%. As a result, the operational simulation model is able to fulfill the disaggregated demand by an increase of 5% in costs. In the next section, we explore the impacts of sustainability in supply chain planning levels.

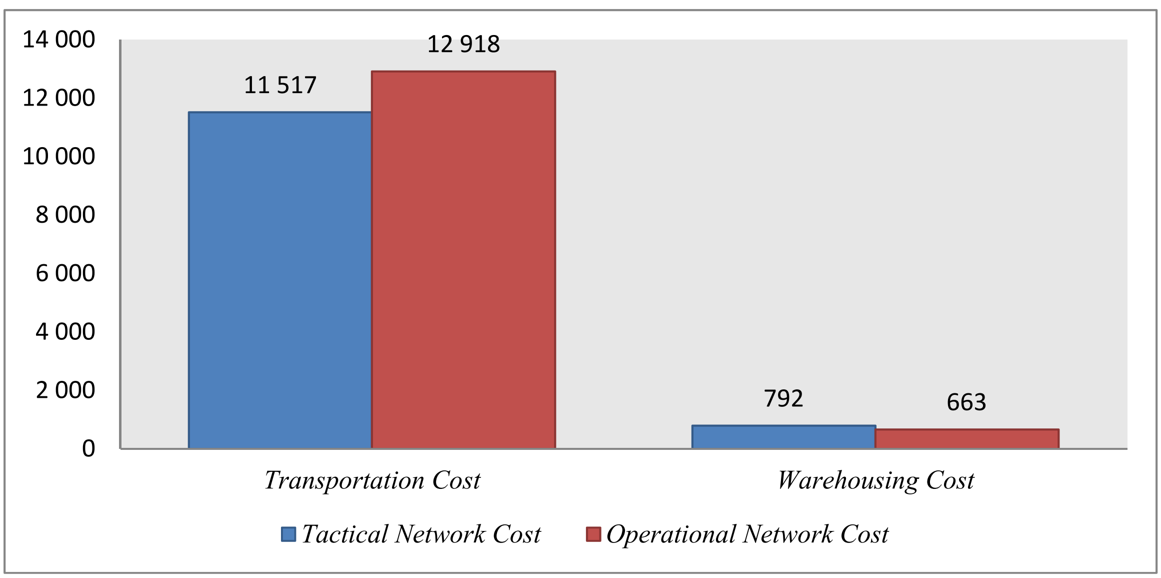


Figure 4.4 Tactical network costs vs. operational network cost

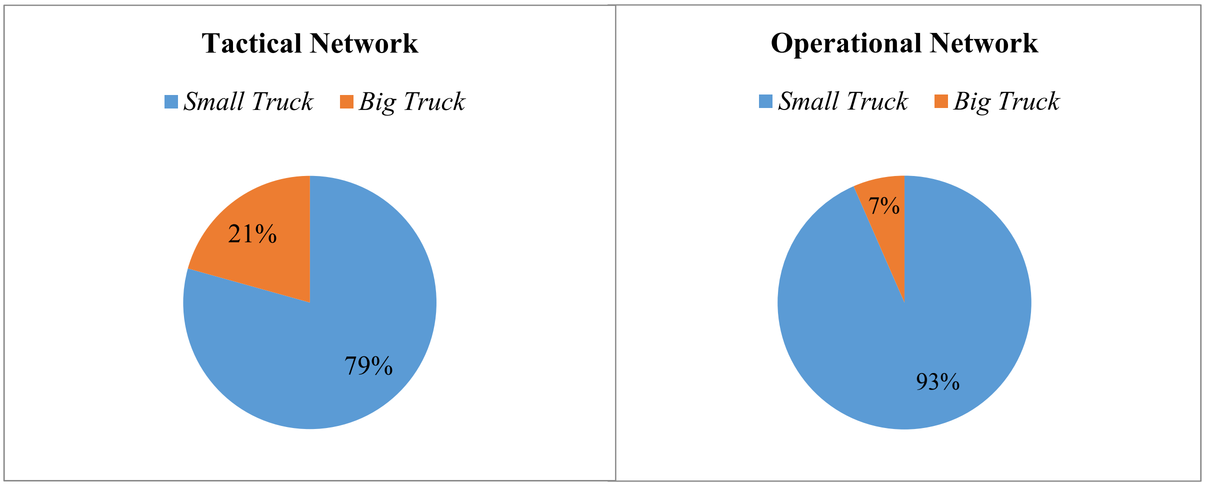


Figure 4.5 Distribution of trucks in tactical and operational networks

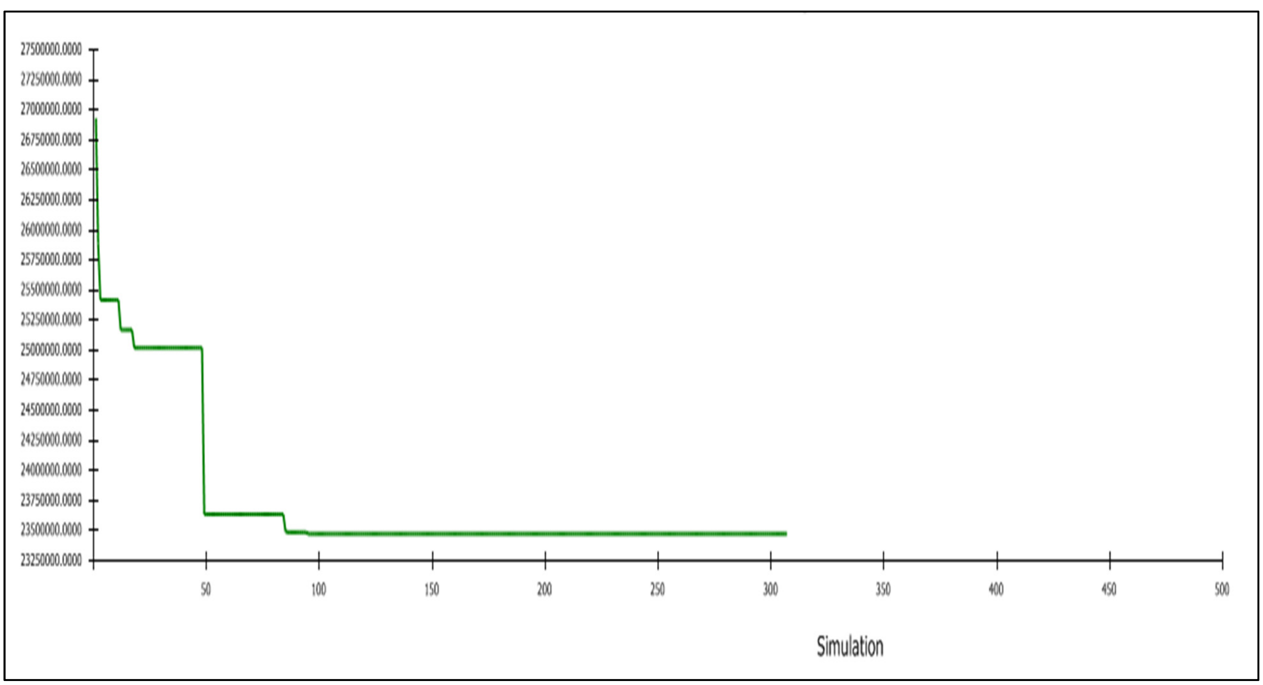


Figure 4.6 Solution improvements over simulation runs

4.6 Computational results

4.6.1 Hierarchical tactical and operational sustainable supply chain planning

The company is willing to identify potential strategies to reduce environmental impacts and promote social responsibilities besides cost reduction. According to the company's strategy, we consider the scenario with equal weights as a base case to examine the network configuration which minimizes the cost and environmental impacts, as well as maximizing social objectives. The result will be used as input for the simulation model to analyze the operational cost associated with this configuration. The result from the optimization model shows that only 18 distribution centers out of 30 are selected in the optimal network. Under this supply chain strategy, the disaggregated demand cannot be fully met, and the service level is not 100 %. Therefore, the sustainable strategy defined at the tactical level cannot be achieved. Given the number of workers selected at manufacturing sites (see Figure 4.7), the simulation model is not able to find a solution which fulfills the disaggregated demand. Besides, only 18 distribution centers are selected in this configuration with limited capacities which might be another reason to cause infeasibility in operational decisions. As a result, integrating sustainability into decision-making process can cause inconsistency of decisions at the lower planning level. Table 4.4 gives a summary of hierarchical tactical-operational decisions obtained in equal weights scenario and compared with the traditional supply chain network configuration. As addressed in table 4.4, estimated and operational network costs are increased in the sustainable supply chain configuration, while environmental and social impacts of the network are significantly decreased. Furthermore, going towards sustainability goals, the given configuration is not able to fulfill the disaggregated demand at the operational planning level which is in contradiction to the company's goals.

