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OPTIMIZING AN INTEGRATED SUPPLY CHAIN

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ABSTRACT

Many optimization models have been developed to make specific decisions in supply chains. However, when these decisions are integrated together, supply chains may operate more efficiently. This research presents a basic model for designing a supply chain network and two integrated models that were developed from this basic model: a strategic-tactical (S-T) model and a tactical-operational (T-O) model. The basic model is a single-period model that makes the tactical decisions of determining the optimal configuration of the manufacturing plants, independent distributors, and customers in the distribution network assuming that there is only one distribution center (DC) with infinite capacity. The S-T model is similar to the basic one but includes multiple periods and makes the decisions for the locations and sizes of several DC's. The DC sizes and locations are considered as strategic decisions since these are made for long periods of time, and the distribution decisions for each customer are considered as tactical since these are made for each period in the model and are used for planning purposes. The T-O model is a multi-period model that makes the distribution decisions of supplying the customer demands and making the replenishment orders for the DC's. It uses as part of the input the results from the S-T model for DC locations and sizes and the final list of customers as well as the actual customer orders. This research also presents a step-by-step procedure to deal with the sensitivity and uncertainty in demand that is incurred in the S-T model due to the use of demand forecasts. All the models developed in this research contain multiple criteria to consider customer service objectives in addition to maximizing the profit. Finally, a flowchart was presented to show the integration of the S-T and T-O models. The functionality and applicability of all these models were shown by implementing them in a real-world case study of a consumer goods company.

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DEDICATION

This work is dedicated to my entire family for their unconditional love and support through this journey. It would have not been made possible without the support and prayers of all my family members, in particular Mami, Papi, Edgardo, Yari, Abuela Magda, Abuela Pila, Abuelo, Mama Mary, and Madrinita. Los quiero!

Chapter 1

INTRODUCTION AND PROBLEM STATEMENT

1.1 Introduction

Companies are continuously looking for ways to improve their performance and stay competitive in their markets. Ambrosino and Grazia (2005) mentioned that "all companies that aim to be competitive on the market have to pay attention to their organization related to the entire supply chain." A large amount of optimization models and algorithms have been developed to make different decisions along the supply chain. Most of the research to date presents models that make decisions for only one supply chain function at a time (e.g., production scheduling, facilities planning, inventory policies, etc.). The purpose of this research is to consider some of these functions simultaneously in one integrated model to obtain a better supply chain performance.

The decisions in a supply chain can be classified into three different types: strategic, tactical, and operational. Strategic decisions as those that are typically made for the long term (e.g., years) and are very expensive to alter on the short notice. Examples of strategic decisions include: facilities' planning and the design of the supply chain network. Tactical decisions are those decisions made from a quarter to a year. The tactical decisions may include inventory policies, price promotions, discounts and allowances, etc. Finally, the decisions that are made weekly or daily are considered as operational decisions. Patel *et al.* (2009) describe as operational the decisions for coordinating the logistics network to be responsive to customer demand (e.g., optimal routing, order scheduling, etc.). The research presented in this document intends to integrate some of these decisions in a single model. This study will have two integrated models: one that combines strategic and tactical decisions and another that integrates tactical and operational decisions.

The next sections in this chapter present an introduction of the different topics to be discussed in this dissertation. Section 1.2 describes the supply chain being studied with all its components and flows. Moreover, Section 1.3 presents an introduction of the optimization models used in supply chain modeling. Section 1.4 introduces the company that is used as a case study to show the functionality and applicability of the models proposed. Finally, Section 1.5 presents an overview of this thesis.

1.2 Supply chain in this study

A supply chain, as defined by Chopra and Meindl (2007), consists of all the parties involved, directly or indirectly, in fulfilling a customer request. They mention that typically the parties involved in a supply chain are: suppliers, manufacturers, wholesalers/distributors, retailers, and customers. However, this research focuses in the distribution stage. The parties considered at this stage are: the manufacturers, the company's regional distribution centers (DC's), the independent distributors, and the retailers. An illustration of the interaction between these parties is shown in Figure 1.1. As it can be observed, the end-customers buy the products from the retailers, whereas the retailers can receive products from three different parties: distributors, manufacturers, and DC's. The distributors can be supplied by the manufacturers and/or the DC's, while the DC's are supplied only by the manufacturers.