In the next section, we use the proposed integrated model to find a solution with the least deviation from the base case scenario through interaction with decision makers. This strategy helps decision makers find a network configuration which is close to the company's goals.

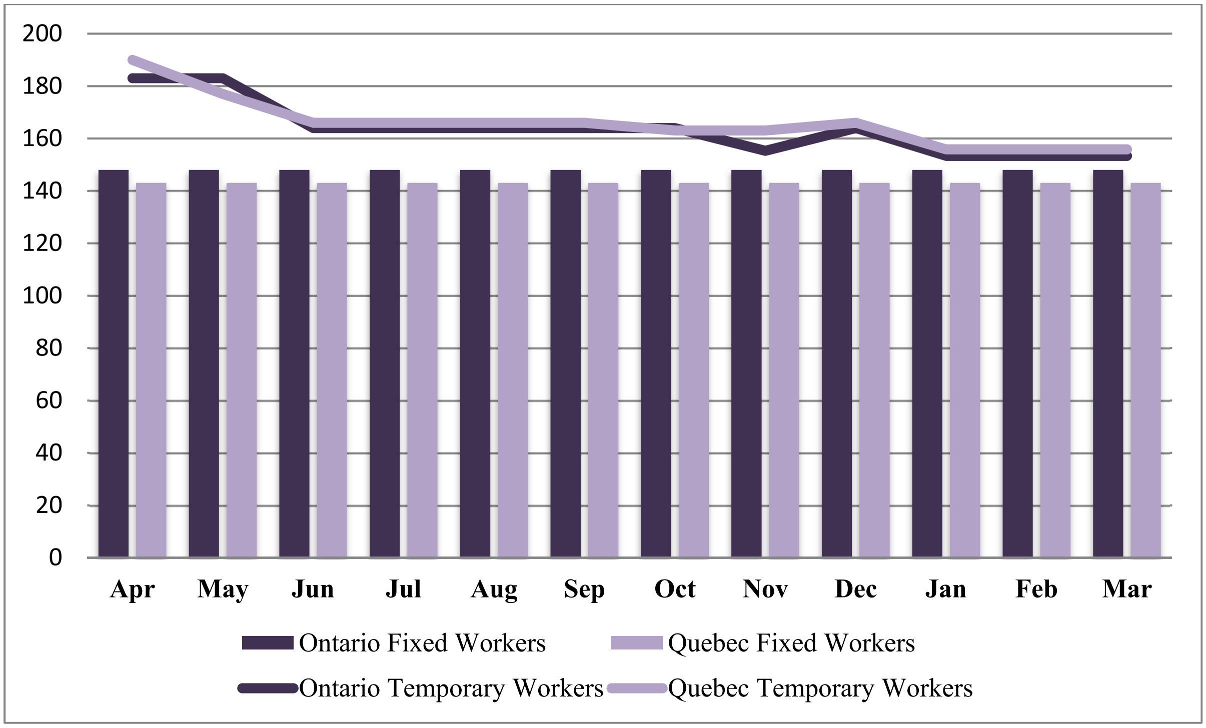


Figure 4.7 Number of fixed and temporary workers at manufacturing sites (equal weights scenario)

Table 4.4 Summary of hierarchical tactical-operational SC decisions

	Optimization model	Simulation model							
	Estimated Network Cost	Operational Network Cost	Sustainability Targets		Amount of Unmet Demand (Pallet)				Service level (%)
			Environmental	Social	P1	P2	P3	P4	
Traditional SC	23,858 $	25,130 $	3,760	406	-	-	-	-	100
Sustainable supply chain (equal weight)	24,925 $	26,118 $	1,083	150	117	102	45	-	99.42
Difference	+4.47 %	+3.93 %	-71 %	-63 %	+117	+102	+45	-	-0.58 %

4.6.2 Integrated tactical-operational supply chain decisions

As shown in the previous section, the interaction between decision planning levels is necessary to avoid inconsistency and infeasibility of decisions. However, solving the problem in a hierarchical manner leads to sub-optimality for the overall problem. Therefore, we used the proposed integrated approach to find a feasible strategy which helps the company achieve its goals. However, interaction with decision makers is crucial to find a proper sustainable strategy. To help decision-makers make a trade-off between economic, environmental and social objectives and get insights on the costs associated with improving environmental and social performances, we run some scenarios with different weights for which it is not possible to improve one performance without degrading other ones. The weights are randomly generated to examine how different network configurations impact the supply chain performances. It will also give manager insights on how much costs to bear to minimize environmental impacts and maximize social responsibilities in the network. Then, the simulation model evaluates the feasibility of the configuration and associated costs with respect to the sustainability targets. A penalty cost for unmet demand is considered in the operational model. Besides, the environmental impact is bound by the target value obtained at the tactical level to ensure that supply chain configuration can meet the demand with respect to the environmental target defined in upper planning level. As shown in table 4.5, not all supply chain configurations are capable of satisfying the disaggregated demand while they respect sustainability targets.

Table 4.5 Sustainable supply chain strategies using different weights

Scenario	Weights			Operational Network Cost	Sustainability Targets		Amount of Unmet Demand (Pallet)				Service level (%)
	w_1	w_2	w_3		Environmental	Social	P1	P2	P3	P4	
1	0.7	0.3	0	26,926 $	1,121	410	108	-	-	115	99.51
2	0.6	0.2	0.2	24,512 $	1,123	55	-	-	-	-	100
3	0.5	0.5	0	30,527 $	1,015	387	-	-	-	-	100
4	0.5	0.25	0.25	26,375 $	1,080	404	102	83	-	-	99.60
5	0.6	0.3	0.1	26,818 $	3,948	370	-	-	-	-	100
6	0.5	0	0.5	24,993 $	5,000	0	-	-	-	-	100
7	0.3	0.7	0	30,822 $	2,507	387	-	-	-	-	100
8	0	0.8	0.2	32,932 $	559	250	85	162	34	78	99.22

We compare the base case scenario with different scenarios in order to find a solution with the least deviation. In the end, it is up to managers to decide which scenario leads the company to achieve its goals. Table 4.6 addresses the percentage deviation of feasible scenarios for cost, GHG emissions, and social impacts from the base case scenario.

As indicated in Table 4.6, the network cost can be improved in scenarios 2 and 6 by almost 5 percent, while the service level is fully satisfied. As a result of this improvement of the base case scenario, environmental impact is significantly increased in scenarios 6. The social impacts are at its optimum level in scenario 6. However, a small increase in environmental impacts can be seen in scenario 2, while social responsibility and network cost are improved, and service level is 100 %. As a result, scenario 2 is the closest options to be replaced by a base case scenario. Besides, while deviation for cost and environmental impacts in scenario 1 and 4 is around 5 %, social responsibility is significantly worsened, and the service level is not fully met. According to scenario 2, it can be concluded that with around a 4% decrease in environmental impacts, a desirable level of service level, cost, and social responsibilities can be achieved.

In scenario 1, in order to keep the inventory emission low, only 16 DCs with limited capacities are selected. These DCs typically use more environmentally friendly energy sources, but at the same time, they have higher holding costs. As a result of this configuration, production rates fluctuate over the planning horizon by hiring and laying-off workers. This fluctuation decreases the social responsibility by 410 workers hired and laid-off in different periods. Although this configuration slightly increases the cost and keeps the emissions low, the demand is not completely met. The operational model is not able to find a solution to satisfy the disaggregated costumer's demand with sustainability boundary defined in this scenario. In scenario 4 and 8, the disaggregated demand also cannot be fulfilled. Indeed, the details considered in operational planning model may cause the infeasibility of targets set at the tactical planning level.

In scenario 2, the weights assigned to the objective functions are 0.6, 0.2 and 0.2 for economic, environmental and social objectives respectively. Despite a few emissions reported in this scenario, the model can efficiently manage to meet the demand while the operational cost is also slightly improved and the environmental target is well maintained. By giving more weights to the environmental objective in scenario 8, only 11 DCs are selected which are located in two Canadian provinces (i.e. Ontario and Quebec) which use environmentally friendly energy sources (Mostly Hydroelectric and Nuclear). This is the reason why transportation and warehousing costs are significantly increased in this scenario.

Table 4.6 Percentage deviation from base case scenario

	S2	**S3**	**S5**	**S6**	**S7**
Network Cost	6.15	-16.88	-2.68	4.31	-18.01
Environmental Impacts	-3.69	6.20	-264.54	-361.68	-131.49
Social Impacts	63.33	-158.00	-146.67	100.00	-158.00

Figure 4.8 compares the GHG emission of each scenario with the optimum value of environmental impact obtained at the tactical planning level. The environmental impact of scenarios in which the weights associated with the economic objective is 30% or more, has typically increased by more than 50 percent. However, reducing environmental impact always increases total cost and social impact. Furthermore, in scenario 8 in which GHG emissions are at the lowest level, the disaggregated demand is not fulfilled. This is typically due to the number and location of DCs selected in these scenarios.