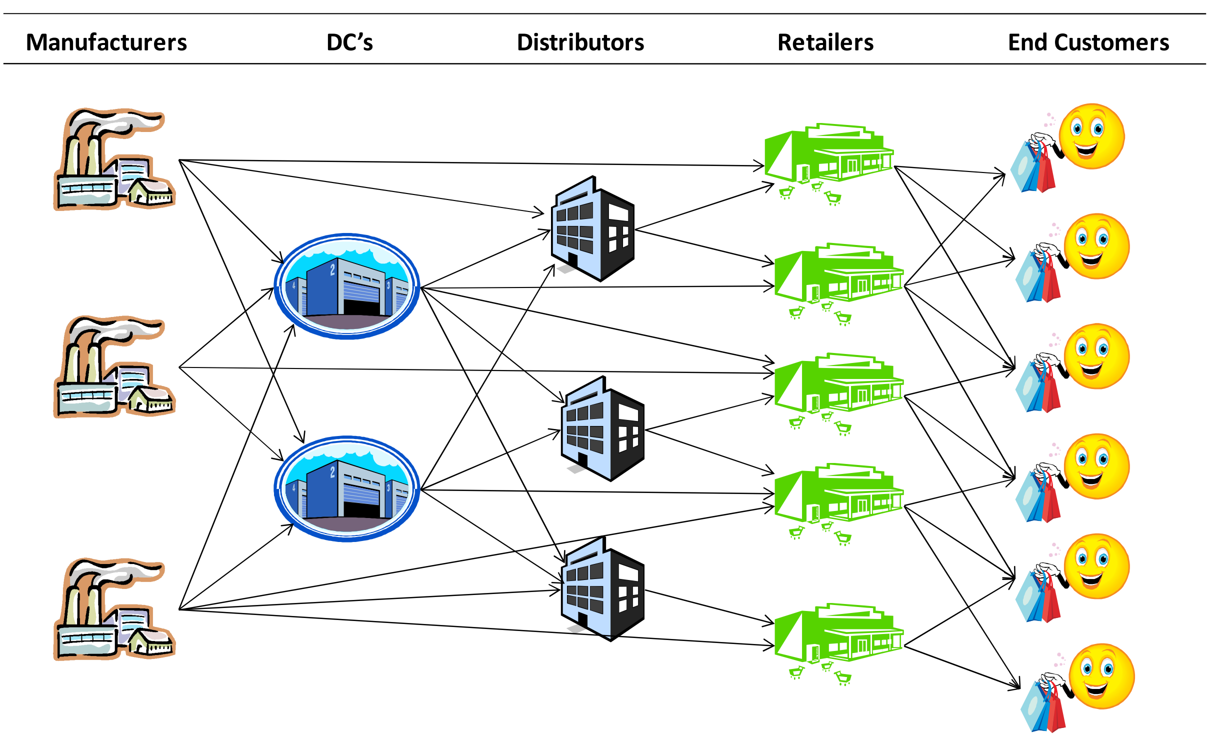

Figure 1.2. Supply chain at the distribution echelon

Most companies have several manufacturing plants producing different products. These plants supply the distribution centers in the different regions according to the region's demand. However, when distributors or retailers have large demands they may be able to receive their products directly from these plants. For example, a policy of some companies is that if a distributor/retailer can fill a container from products of one plant, they can receive directly from that plant. Distributing directly from the plant is cheaper since no storage costs at the DC's are incurred.

Third party distributors are companies' customers who do the same functions as the company's DC's. Distributors buy products from the company at a discounted price and store them in a warehouse to supply the retailers. Distributors are mostly used to supply retailers with low demand, for example, a family's mini-market. To supply customers with low demand through distributors is cheaper for the company since a third party is incurring the storage and distribution costs.

The decision making process of the interaction between the parties in the supply chain network can be facilitated through optimization models. In this case this is known as the distribution network design. The decisions depend on the feasibility of the interactions (e.g., it is infeasible for a retailer to receive the products from a manufacturer if their demand is not high enough to get a full container) and the optimization of some criteria. Most companies use the design that minimizes cost as the best distribution option, but some may include other criteria in their decision making process (e.g., lead time, customer responsiveness, customer's credit history, etc.).

This research intends to improve the performance of the supply chain described above. To achieve this, different optimization models are studied and integrated to make important supply chain decisions simultaneously. The next section describes the different types of optimization models that have been studied in supply chain optimization.

1.3 Supply chain optimization

Supply chain optimization can be interpreted as the management of the flows shown in the supply chain through optimization models. Simchi-Levi *et al*. (2008) define supply chain management as a set of approaches used to integrate all the supply chain components efficiently, so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, in order to minimize system-wide costs while satisfying service level requirements. In the line of this definition, most supply chain models include either a single objective (i.e., minimize cost) or two criteria (i.e., minimize cost while maximizing service level). However, several other criteria have been shown by other researchers to be important when optimizing the supply chain (e.g., customer response time, retailers' credit performance, etc).

Some of the major optimization models used is supply chain are those for production and inventory. It is very important to produce the right amount at the right time and to have the adequate inventory levels (not too high, not too low). With an accurate demand forecast, production optimization models can be used to obtain the amount to be produced so that manufacturing costs are minimized while demand is met. Hopp and Spearman (2000) mention that the goal of production scheduling optimization is to strike a profitable balance among the following criteria: on-time delivery, minimal work in process, short customer lead times, and maximum utilization of resources. In addition, optimal inventory levels at the warehouses can be obtained by minimizing costs while maintaining a high service level. Chopra and Meindl (2007) discuss several inventory management procedures, from the most basic Economic Order Quantity (EOQ) model to models including quantity discounts or stochastic demand.

Distribution network design optimization is another highly researched area in supply chain optimization. This area is very broad and is interpreted in different ways by different scholars. It may include models that predict the number of warehouses and plants needed, their locations, the production rates and inventory levels needed in these plants and warehouses, optimal routings when distributing demand, and other distribution decisions. Several objectives can be considered when designing the network. The most commonly used is to minimize cost or maximize profit. Other criteria that are also considered in some models are the distribution lead time and customer service levels. Portillo (2008) modeled a multi-echelon supply chain design process, including facilities location and allocation, capacity requirements, production and distribution network planning, and other international issues, such as currency changes. He used multicriteria selection techniques to integrate multiple objectives in the model: financial, customer service, risk, and strategic factors.

The number of existing supply chain optimization models is extremely high. However, the models mentioned in this section are some of the most researched and the most relevant to the topics studied in this research. Also, even though most models consider only one objective (e.g., minimize cost), this model will consider multiple criteria, like for example: maximizing profit, minimizing customer response time, maximizing credit performance, etc. Moreover, this research will consider some of these models simultaneously instead of using them independently. The next sub-section describes the integration of optimization models.

1.3.1 Integrated supply chain

The models mentioned above are mostly used independently. The purpose of this research is to integrate these models to obtain a better supply chain performance. As Chung and Wee (2007) said, an integrated approach improves the global system performance and cost efficiency. Integrated supply chains consider more than one decision levels when modeling: strategic, tactical, and/or operational decisions. The optimization model presented in this research contains the three decision levels in two models that are solved sequentially.

Many researchers have integrated subsets of the models mentioned in the previous section but largely integrated models are still missing in the literature. Most of the integrated models presented in the literature combine production and inventory models or production and distribution models. Integrated production-inventory models provide the optimal production rate and inventory levels of finished goods. Production-distribution models give optimal production rates and a distribution strategy. Distribution strategies include from which location to distribute to the retailers and what vehicles and routes to use. The supply chain being studied in this research does not include production decisions but integrates inventory and distribution models.

In this research two models that integrate the three levels of decisions are developed. The first model integrates strategic and tactical decisions and provides: optimal locations and capacities of the DC's, and the flow in the distribution network design. The optimal locations and capacities of the DC's are considered strategic decisions since contracts are required for leasing the DC's and companies do not want to change locations continuously due to the high relocation costs. The allocation part of the model provides tactical decisions that can be checked every few months. This model has some uncertainty since demand forecasts must be used as the demand data. The second model integrates tactical and operational decisions by introducing cross-docking decisions into the distribution network design. The cross-docking decisions as well as some distribution decisions (e.g., from which location to supply each customer) are considered operational since they have to be made more frequently, and if possible with customer order data.