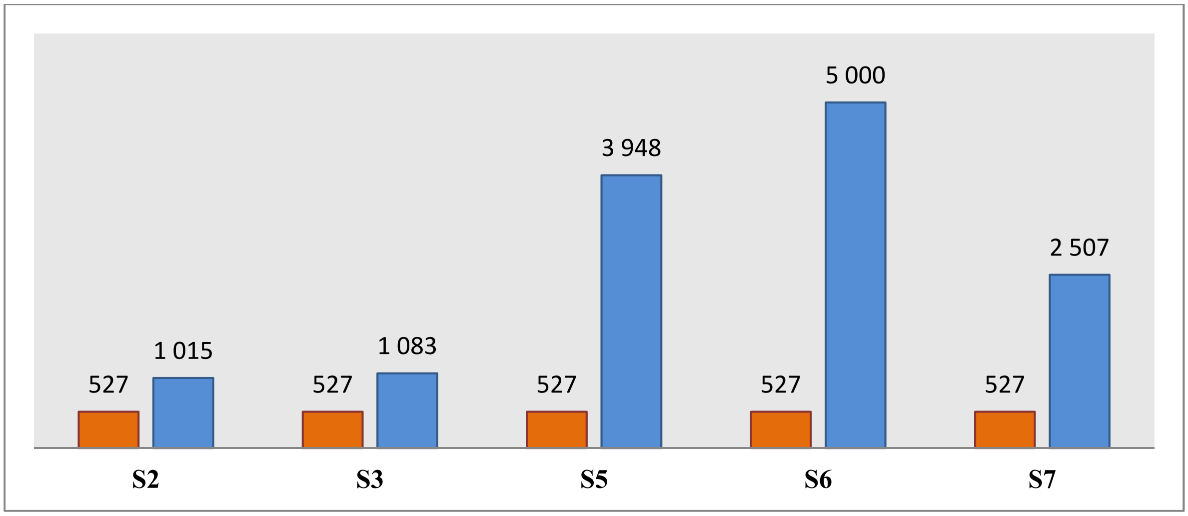


Figure 4.8 Environmental targets in each scenario vs. optimal environmental impact (Ton CO_2)

As shown in Figure 4.9, in order to keep the network cost and GHG emission down, we must degrade social responsibility. However, social impact is significantly decreased by giving weights of more than 20% to this objective in scenario 2 and 6. As one of the outcomes of this change, GHG emission is intensely raised in scenario 6.

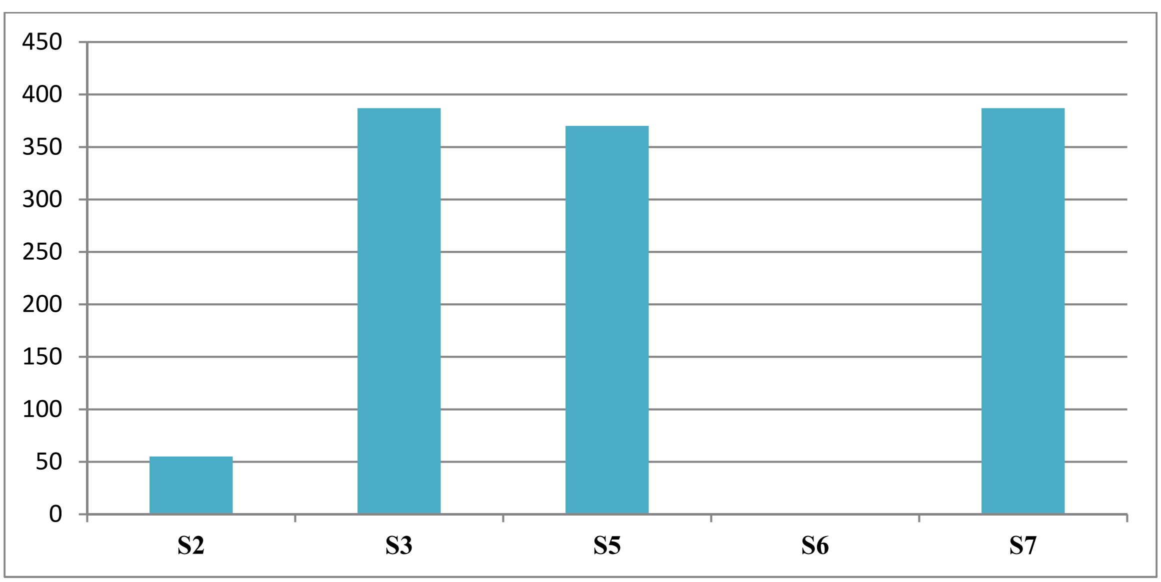


Figure 4.9 Impact of social responsibility on different scenario

The detailed network cost associated with each scenario is described and compared with the base case scenario in table 4.7. As illustrated, the transportation cost is significantly increased in some scenarios, compared with the transportation cost at base case. However, the warehousing cost is decreased in most of the scenarios, which is typical because of the selected DCs.

Table 4.7 Detailed Tactical and operational SC network costs in each scenario vs. base case

Scenario	No. of DCs	Production Cost		Transportation Cost		Warehousing Cost	
		Operational	%Change	Operational	%Change	Operational	%Change
S2	20	11,538	-0.02	12,128 $	-6.2	845 $	-19.45
S3	19	11,542	0.02	18,069 $	39.76	916 $	-12.68
S5	19	11,554	0.12	14,327 $	10.81	937$	-10.68
S6	20	11,530	-0.09	12,394 $	-4.14	1038 $	-1.5
S7	19	11,552	0.1	18,299 $	41.53	971 $	-7.44

The result of the case study showed that sustainable SC strategies set at tactical level might be infeasible due to sustainability boundaries. The disaggregated demand could not be met in some periods. This mainly occurs because the production and inventory capacities chosen at a tactical level would not be sufficient to meet the disaggregated demand. According to three conflicting goals, it is more costly for the company to keep GHG, social objective and service level at acceptable levels, compared to a situation in which only economic objective is considered.

As indicated, the design prescribed by the tactical model in some cases would not be implementable when sustainability considerations are taken into account. That infeasibility occurs because the quantity of products that are transported to the retailers would not be sufficient to meet the disaggregated demand. That is why the service levels are not fully satisfied in some instances (scenario 1, 4 and 8). Moreover, in cases with seasonality, the variations in demand or supply might cause infeasibility to fulfill the demand. Therefore, developing an integrated tactical and operational model to address sustainability objectives and seasonality seems to be unavoidable for the case under study. In order to cope with seasonality, the frequency of shipments would be increased, which would increase transportation costs and emissions that were not considered in the tactical model. The integrated approach obtains a better estimation of SC costs since it considers sustainability concerns and seasonality.

4.7 Conclusion

This chapter studies an integrated tactical and operational planning for sustainable SC management in the case of food SC. An integrated long-short term decision model is developed and solved iteratively. A hybrid optimization-simulation is adopted to solve the integrated decision planning model. The decisions obtained at the upper planning level impose constraints for the successive lower decision level. A solution strategy is also applied in the short-term decision model in order to obtain the decisions at the lower level. Using a case study in Canada, it was shown that the solution obtained from the tactical optimization model would be infeasible at the operational planning level. First, the disaggregated demand of some retailers could not be met in some periods. Second, the production and inventory capacities chosen by the tactical model would be insufficient to meet the disaggregated demand. Lastly, the design prescribed at a tactical level might be infeasible due to sustainability boundaries. The proposed integrated approach attempts at solving the issues above. In the integrated model, decisions related to the facilities, location, transportation, and warehousing activities were made at the tactical planning level, while decisions related to delivery and inventory were addressed at the operational planning level. Instead of considering only the SC costs, the environmental impacts of transportation and warehousing activities, as well as the social impacts related to workers, were taken into account.

The integrated approach can help decision makers prevent infeasibility issues. The numerical results can provide managerial and practical insights on a) the impact of economic, environmental and social sustainability on the tactical and operational planning of SC; b) the trade-off analysis among environmental, social implications and associated costs in order to make more informed sustainable SC planning decisions. The integrated tactical-operational model is developed as a general model; thus, it applies to similar studies in other areas where sustainability and seasonality exist.