The integrated supply chain models to be developed in this research are applied to strategic, tactical, and operational decisions of the supply chain of a consumer goods company. This case study demonstrates the feasibility of these models in real life applications. The next section presents a brief overview of the company in study.

1.4 Case study: Consumer goods company application

The models to be developed in this research will be applied to one specific region of a consumer goods company. This company is a major global competitor in its area, selling approximately $20 billion per year worldwide. The company has markets in more than 150 countries and its brands are in first or second position in most of these markets.

The country analyzed in this research has sales of approximately $86 million per year. Its market includes 71 customers (66 retailers and 5 distributors) and receives products from 4 manufacturing plants (all outside this country). To distribute the demand in this region, the company owns one distribution center located in this region. The company is interested in reducing the distribution costs in this region, which is the reason for implementing the optimization models developed in this research.

The results of the integrated supply chain models will help the company in making several decisions. First, the company will be able to evaluate the location of their DC and its capacity or if more than one DC is needed and their optimal locations. Also, the model will identify the best source (i.e., the manufacturing plants, the DC, or a distributor) to serve the demand of each customer. Also, if the demand is supplied from the DC, the model will select which vehicles to use and when to use cross-docking. Overall, the models developed in this research are expected to benefit the company largely, keeping it competitive in this market. At the same time, the models are general enough that they can be applied to other industries.

1.5 Overview

The main topic being studied in this research is the design and optimization of integrated supply chains. Two integrated models were developed: one that integrates strategic and tactical decisions, and one that combines tactical and operational decisions. Strategic decisions are the highest level of decisions. These decisions are meant for long term objectives; that is, they involve long periods of time (e.g., years) and investments are normally high. In this research, the strategic decisions are the opening of DC's (e.g., DC locations and sizes) and the decisions for moving customers to independent distributors. Tactical decisions are medium range decisions that tend to have moderate consequences and are meant to be made for slightly long periods of time (e.g., two weeks to one year). The tactical decisions in the S-T model are the demand distribution plans (e.g., supplying the products through direct shipments from the plants or from a DC, and the vehicles to use to deliver the products from the DC). The decisions considered as tactical in the T-O model are the distribution plans for the later periods, as these may change due to modifications to orders, new incoming orders, or other factors, and hence are used for planning. Finally, the operational decisions are those that are meant to be made for the day to day operations and usually have a low cost. All the decisions made by the T-O model for the earlier periods are considered operational and are meant to be implemented. For example, these are the distribution plans for the first periods in the planning horizon.

This research presents the integration of two models that are used to make supply chain distribution network decisions. First, a strategic base model is developed to make distribution network decisions (e.g., customers receiving direct shipments from the plants and customers to be moved to an independent distributor). The base model is then used as a foundation to develop the first integrated model, called the Strategic-Tactical (S-T) model. The S-T model makes strategic and tactical decisions and is used to select the locations and sizes of the DC's, and to choose which customers, if any, should be moved to independent distributors. Then a second integrated model developed makes tactical and operational decisions. This second model, called the Tactical-Operational (T-O) model, uses the decisions from the S-T model to make distribution decisions. These models are applied to a real supply chain problem for a consumer goods company to show the models' applicability, functionality, and scalability.

In the next chapter of this thesis a literature review of related topics is presented. The topics included in this review are mostly related to supply chain modeling. Some of these topics are: multi-criteria optimization, distribution network design, cross-docking, and integrated supply chains. Moreover, topics such as supply chain risks and model uncertainties are also reviewed. Studying model uncertainty is very important with the models being developed in this research, since different levels of decisions are being made. Specifically, in the first model, where strategic and tactical decisions are being considered, long time periods increase the uncertainty since data may change over time (e.g., demand forecasting variability).

Chapter 3 presents the base model for the distribution network design. This model only takes care of the flow of products between the manufacturing plants, the DC, the distributors, and the retailers. Also, it assumes only one DC with infinite capacity. This model was expanded to develop the two integrated models that are shown in Chapters 4 and 5.

Chapter 4 includes the strategic-tactical integrated model that makes distribution decisions including the location of DC's. This model uses demand forecasts for a set of periods to decide the size and location of different DC's and to which customers each DC will supply. The DC size and location are considered as strategic decisions since these decisions are made for long periods of time (e.g., more than a year). The distribution decisions for each customer are considered tactical since these are made for each period in the model and are used for planning purposes since these can change constantly depending on the customer orders.

Chapter 4 also includes procedures for dealing with the sensitivity and uncertainty in demand. A simple step-by-step procedure is presented to analyze the model results for different demand patterns in order to select the solution to be implemented. Also, a similar procedure is suggested for dealing with the demand uncertainty, where discrete economic-scenarios of the demand are used. This is because the model uses demand forecasts, which are reasonable to predict demand but uncertain.

The results from Chapter 4 (DC location and sizes and the customers that will be supplied by a distributor) are then used as input data for the tactical-operational model developed in Chapter 5. This model uses actual orders from the customers to decide which distribution option to use, and includes decisions for replenishment orders.

At last, a conclusion chapter is included to summarize the work done in this dissertation and to show the contributions made, as well as the future research to be considered.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

This chapter summarizes the research related to supply chain optimization and integrated models. Recently, integrating supply chain optimization models has been a topic of interest for some researchers. For many years, the supply chain was being optimized with one decision level (e.g., strategic, tactical or operational) at a time. However, integrating some of these decisions into one model might improve the supply chain performance.

The literature topics presented in this chapter are those related to the optimization models that are being studied in this research. First, an overview of supply chain modeling is presented. Within that section, some sub-sections are used to show a literature review on more detailed topics in supply chain modeling: multicriteria optimization, distribution network design, including cross-docking in optimization models, and integrated supply chain modeling. Then, the literature about dealing with uncertainty in supply chain optimization models is presented. In general, this chapter presents the literature related to the topic being studied and compares it to this research to show its contribution to this area.

2.2 Supply chain modeling

The work in supply chain modeling is very extensive. Many formulations and solution techniques have been developed to date. Mixed-integer programming (MIP) models are highly used in supply chain modeling, but other type of formulations are also used, such as the analytical methods developed by Burns *et al.* (1985) and the stochastic submodels developed by Cohen and Lee (1988). This review will focus on MIP models, which is the type of formulation used in this research. MIP models are highly used for supply chain models, and a large number of solution procedures and softwares exist.

A large amount of supply chain models exist. Most of these models are used to make a single type of decision (e.g., strategic, tactical or operational). Within each decision level, a large number of supply chain models exist, according to the different areas or echelons in the supply chain. The sub-sections below present a literature review in several supply chain models related to this study.

2.2.1 Distribution network design

The design of a distribution network can be quite broad; many different decisions have to be taken when planning the supply chain. Chapter 3 presents a "simpler" mathematical model to get the best distribution network design that complies with the decision makers' preferences. While this study intends to select the best distribution assignments to supply the customers' demand, many researchers have considered other aspects in the distribution network design process. While some scholars base their research on the number of warehouses and plants needed and their locations, a number of researchers consider production and inventory levels in their models, and others look at optimal routing plans. Moreover, some researchers consider more specialized applications. Along the same line, this research uses a case study to show the functionality of the models for the distribution network of a region of a consumer goods company.

2.2.1.1 Single objective distribution network design models

The most researched topic in distribution network design is that of determining the number of plants and warehouses needed and their locations. Selim and Ozkarahan (2006) worked on the delivery of products to retailers, but focusing at the number of locations and capacity levels needed for plants and warehouses. Wang *et al*. (2005) formulated a multi-echelon distribution network design problem with transportation and inventory considerations, in addition to the facility location problem. Similarly, Rabbani *et al*. (2008) presented a distribution network design problem in a multi-product supply chain system that located production plants and warehouses, and determined the best distribution strategy from plants to warehouses and from warehouses to customers. Lee *et al*. (2008) studied a distribution planning model to supply products to customers from warehouses and distribution centers by minimizing the logistics cost. Moreover, Ambrosino *et al*. (2009) studied a distribution network where the company had one depot, a heterogeneous fleet of vehicles, and customers were divided by regions. Their goal was to minimize the distribution costs by placing one depot in each region, assigning some vehicles to each region, and designing the vehicle routes, each starting and ending at the central depot. Furthermore, Sourirajan *et al.* (2007) considered service levels and lead times when deciding where to locate distribution centers in the network such that the sum of the location and inventory (pipeline and safety stock) costs was minimized. Marian *et al.* (2008) studied capacitated location-allocation problems, where they used genetic algorithms to optimize the distribution network. Similarly, Altiparmak *et al.* (2009) developed a solution procedure based on steady-state genetic algorithms for the design of a single-source, multi-product, multi-stage supply chain network.