In this work, the focus was on the tactical and operational planning of SC and consideration of strategic planning level was ignored in the proposed methodology. For some real-world cases, due to intensive data scale, considering the whole complexity and dynamic nature of supply chain is almost impossible. Therefore, some model simplifications are required. Besides demand, the inclusion of other uncertain parameters in planning levels would be a possible direction for future research. Another extension would be the inclusion of more realistic constraints such as vehicle routing practices which might be useful to reduce transportation costs and emissions. More efficient methodologies can be developed to determine the weights associated with each objective. In this study, social aspects of sustainability are limited only to job stability in manufacturing plants. Social sustainability, however, is linked to reducing the risk related to unsafe work condition, low salary, excessive working hours and so forth, which were not taken into consideration.

CONCLUSION

Moving toward sustainability, organizations need to change the way their supply chain is managed and designed through simultaneous consideration of economic, environmental and social measures at strategic, tactical and operational planning levels. Traditionally, sustainable supply chain management is treated independently at strategic, tactical and operational levels. Although the integrated planning approach adds a level of complexity to an existing problem, it makes the problem more realistic and efficient for the decision making process. In this work, a novel and more realistic approach is proposed to design sustainable supply chains.

General conclusion

Overall, this work contributes mainly to the integration of tactical and operational levels while sustainability factors and more specifically environmental and social aspects are taken into consideration. Furthermore, different Operation Research approaches including simulation and multi-objective optimization methods such as weighted-sum method, goal programming, and epsilon constraint have been used or also improved in order to design and give insights on evaluating sustainable supply chain strategies. This work gives researchers and practitioners insights on how to design/redesign a sustainable supply chain and evaluate supply chain performance in order to achieve sustainability goals.

In the second chapter, this study proposed a multi-objective MILP model to support the tactical planning of a sustainable supply chain network. This chapter aimed at answering our first research question: How to effectively develop an integrated sustainable production/distribution decision model for Frozen food supply chains. We provided a supply chain planning model that integrates the three objectives of sustainability: total cost, GHG emissions, and social responsibilities. In this chapter, we proposed a mathematical formulation that allows supply chain decision makers to analyze the performance of the frozen food supply chain and identify actions to implement a sustainable supply chain strategy. A case study is proposed to show the applicability of the model in a real industry setting. First, we optimized each objective independently to see how supply chain configuration is affected by each performance. Then, different scenarios are designed and analyzed in order to give insights about the trade-off between the three conflicting objectives. The weighted-sum method is applied for comparing the different objectives. Due to the huge amount of energy consumed in the food sector, the trade-off between environmental and economic objective is more challenging, compared to other industries. This is even more complicated when the social aspects of the problem are also taken into account. Social performance is mainly influenced by seasonality of demand. The study shows how seasonality in the supply chain can affect the sustainability aspects of the network.

In the third chapter, we extended our model in order to ensure a more realistic representation of the supply chain considered in this research. This chapter aimed at answering our second research question: How to solve the sustainable supply chain distribution model with many variables and multiple conflicting objectives, leading to a large-scale multi-objective optimization problem. A multi-criteria optimization model and a goal programming approach were presented to cope with multiple conflicting objectives. The results show that the proposed methodology can cope with multiple conflicting objectives at a reasonable solution time. We proposed a general model by considering the most appropriate decisions criteria (attributes) from literature and aligned with the overall supply chain performance evaluation system. The finding of this chapter shows that existing multi-criteria optimization models are not efficient to cope with multiple conflicting objectives with many decision variables.

In the fourth chapter of the thesis, a hybrid optimization simulation approach is proposed to validate the decisions made in chapter 2 and ensure the feasibility of sustainability goals set in the optimization model. This chapter aimed at answering our third research question: How to integrate supply chain decisionn levels to ensure the feasibility of a sustainable supply chain strategy. A framework consisting of two stages is proposed. The first stage planning model is related to the decisions required to the tactical planning of supply chain network in long-term planning horizon, and a detailed short-term planning model is developed to assess the feasibility of the proposed supply chain design. The model could help decision makers to make decisions based on supply chain performance level (including sustainability criteria) they want to achieve and ensure the feasibility of decisions and applicability of sustainable supply chain strategies. Using the case study introduced in chapter 2, this study shows that the proposed optimization-simulation methodology is very efficient and offers a decision support tool for decision makers seeking to identify the best tactical decisions to achieve sustainability objectives. The results of this chapter show that an integrated approach that considers sustainability criteria at both levels is more efficient for the decision-making process.

Limitation

The results and findings of the presented study have some limitations.

As was shown in the results of chapter 2, the storage and transportation of food products are sensitive parts of this supply chain. However, deterioration and quality changes of products during these phases were not considered in this research. The environmental impact of the problem is restricted to GHG emitted from transportation and warehousing activities, while other environmental indicators such as waste, land use and water consumption could be investigated.

In chapter 4, the focus was on the tactical and operational planning of the supply chain and consideration of strategic planning level was ignored in the proposed methodology. Simultaneous work with several methods and creating a balance between simulation, optimization, and heuristic parts are challenging and require professional skills. For some real-world cases, due to intensive data scale, considering the whole complexity and dynamic nature of supply chain is almost impossible. Therefore, some model simplifications are required.

In this study, social aspects of sustainability are limited only to job stability in manufacturing plants. Social sustainability, however, is linked to reducing the risk related to unsafe work condition, unfair salary, excessive working hours and so forth, which are not taken into consideration. Furthermore, in chapter 3, this study attempted to identify the key performance indicators from existing literature and integrated them into the decision-making process, while incorporation of social measures was excluded.

Future research

The tactical model in chapter 2 is extendable in multiple ways which can be suggested as future research areas. It is valuable to investigate supplier selection and capacity expansion for general networks. Incorporation of other environmental and social indicators mentioned in the previous section can also be investigated. For instance, other sources of emissions such as emission from refrigeration in more details, and other sustainability performances such as water consumption and waste can be further explored. Also, we assume that all parameters used in this model are deterministic. However, in a real-world problem, some parameters such as demand and price are uncertain. To overcome this issue, the use of stochastic programming, robust and fuzzy models are suggested.

The model introduced in chapter 3 can also be extended to the incorporation of other criteria, empirical application, and consideration of supply chain dynamics. Regarding multi-objective problems, developing efficient solution methodologies which can cope with large-scale problems can be the future directions of multi-objective problems. It is noticeable that the complexity of multi-objective problems adds a computational burden. In this situation, using heuristics and metaheuristics algorithm might be useful to solve the problem in an affordable time. Eventually, from an application standpoint, exploring different industrial application is necessary to ensure the applicability of the proposed methodology.

In chapter 4, the study can be extended to include the strategic planning level which would lead to more feasible and reliable planning model. The model can also be modified at the operational level. Various operational policies can be studied in order to investigate the best policy for a given configuration. Another extension would be the inclusion of more realistic constraints such as vehicle routing practices which might be useful to reduce transportation costs and emissions. One of the possible directions for future studies is to include uncertain parameters beside demand in the problem. This will add a higher level of complexity to the problem and require more efficient solution methodology to overcome this problem.

APPENDIX

The operational model is developed as a discrete-event simulation model in the Arena Simulation package. Decisions variables obtained in the optimization level can be used as input for the simulation model. As an optimizer, OptQuest is chosen because it is the best tool for evaluating the simulation model results conducted in Arena simulation software. OptQuest searches for the optimal solution within the simulation model which minimizes/maximizes an objective function while defined constraints are satisfied. OptQuest incorporates some metaheuristic algorithm such as tabu search, scatter search or neural networks to lead its search for a better solution. In this section, different modules of our supply chain network developed in the simulation model are explained in detail.

- *Optimizer*: Optimizer aims to find the best possible set of production quantities for operational periods at each tactical planning period which minimize the objective function. In particular, if we consider operational planning as weekly and tactical planning as monthly, each tactical planning period is equal to four operational planning periods. We ensure that summation of production quantities at operational periods does not exceed the corresponding production quantity at tactical planning by imposing constraints. The objective of this optimizer is to minimize the transportation and warehousing cost while keeping service level goal in check. A penalty cost is considered in the objective function to avoid unmet demand in the network as much as possible. Furthermore, environmental impacts produced from transportation and warehousing activities are limited to the targeted environmental impacts achieved at tactical planning level by imposing a constraint.