Some researchers included production and/or distribution considerations into their supply chain design models. Jung and Mathur (2007) considered the inventory and distribution decisions jointly in a two-echelon distribution system consisting of one warehouse and N retailers, where inventory is kept at the retailers as well as at the warehouse. Park (2005) analyzed the production and distribution systems simultaneously by integrating the production and distribution planning to maximize the total net profit. A heuristic was used to make operational decisions for production and distribution planning in multi-plant, multi-retailer, multi-item, and multi-periodic environments. Likewise, Thanh *et al.* (2008) developed a mixed-integer linear program (MILP) for the design and planning of a production-distribution system. This model was developed to make strategic and tactical decisions, such as opening, closing or enlargement of facilities, supplier selection, and flows along the supply chain. Moreover, Tsiakis and Papageorgiu (2008) introduced financial constraints (e.g., production costs, transportation costs, and duties for the material flowing within the network subject to exchange rates) on top of the usually used operational constraints (e.g., quality, production and supply restrictions, allocation of production, and the work-load balance). They proposed an MILP model to describe the optimization problem of determining the best configuration of production and distribution subject to the operational and financial constraints.

Several researchers studied specific optimization problems of distribution network design with the use of case studies. Ahire *et al*. (2007) used operations research techniques to help Standard Register Company to optimally allocate the production orders across its production-distribution network in order to minimize the total landed cost. They used regressions, optimization modeling, and simulation modeling to solve their problem. Jonsson *et al.* (2007) used three case studies to show how advanced planning systems (APS) are used to solve strategic network planning and master production scheduling problems. Goetschalckx *et al.* (2002) presented two case studies to demonstrate the potential savings generated by integrating the design of strategic global supply chain networks with the determination of tactical production-distribution allocations and transfer prices. An anonymous author (2000) presented a case study from Pepsi Co. to show the decision support system developed by the company as part of their supply chain optimization initiative. The model's purpose was to provide a tool that could plan production and distribution for companies that produce and distribute via regional business units and franchises across the USA, while eliminating any need for external training and support, and removing obstacles of time, expense and confusion to make the tool useful tactically. Le Blanc *et al*. (2006) studied the distribution network using Factory Gate Pricing (FGP), where the retailer buys the product directly from the factory and is in charge of all the costs after the product leaves the company. They showed all the benefits obtained (reduced costs and improved coordination) for a Dutch retail distribution network. This is slightly similar to the direct shipments from the plants' warehouses presented in this study.

2.2.1.2 Multi-criteria optimization in supply chain design

Several researchers believe that more than one objective should be considered when modeling a supply chain network. For example, most models are focused only on minimizing costs, whereas some scholars believe that other objectives, like minimizing lead time or response time, should also be considered while minimizing costs. The research in multicriteria supply chain optimization is considerably scarce as compared to the number of single-objective models.

Some multicriteria models exist for the location and allocation problem. Portillo (2008) developed linear and integer programming models to aid a multi-echelon supply chain design process, including the location and allocation of new facilities, capacity assignments, production and distribution network variables, and other international issues. His model integrates financial, customer service, risk, and strategic factors based on multicriteria selection techniques. Also, Min and Melachrinoudis (1999) used a multiple-objective approach to solve the problem of relocating manufacturing and distribution facilities, where they used the Analytic Hierarchy Process (AHP) and normal ranking methods to weight their criteria and compare a small number of discrete alternatives. Melachrinoudis and Min (2000) then extended their work to a multi-period mixed integer linear program with two equally weighted objectives, which they solved using non-preemptive goal programming. Moreover, Pokharel (2008) proposed a bi-criteria model for making strategic decisions in the supply chain network design of a single product, considering supplier, manufacturing facilities, and third party warehouses capacity constraints. The two objectives were to minimize total cost and to maximize customer service levels.

Other researchers used multicriteria optimization to study the supply chain network based on the supply chain configuration and the flow of products. Ding *et al.* (2009) developed a model for the design of production-distribution networks including both supply chain configuration and related operational decisions such as order splitting, transportation allocation, and inventory control. Their goal was to achieve the best compromise between cost and customer service level. Sabri and Beamon (2000) developed multicriteria strategic and operational submodels for designing a supply chain that are solved sequentially using an iterative procedure. The strategic submodel optimizes the supply chain configuration and material flow, whereas the operational model optimizes production and inventory variables. Later on, Talluri and Baker (2002) developed a multi-phase mathematical programming approach for effective supply chain design, where they apply a combination of multicriteria efficiency models based on game theory concepts and linear and integer programming methods. Moreover, Korpela *et al*. (2002) proposed an AHP model to solve the production allocation problem by maximizing the strategic importance and preference of customers while minimizing customer related risks.

A bi-criteria model was developed by Zhou *et al*. (2003) for the allocation of customers to DC's, where they minimize costs as well as the transit time between DC's and customers. Similarly, the order distribution problem in a supply chain network was solved by Chan and Chung (2004) with a multiobjective genetic algorithm, and by Erol and Ferrell (2004) with a multicriteria optimization modeling framework for minimizing cost and maximizing customer satisfaction. Chan *et al.* (2005) developed a hybrid approach based on a genetic algorithm and AHP for production and distribution problems. Similarly, Gaur and Ravindran (2006) studied inventory aggregation in distribution networks by using a bi-criteria non-linear stochastic integer program that minimizes costs while maintaining high levels of customer responsiveness. They used optimization techniques to solve the problem and AHP to rank the alternatives. Furthermore, Fulya *et al*. (2006) proposed a genetic algorithm approach for multi-objective optimization of supply chain networks allowing decision makers to evaluate a greater number of alternative solutions.

Bachlaus *et al.* (2008) explored the integration of production, distribution and logistics activities at the strategic decision making level with the intention of designing a multi-echelon supply chain network considering agility as a key design criterion. The problem was mathematically formulated as a multi-objective optimization model that aims at minimizing the cost (fixed and variable) and maximizing the plant flexibility and volume flexibility. Later on, Bachlaus *et al*. (2009) conceptualized the integration of tangible and intangible factors into the design consideration of a resource assignment problem for a product-driven supply chain. The problem was formulated mathematically as a multi-objective optimization model to maximize the broad objectives of profit, ahead of time of delivery, quality, and volume flexibility. Also, Solo (2009) developed a two-phase stochastic programming model integrating manufacturing and distribution decisions. His model intends to maximize profit while fulfilling uncertain demand and minimizing supply chain response time.

Azaron *et al.* (2008) developed a multi-objective stochastic programming approach for supply chain design under uncertainty. To develop a robust model, two additional objective functions were added into the traditional comprehensive supply chain design problem. Their multi-objective model includes (i) the minimization of the sum of current investment costs and the expected future processing, transportation, shortage and capacity expansion costs, (ii) the minimization of the variance of the total cost, and (iii) the minimization of the financial risk or the probability of not meeting a certain budget.

2.2.2 Cross-docking in optimization models

Galbreth *et al*. (2008) described cross-docking as the practice of transferring materials from an incoming shipment to an outgoing shipment without storing them at the transfer point. Cross-docking is an option to reduce lead times and inventories and to improve customer response time in supply chains (Vis and Roodbergen, 2008). Cross-docking centers are dynamic environments where products arrive, are regrouped, and leave the same day. Kinnear (1997) considered cross-docking as a powerful business tool for supply chain management that helps to achieve the key business objectives of stock reduction, fixed resource reduction, and more responsive operating systems. One of the models to be developed in this research incorporates cross-docking to decide when is it best to perform this strategy or when should the products be stored in inventory.

Ross and Jayaraman (2008) developed new heuristics solution procedures for the location of cross-docks and distribution centers in supply chain network design. The model is contains multiple product families, a central manufacturing plant site, multiple cross-docking and distribution center sites, and retail outlets which demand multiple units of several commodities. Similarly, Sung and Yang (2008) proposed a branch-and-price algorithm for solving the cross-docking supply chain network design problem developed by Sung and Song (2003). Their model optimally locates cross-docking centers and allocates vehicles for direct transportation services from the associated origin node to the associated cross-docking centre or from the associated cross-docking centre to the associated destination node so as to satisfy a given set of freight demands at minimum cost subject to the associated service (delivery) time restriction.