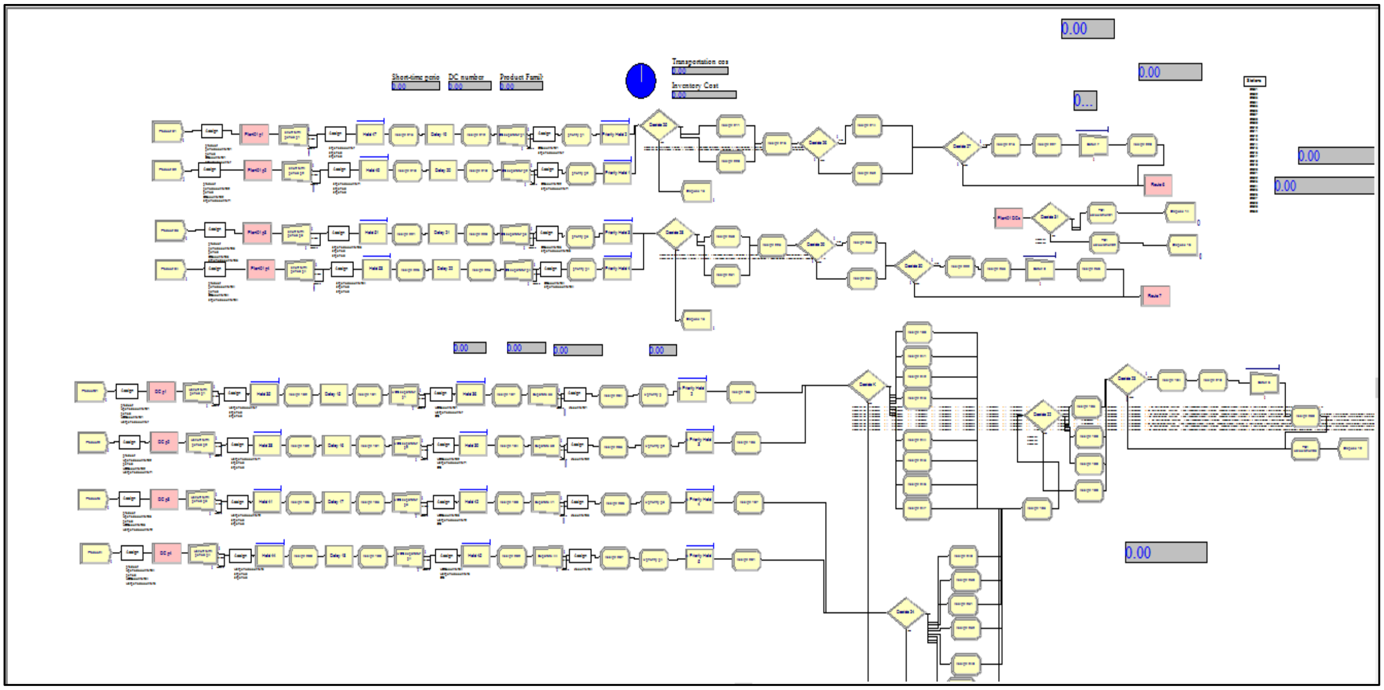
- *Production:* Manufacturing sites are created as separate modules in the simulation model. Each manufacturing site is assigned to several product families. The values of production quantities for different products are obtained from the optimizer. Products are aggregated into product families. Products are distinguished as product family using different assigned attributes.

- *Inventory policy:* Products are sent to distribution centers if there is production quantity at the manufacturing site and enough capacity in distribution centers for specific product family in that period. The capacities of distribution centers are determined using obtained inventory levels at the tactical planning level. Products will be sent to the closest distribution centers which have the capacity for that product per period. For this purpose, a priority table is defined. Distribution centers with shorter distances to manufacturing sites are assigned to higher priority attributes compared to those with longer distances. If the production quantity at that period exceeds inventory capacity per product, the difference of the production quantity and inventory will be transferred to the distribution center. The remaining will be stored for the next period. Then, the inventory level, warehousing cost, and emission at the operational planning period will be updated accordingly.

- *Transportation policy:* Shipments between nodes are carried out using different transportation modes. In this module, the transportation costs of available transportation modes are calculated and compared. The shipment will be sent to the assigned location using the cheapest transportation option. The transportation cost will be calculated according to the selected transportation mode and quantity of flow.

- *Demand:* Demands for each product per period at retailers are predefined in the simulation model. First, the model checks whether there is enough inventory level at distribution centers for a specific product at that period. Next, the model searches for the closest retailer with demand for that product at that period. The required amount will be sent to the retailer. If the total amount of inventory for the product in that period is less than the demand, the difference will be considered as a lost sale. However, if the total inventory exceeds the total demand, the difference will be stored as surplus which can be used to fulfill the demand in the next period.

- *Output:* The output of the simulation model would be a detailed production and distribution planning of the network, the amount of unmet demand for products and total costs at the operational level.



Arena Simulation Model

BIBLIOGRAPHY

Adekomaya,O., Jamiru, T., Sadiku,R., Huan,Z., (2016). "Sustaining the shelf life of fresh food in cold chain – A burden on the environment", Alexandria Engineering Journal.

AFFI: American Frozen Food Institute (2015), "Economic Contribution of the frozen food Manufacturing Industry (NAICS 31141) To the U.S. Economy in 2012".

Aguilar-Savén, R. S. (2004). "Business process modelling: Review and framework." International Journal of Production Economics 90(2): 129-149.

Ahumada, O. and J. R. Villalobos (2009). "Application of planning models in the agri-food supply chain: A review." European Journal of Operational Research 196(1): 1-20.

Akhtari, S. Sowlati, T. Griess, V. C. (2017). "Integrated strategic and tactical optimization of forest-based biomass supply chains to consider medium-term supply and demand variations", In Applied Energy, ISSN 0306-2619,

Akkerman, R. Wang, Y. and Grunow, M. (2009). "MILP approaches to sustainable production and distribution of meal elements," International Conference on Computers & Industrial Engineering, Troyes, 973-978.

Akkerman, R., Farahani, P., Grunow, M. (2010). "Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges." OR Spectrum 32(4): 863-904.

Aliev, R. A., Fazlollahi, B., Guirimov, B. G., & Aliev, R. R. (2007). "Fuzzy-genetic approach to aggregate production-distribution planning in supply chain management". Information Sciences, 177(20): 4241–4255.

Allaoui, H. Yuhan, G. Alok K, C. Jacqueline, B. (2017). "Sustainable agro-food supply chain design using two-stage hybrid multi-objective decision-making approach". Computers & Operations Research, 89(0): 369-384.

Almeder, C., M. Preusser, and R. F. Hartl. (2009). "Simulation and Optimization of Supply Chains: Alternative or Complementary Approaches?" OR Spectrum 31 (1): 95–119.

Altiparmak, F., Gen, M., Lin, L., and Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. Comput. Ind. Eng. 51, 1 (Sep. 2006), 196-215.

Amalnick, M. S., & Saffar, M. M. (2017). "A new fuzzy mathematical model for green supply chain network design". International Journal of Industrial Engineering Computations, 8(1), 45–70.

Amaro, A.C.S. ., A.P.F.D. Barbosa-Póvoa. (2009). "The effect of uncertainty on the optimal closed-loop supply chain planning under different partnerships structure" , Computers & Chemical Engineering, 33 (12): 2144-2158.

Amin, S. H., & Zhang, G. (2012). "An integrated model for closed-loop supply chain configuration and supplier selection: Multi-objective approach". Expert Systems with Applications, 39(8), 6782–6791.

Anthony, R.N., (1965). "Planning and control systems: A framework for analysis". Working paper, Harvard University, Graduate School of Business Administration, Cambridge, MA, USA.

Arampantzi, C. IMinis, I. (2017) "A new model for designing sustainable supply chain networks and its application to a global manufacturer". In Journal of Cleaner Production, 156(0): 276-292.

Badri, H., Bashiri, M., Hossein Hejazi, T., (2013). “Integrated strategic and tactical planning in a supply chain network design with a heuristic solution method”, In Computers & Operations Research, 40(4):1143-1154.

Balaji M., Arshinder K., (2016). “Modeling the causes of food wastage in Indian perishable food supply chain”, Resources, Conservation and Recycling, 114(0): 153-167.

Balaman, Y., & Selim, H. (2014). "A fuzzy multi-objective linear programming model for design and management of anaerobic digestion based bioenergy supply chains". Energy, 74(0): 928–940.

Baldwin, C. J. (2009). Sustainability in the Food Industry.

Balfaqih, H. Nopiah, Z.H. Saibani, N. Al-Nory, M.T. (2016). “Review of supply chain performance measurement systems: 1998–2015”, Computers in Industry 82(0): 135-150.

Banasik, A., J. M. Bloemhof-Ruwaard, A. Kanellopoulos, G. D. H. Claassen, and J. G. A. J. van der Vorst (2016). “Multi-criteria decision making approaches for green supply chains: a review”. Flexible Services and Manufacturing Journal, 1–3.

Barbosa-Povoa , A.P. da Silva , C. Carvalho , A. (2017) "Opportunities and Challenges in Sustainable Supply Chain: An Operations Research Perspective". European Journal of Operational Research.

Barton, R. R. and M. Meckesheimer (2006). "Chapter 18 Metamodel-Based Simulation Optimization. Handbooks" in Operations Research and Management Science. G. H. Shane and L. N. Barry, Elsevier. 13(0): 535-574.

Beda, A., Bodo, R (2004). "La responsabilità sociale d'impresa. Strumenti e strategie per uno sviluppo sostenibile dell'economia". (Il Sole 24 Ore, Milan).

Bellman, R.E. & Zadeh, L.A., (1970). "Decision-Making in a Fuzzy Environment. Management Science", 17(4), B141-B164.

Benoıt, C., Mazijn, B. (2009). "Guidelines for Social Life Cycle Assessment of Products". UNEP.

Bilgen, B. (2010). "Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem". Expert Systems with Applications, 37(6), 4488–4495.

Bortolini, M. Faccio,M. Ferrari, E. Gamberi, M. Pilati, F. (2016). "Fresh food sustainable distribution: cost, delivery time and carbon footprint three-objective optimization". Journal of Food Engineering, 174(0): 56-67.

Bouchard, M., D'Amours, S., Rönnqvist, M., Azouzi, R., Gunn, E., (2017). "Integrated optimization of strategic and tactical planning decisions in forestry". European Journal of Operational Research, 259(3): 1132-1143.

Boukherroub, T., A. Ruiz, A. Guinet and J. Fondrevelle, (2015). "An integrated approach for sustainable supply chain planning." Computers & Operations Research. 4(0): 180-194.

Bloemhof, J.M., Jack G.A.J. van der Vorst, Marko Bastl & Hamid Allaoui (2015) "Sustainability assessment of food chain logistics". International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management, 18:2, 101-117.

Campuzano, F. M., J. (2001). Supply Chain Simulation.

Cardoso, S. R., Barbosa-Póvoa, A. P., Relvas, S., (2013). "Design and planning of supply chains with integration of reverse logistics activities under demand uncertainty." European Journal of Operational Research 226(3): 436-451.

Carter, C. R. and D. S. Rogers (2008). "A framework of sustainable supply chain management: moving toward new theory." International Journal of Physical Distribution & Logistics Management 38(5): 360-387.

CDP (2015). The forgotten 10% Climate mitigation in agricultural supply chains.

Celikbilek, C., Erenay, B., & Suer, G. A. (2015). "A Fuzzy Approach for a Supply Chain Network Design Problem". Proceedings of 26th Annual Production and Operations Management Society Conference.

Chaabane A. and Geramianfar R, (2015). "Sustainable supply chain planning and optimization trade-offs between cost, GHG emissions and service level," Advanced Logistics and Transport (ICALT), 4th International Conference on Valenciennes. 327-332.

Chaabane, A., Ramudhin, A., Paquet, M., (2012). "Design of sustainable supply chains under the emission trading scheme." International Journal of Production Economics 135(1): 37-49.

Chardine-Baumann, E., and Botta-Genoulaz, V. (2014). "A framework for sustainable performance assessment of supply chain management practices". Computers and Industrial Engineering, 76(1), 138–147.

Chaudhuri, A., I. Dukovska-Popovska, C. Damgaard, H.-H. Hvolby, (2014). "Supply uncertainty in food processing supply chain: sources and coping strategies" B. Grabot, B. Vallespir, S. Gomes, A. Bouras, D. Kiritsis (Eds.), Advances in Production Management Systems. Innovative and Knowledge-based Production Management in a Global-local World, Springer Berlin Heidelberg.

Chen C-L. and . Lee, W-C, (2004). “Multi objective optimization of multi echelon supply chain networks with uncertain product demands and prices”, Computers & Chemical Engineering, 28 (6-7): 1131-1144.

Chiu, C.-T., Hsu, T. H., Yang, W., (2008). "Life cycle assessment on using recycled materials for rehabilitating asphalt pavements." Resources, Conservation and Recycling 52(3): 545-556.

Chopra, S., & Meindl, P. (2016). "Supply Chain Management: Strategy, Planning, and Operation (6th ed.)". Pearson Prentice Hall.

Clift, R. (2003). "Metrics for supply chain sustainability." Clean Technologies and Environmental Policy 5(3-4): 240-247.

Cooper, M. C., Douglas M. Lambert, Janus D. Pagh, (1997) "Supply Chain Management: More Than a New Name for Logistics", The International Journal of Logistics Management, 8(1): 1-14.

Craig, R. C. and P. L. Easton (2011). "Sustainable supply chain management: evolution and future directions." International Journal of Physical Distribution & Logistics Management 41(1): 46-62.

Cruz, J. M. (2009). "The impact of corporate social responsibility in supply chain management: Multicriteria decision-making approach." Decision Support Systems 48(1): 224-236.

Dabbene, F., Gay, P., Saccoc. N., (2008). "Optimisation of fresh-food supply chains in uncertain environments, Part I: Background and methodology." Biosystems Engineering 99(3): 348-359.

Dehghanian, F. and S. Mansour (2009). "Designing sustainable recovery network of end-of-life products using genetic algorithm." Resources, Conservation and Recycling 53(10): 559-570.

Dehghanian, F. and S. Mansour, (2009). "Designing sustainable recovery network of end-of-life products using genetic algorithm." Resources, Conservation and Recycling. 53(10): 559-570.

Dellino, G. (2007). "Robust Simulation-Optimization Methods using Kriging Metamodels". Dottorato di Ricerca in Matematica.

Demirli, K. & Yimer, A.D.(2006). "Production-distribution planning with fuzzy costs, fuzzy information processing society", Annual meeting of the north American, 702-707.

Díaz-Madroñero, M., and Peidro, D., (2011). "A Fuzzy Goal Programming Approach for Collaborative Supply Chain Master Planning, Supply Chain Management - Pathways for Research and Practice", Prof. Dilek Onkal (Ed.), ISBN: 978-953-307-294-4,

Dreyer, B. and K. Grønhaug (2012). "Coping with unpredictable supply: the role of flexibility and adaptation." European Journal of Marketing 46(10): 1268-1282.

Egilmez, G., Kucukvar, M., Tatari, O., Bhutta, M. K. S., (2014). “Supply chain sustainability assessment of the U.S. food manufacturing sectors: A life cycle-based frontier approach”, Resources, Conservation and Recycling, 82(0): 8-20.

Elhasia. T, N., B, Zhao. L (2013). "Simulation of a Sustainable Cement Supply Chain; Proposal Model Review". World Academy of Science, Engineering and Technology. 7: 03-28.

Elkington, J. (1998). "Cannibals with Forks: The Triple Bottom Line of 21st Century Business", New Society Publishers.

El-Sayed, M., Afia, N., El-Kharbotly, A., (2010). "A stochastic model for forward–reverse logistics network design under risk." Computers & Industrial Engineering 58(3): 423-431.

Esmaelikia, M, Fahimnia, B, Sarkis, J, Govindan, K, Kumar, A and Mo, J (2014). 'Tactical supply chain planning models with inherent flexibility: definition and review". Annals of Operations Research, 1-21.

FAO: Food and Agriculture Organization, (2013). "Sustainability Assessment of Food and Agriculture systems (SAFA)".

Fleischmann, B., & Meyr, H. (2003). "Planning hierarchy, modeling and advanced planning systems. In A. de Kok & S. Graves (Eds.), Supply chain management: Design, coordination, operation. Handbooks". Operations Research and Management Science (Vol. 11, pp. 457–523). Amsterdam: North-Holland.

Fleischmann, M., et al. (2001). "THE IMPACT OF PRODUCT RECOVERY ON LOGISTICS NETWORK DESIGN." Production and Operations Management 10(2): 156-173.

Fredriksson, A., and K. Liljestrand. (2015). “Capturing Food Logistics: A Literature Review and Research Agenda.” International Journal of Logistics Research and Applications 18 (1): 16–34.

Friedman (1996). "The Simulation Metamodel." SPRINGER.

Frota Neto, J. Q., et al. (2008). "Designing and evaluating sustainable logistics networks." International Journal of Production Economics 111(2): 195-208.

GFCCC : Global Food Cold Chain Council, (2015). “Assessing the potential of the cold chain sector to reduce GHG emissions through food loss and waste reduction” Food Waste Reduction & Cold Chain Technologies.

Ghorbani, M. ., Arabzad, S. M. ., & Tavakkoli-Moghaddam, R. . (2014). "A multi-objective fuzzy goal programming model for reverse supply chain design". International Journal of Operational Research, 19(2), 141–153.

Govindan, K., A. Jafarian, R. Khodaverdi and K. Devika, (2014). "Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food." International Journal of Production Economics. 152(0): 9-28.

Govindan, K., et al. (2014). "Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food." International Journal of Production Economics 152(0): 9-28.

Govindan, K., et al. (2015). "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future." European Journal of Operational Research 240(3): 603-626.

GRI (2011). "Sustainability reporting guidelines", version 3.1. Available at: www.globalreporting.org.

Group, G. T. (2007) "Dynamic Simulation and Supply Chain Management".

Grunow, M. and J. van der Vorst (2010). "Food production and supply chain management." OR Spectrum 32(4): 861-862.

Guillén, G., F.D. Mele, M.J. Bagajewicz, A. Espuña and L. Puigjaner, (2005). “Multi objective supply chain design under uncertainty”, Chemical Engineering Science, 60 (6):1535-1553.

Guillén-Gosálbez, G. and I. E. Grossmann (2009). "Optimal design and planning of sustainable chemical supply chains under uncertainty." AIChE Journal 55(1): 99-121.

Guillén-Gosálbez, G. and I. Grossmann (2010). "A global optimization strategy for the environmentally conscious design of chemical supply chains under uncertainty in the damage assessment model." Computers & Chemical Engineering 34(1): 42-58.

Gumus, A. T., Guneri, A. F., & Keles, S. (2009). "Supply chain network design using an integrated neuro-fuzzy and MILP approach: A comparative design study". Expert Systems with Applications, 36(10), 12570–12577.

Hassini, E., et al. (2012). "A literature review and a case study of sustainable supply chains with a focus on metrics." International Journal of Production Economics 140(1): 69-82.

Hsu, C.C., Tan, K.C. and Mohamad Zailani, S.H., (2016). “Strategic orientations, sustainable supply chain initiatives, and reverse logistics: empirical evidence from an emerging market”, International Journal of Operations & Production Management 36 (1): 86-110.

Hsueh, C.-F. (2015). "A bilevel programming model for corporate social responsibility collaboration in sustainable supply chain management. Transportation Research Part E".Logistics and Transportation Review, 73, 84–95.

Hugo, A. and E. N. Pistikopoulos (2005). "Environmentally conscious long-range planning and design of supply chain networks." Journal of Cleaner Production 13(15): 1471-1491.

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

Iakovou. E, V. D., . Achillas. Ch, Anastasiadis. F (2014). "Design of sustainable supply chains for the agrifood sector: a holistic research framework." Agric Eng Int: CIGR Journal.

Iman, R. L. and J. C. Helton (1988). "An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models." Risk Analysis 8(1): 71-90.

IPCC: Intergovernmental Panel on Climate Change. (2011). “Special Report on Renewable Energy Sources and Climate Change Mitigation”.

ISO (2010). "Final Draft International Standard ISO/FDIS 26000:2010(E), Guidance on social responsibility."

Ivanov, D. (2010) "An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations". International Journal of Production Research, 48:13, 3999-4017.

Ivanov, D. (2010). “An Adaptive Framework for Aligning (re)planning Decisions on Supply Chain Strategy, Design, Tactics, and Operations.” International Journal of Production Research 48 (13): 3999–4017.

Kanyalkar A. P. & Adil G. K. (2005), "An integrated aggregate and detailed planning in a multi-site production environment using linear programming". International Journal o Production Research, 43:20, 4431-4454.

Kleijinen, J. P. C. (1998). "Experimental design for sensitivity analysis, optimization, and validation of simulation models".

Kleijnen, J. P. C., et al. (2004). "Response surface methodology's steepest ascent and step size revisited." European Journal of Operational Research 159(1): 121-131.

Klibi, W., et al. (2010). "The design of robust value-creating supply chain networks: A critical review." European Journal of Operational Research 203(2): 283-293.

Koski, J. (1984). “New Directions in Optimum Structural Design”, Proceedings of the Second International Symposium on Optimum Structural Design, Tucson, AZ, October 19-22, 1981. ed. / Erdal Atrek; R.H. Gallagher; K.M. Ragsdell; O.C. Zienkiewicz. New York : John Wiley & Sons. (Wiley Series in Numerical Methods in Engineering).

KPMG (2005). "International Survey of Corporate Responsibility Reporting University of Amsterdam", Amsterdam.

Law, A. M. and W. D. Kelton (1991). "Simulation modeling and analysis, McGraw-Hill." New York.

Levén, E., Segerstedt, A., (2004) "Polarica's wild berries: an example of a required storage capacity calculation and where to locate this inventory", Supply Chain Management: An International Journal, 9(3): 213-218.

Liotta, G., Kaihara, T., & Stecca, G. (2016). "Optimization and Simulation of Collaborative Networks for Sustainable Production and Transportation". IEEE Transactions on Industrial Informatics, 2(1),417–424.

Maignan, I. (2001). "Consumers' Perceptions of Corporate Social Responsibilities: A Cross-Cultural Comparison." Journal of Business Ethics 30(1): 57-72.

Mansoornejad B., Pistikopoulos, E. N., & Stuart, P. (2013). "Metrics for evaluating the forest biorefinery supply chain performance". Computers and Chemical Engineering, 54, 125–139.

Manzini R, Accorsi R, (2013). "The new conceptual framework for food supply chain assessment, Journal of Food Engineering"; 115(2): 251-263.

Martin, P. L. (19991). "Hearings of the Commission on Agricultural Workers", Labor Management Decisions. 1(1), 6–7.

Martins, S. Amorim, P. Figueira, G. Almada-Lobo, B. (2017). "An optimization-simulation approach to the network redesign problem of pharmaceutical wholesalers". In Computers & Industrial Engineering, 106(0): 315-328.

Mavrotas, G. (2009). "Effective implementation of the ε- constraint method in Multi-Objective Mathematical Programming problems". Applied Mathematics and Computation, 213: 455-465

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). "Facility location and supply chain management - A review". European Journal of Operational Research, 196(2), 401–412.

Mentzer, J. T., William DeWitt, James S. Keebler, Soonhong Min, Nancy W. Nix, Carlo D. Smith, Zach G. Zacharia (2001). "DEFINING SUPPLY CHAIN MANAGEMENT." Journal of Business Logistics 22(2): 1-25.

Mercier, S., S. Villeneuve, M. Mondor, I. (2017), "UysalTime–temperature management along the food cold chain: A review of recent developments" Comprehensive Reviews in Food Science and Food Safety, 16 (2017), pp. 647-667.

Miles, M. and L. Munilla (2004). "The Potential Impact of Social Accountability Certification on Marketing: A Short Note." Journal of Business Ethics 50(1): 1-11.

Min, H. and G. Zhou (2002). "Supply chain modeling: past, present and future." Comput. Ind. Eng. 43(1-2): 231-249.

Mitra, M., Ravindra D. Gudi, Sachin C. Patwardhan, Gautam Sardar, (2009) "Towards resilient supply chains: Uncertainty analysis using fuzzy mathematical programming". Chemical Engineering Research and Design. 87(7): 967-981.

Molina-Azorín, J. F., Claver-Cortés, E., Pereira-Moliner, J., JoséTarí. J., (2009). "Environmental practices and firm performance: an empirical analysis in the Spanish hotel industry." Journal of Cleaner Production 17(5): 516-524.

Muñoz, E., Capón-García, E., Laínez-Aguirre, J.M., Espuña, A., Puigjaner, L., (2015). “Supply chain planning and scheduling integration using Lagrangian decomposition in a knowledge management environment”, In Computers & Chemical Engineering, 72(0): 52-67.

Nagurney, A. and F. Toyasaki (2003). "Supply chain supernetworks and environmental criteria." Transportation Research Part D: Transport and Environment 8(3): 185-213.

Paksoy, T., & Yapici Pehlivan, N. (2012). "A fuzzy linear programming model for the optimization of multi-stage supply chain networks with triangular and trapezoidal membership functions". Journal of the Franklin Institute, 349(1), 93–109.

Paradis G, LeBel L, D’Amours S, Bouchard M. (2013). "On the risk of systematic drift under incoherent hierarchical forest management planning". Can. J. For. Res. 43(5): 480-492.

Peidro, D., Mula, J., Poler, R., & Verdegay, J. L. (2009). "Fuzzy optimization for supply chain planning under supply, demand and process uncertainties". Fuzzy Sets and Systems, 160(18), 2640–2657.

Pishvaee, M. S. and J. Razmi (2012). "Environmental supply chain network design using multi-objective fuzzy mathematical programming." Applied Mathematical Modelling 36(8): 3433-3446.

Pishvaee, M. S. and S. A. Torabi (2010). "A possibilistic programming approach for closed-loop supply chain network design under uncertainty." Fuzzy Sets and Systems 161(20): 2668-2683.

Pishvaee, M. S., J. Razmi and S. A. Torabi, (2014). “An accelerated Benders decomposition algorithm for sustainable supply chain network design under uncertainty: A case study of medical needle and syringe supply chain.” Transportation Research Part E: Logistics and Transportation Review. 67(0): 14-38.

Pishvaee, M. S., J. Razmi and S. A. Torabi, (2012). “Robust possibilistic programming for socially responsible supply chain network design: A new approach”, Fuzzy Sets and Systems; 206:1-20.

Pishvaee, M. S., Rabbani, M., Torabi, S. A., (2011). "A robust optimization approach to closed-loop supply chain network design under uncertainty." Applied Mathematical Modelling 35(2): 637-649.

Pochampally, K. K., & Gupta, S. M. (2012). "Use of linear physical programming and Bayesian updating for design issues in reverse logistics". International Journal of Production Research, 50(1), 1349–1359.

Pop, P. C., et al. (2015). "An efficient Reverse Distribution System for solving sustainable supply chain network design problem." Journal of Applied Logic 13(2, Part A): 105-113.

PWC (2011) "Minerals and metals scarcity in manufacturing: the ticking time bomb". Sustain Mater Manag.

Qin, Z. and X. Ji (2010). "Logistics network design for product recovery in fuzzy environment." European Journal of Operational Research 202(2): 479-490.

R Singh, H. S., G Godding (2004). "Design of scalable simulation models for semiconductor manufacturing processes". The Summer Computer Simulation Conf.

Ramos, T. R. P., Gomes, M. I., & Barbosa-Póvoa, A. P. (2014). "Planning a sustainable reverse logistics system: Balancing costs with environmental and social concerns". Omega (United Kingdom), 48, 60–74.

Sabio, N. Kostin, A. Guillén-Gosálbez, G. Jiménez, L. (2012). "Holistic minimization of the life cycle environmental impact of hydrogen infrastructures using multi-objective optimization and principal component analysis". In International Journal of Hydrogen Energy, 37(6): 5385-5405.

Sabri, E. H., Beamon, B. M., (2000). "A multi-objective approach to simultaneous strategic and operational planning in supply chain design", In Omega, 28(5) :581-598.

Sacks, J., William J. Welch, Toby J. Mitchell, and Henry P. Wynn. (1989). "Design and Analysis of Computer Experiments." Statistical Science 4(4): 409-423.

Sakawa, M., Nishizaki, I. & Uemura, Y. (2001). "Fuzzy programming and profit and cost allocation for a production and transportation problem". European Journal of Operational Research,131 (1), 1-15.

Salema, M. I. G., et al. (2007). "An optimization model for the design of a capacitated multi-product reverse logistics network with uncertainty." European Journal of Operational Research 179(3): 1063-1077.

Santoro, S., (1992). "Global methods in multi-objective optimization and their application to a mechanical design problem", Computers in Industry. 18(2): 169-175.

Sargent, R. G., (2014). "Verifying and validating simulation models," Proceedings of the Winter Simulation Conference 2014, Savanah, GA, 118-131.

Sarkis, L., (2003). "A strategic decision framework for green supply chain management", In Journal of Cleaner Production, 11(4): 397-409.

Selim, H., Araz, C., & Ozkarahan, I. (2008). "Collaborative production-distribution planning in supply chain: A fuzzy goal programming approach. Transportation Research Part E" Logistics and Transportation Review, 44(3), 396–419.

Seuring, S. (2004). "Industrial ecology, life cycles, supply chains: differences and interrelations." Business Strategy and the Environment 13(5): 306-319.

Seuring, S. (2013). "A review of modeling approaches for sustainable supply chain management." Decision Support Systems 54(4): 1513-1520.

Seuring, S. and M. Müller (2008). "From a literature review to a conceptual framework for sustainable supply chain management." Journal of Cleaner Production 16(15): 1699-1710.

Seuring, S. and M. Müller, (2008). "From a literature review to a conceptual framework for sustainable supply chain management." Journal of Cleaner Production. 16(15): 1699-1710.

Shannon, R. E., Mayer, R., Adelsberger, H. H, (1985). "Expert systems and simulation." SIMULATION 44(6): 275-284.

Sheu, J.-B.,Chou, Y-H., Hu, C-C., (2005). "An integrated logistics operational model for green-supply chain management." Transportation Research Part E: Logistics and Transportation Review 41(4): 287-313.

Shrouf, F., Ordieres-Meré, J., García-Sánchez, A., Ortega-Mier, M., (2014). “Optimizing the production scheduling of a single machine to minimize total energy consumption costs”, In Journal of Cleaner Production, 67(0): 197-207.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2003). "Designing and managing the supply chain: concepts, strategies, and case studies". Journal of Business Logistics,1(1),388-400.

Simpson, D. F. and D. J. Power (2005). "Use the supply relationship to develop lean and green suppliers." Supply Chain Management: An International Journal 10(1): 60-68.

Soysal, M., Bloemhof, J. van der Vorst, J. (2012). "A Review of Quantitative Models for Sustainable Food Logistics Management: Challenges and Issues". International European Forum. Innsbruck-Igls, Austria.

Soysal. M., Bloemhof-Ruwaard. J.M., van der Vorst. J.G.A.J., (2014). "Modelling food logistics networks with emission considerations: The case of an international beef supply chain". In International Journal of Production Economics, 152(0): 57-70.

Sutopo, W., Hisjam, Muh. Yuniaristanto, (2012). "An Agri-food Supply Chain Model to Empower Farmers for Supplying Deteriorated Product to Modern Retailer" "IAENG Transactions on Engineering Technologies: Special Issue of the International MultiConference of Engineers and Computer Scientists.

Tang, C. S., and S. Zhou. (2012). “Research Advances in Environmentally and Socially Sustainable Operations.” European Journal of Operations Research 223: 585–594.

Takey, F.M., Mesquita, M.A., (2006). “Aggregate Planning for a Large Food Manufacturer with High Seasonal Demand” Brazilian Journal of Operations & Production Management. 3 (1): 05-20.

Terzi, S. and S. Cavalieri (2004). "Simulation in the supply chain context: a survey." Computers in Industry 53(1): 3-16.

Tiwari, R.N., Dharmar, S. & Rao, J.R., 1987. "Fuzzy goal programming -- An additive model. Fuzzy Sets and Systems", 24(1), 27-34.

Transparency Market Research, (2013). “Frozen Food Market (Vegetables & Fruits, Potatoes, Ready-to-eat Meals, Meat, Fish/Seafood and Soups) - Global Industry Analysis, Size, Share, Growth, Trends and Forecast, 2013 – 2019”.

Tsai W-H, Hung S-J (2009). "A fuzzy goal programming approach for green supply chain optimization under activity based costing and performance evaluation with a value-chain structure". Int J Prod Res 47(18):4991–5017.

Tsolakis, N., C. Keramydas, A. Toka, D. Aidonis, E. Iakovou, (2014). "Agrifood supply chain management: A comprehensive hierarchical decision-making framework and a critical taxonomy." Biosystems Engineering 120(0): 47-64.

Tuomisto, H. L., et al. (2012). "Does organic farming reduce environmental impacts? – A meta-analysis of European research." Journal of Environmental Management 112(0): 309-320.

Validi, S., A. Bhattacharya and P. J. Byrne,(2015). "A solution method for a two-layer sustainable supply chain distribution model." Computers & Operations Research; 54(0): 204-217.

van der Vorst, J. G. A. J. (2000). "Effective food supply chains : generating, modelling and evaluating supply chain scenarios". [S.l., s.n.]. Proefschrift Wageningen.

van der Vorst, J. G. A. J., S. O. Tromp, and D. J. van der Zee, (2009). "Simulation modelling for food supply chain redesign; integrated decision making on product quality, sustainability and logistics." International Journal of Production Research 47(23): 6611-6631.

Van der, S. (2004). "Measuring effectiveness of food quality management", Wageningen University. PhD.

Varsei M, Polyakovskiy S. (2016). “Sustainable supply chain network design: A case of the wine industry in Australia”. Omega.

Vogel, T., B. Almada-Lobo, C. Almeder. (2017). "Integrated versus hierarchical approach to aggregate production planning and master production scheduling". OR Spectrum 39: 193–229.

Wang, F. Lai, X. Shi, N. (2011). "A multi-objective optimization for green supply chain network design, In Decision Support Systems". 51(2): 262-269.

Weintraub, A., & Cholaky, A. (1991). "A hierarchical approach to forest planning". Forest 629 Science, 37(2), 439-460.

Weintraub, A., Guitart, S., and Kohn, V., (1986), "Strategic planning in forest industries", European Journal of Operational Research 24: 152–162.

Wijngaard. J, (1982). "On aggregation in production planning", In Engineering Costs and Production Economics, 6(0): 259-265.

Xu, J., He, Y., & Gen, M. (2009). "A class of random fuzzy programming and its application to supply chain design". Computers and Industrial Engineering, 56(3), 937–950.

Zanoni, S., Zavanella, L., (2012). “Chilled or frozen? Decision strategies for sustainable food supply chains”. International Journal of Production Economics. 140(2): 731-736.

Zhang, Q. Shah, N. Wassick, J. Helling, R. van Egerschot, P. (2014). "Sustainable supply chain optimization: An industrial case study", In Computers & Industrial Engineering, 74(0): 68-83.