Bachlaus *et al*.'s (2008) network design model addressed a class of five echelons of the supply chain including suppliers, plants, distribution centers, cross-docks and customer zones. The notion of cross-dock was introduced as an intermediate level between distribution centers and customer zones to increase the profitability of manufacturing and service industries. Also, Gümüs and Bookbinder (2004) modeled location-distribution networks that include cross-docking facilities to obtain its impact in the supply chain. They formulated optimization models to minimize total cost in three multi-echelon networks, where cross-docks are to be located between origin and destinations. Kreng and Chen (2008) developed a model where they integrate manufacturer production planning and a distribution center delivery policy. They concluded that the cross-docking distribution strategy results in large savings in the total system cost for the supply chain.

2.2.3 Integrated supply chain optimization

The main area of this research is integrated supply chain optimization. Integrated supply chain models are models where several decisions are taken in the different echelons at the same time. This specific area has not been greatly studied, but researchers have been exploring over in the last few years.

Bidhandi *et al*. (2009) proposed an MILP model and a solution algorithm for solving supply chain network design problems, where they integrate strategic and tactical decisions in the model. Their model integrates location and capacity options for suppliers, plant, and warehouse selection, product range assignment, and production flows. Also, Elhedhli and Gzara (2008) integrated strategic and tactical decisions at a tri-echelon supply chain. They used an MIP to model a tri-echelon, capacitated facility location problem that decides on the location of plants and warehouses, their capacity and technology planning, the assignment of commodities to plants and the flow of commodities to warehouses and customer zones. Similarly, Jayaraman and Pirkul (2001) developed an MIP model that makes two major decisions: 1) where to locate manufacturing plants and warehouses and 2) a distribution strategy from plants to customer outlets through warehouses.

One of the topics most researched in this area is the integration of production and distribution decisions. Chandra and Fisher (1994) demonstrated that coordination of production and distribution is better than the case in which these too are solved separately. They showed this with computational results from an MIP model for the production scheduling and distribution problem. Bachlaus *et al*. (2008) explored the integration of production, distribution, and logistics activities at the strategic decision making level, where the objective is to design a multi-echelon supply chain network. They formulated the problem as a multi-objective optimization model that aims to minimize the cost and maximize the plant and volume flexibility. Jang and Kim (2007) addressed the integrated problem of production, inventory allocation, and distribution in a two-echelon system. Their model computes simultaneously the optimal production quantity before the sales period, the inventory allocation at the beginning of the period, and the distribution sequence during the period.

Tuzkaya and Önüt (2009) considered an integrated warehousing and transportation network with multiple suppliers, a single warehouse, and multiple manufacturers. They propose a linear programming model that maximizes profit for both, the overall supply chain network and the individual functional units of the supply chain. Also, Cunha and Mutarelli (2007) addressed the problem of producing and distributing a Brazilian newsmagazine. They proposed an MILP model to determine the number and location of industrial facilities that should produce the magazines, what destinations should be assigned to each facility, the production sequencing, and the modes of transportation (e.g., air or truck).

Patel *et al*. (2009) claimed to integrate the three levels of decision in one model: strategic, tactical, and operational. They built an MIP model to minimize distribution, storage, inventory, and operations costs while satisfying demand. The decisions made in their model were: DC locations, production and inventory levels, and coordinating the logistics network. Sabri and Beamon (2000) developed strategic and operational sub-models to design a supply chain. The strategic sub-model considered an integrated, multi-product, multi-echelon, and procurement-production-distribution system design problem in a flexible facility network configuration. This model optimizes the material flow throughout the supply chain, provides the optimal number and location of plants and warehouses, and obtains the best assignment of DC's to customer zones. With the results of this model, the operational sub-model determines lot-sizes, reorder points, and safety stocks. Similarly, Solo (2009) developed a two-phase mathematical model for the design and operation of manufacturing-distribution problems. His study includes a strategic sub-model for the supply chain infrastructure design and an operational sub-model for the following operational decisions: raw material purchases, shipments, and inventories, and finished goods production quantities, inventories, and shipments.

2.3 Uncertainty in supply chain models

Most of the research in supply chain models is based on deterministic data. However, in the real world, several of the input parameters used in these models are not known with certainty (e.g., demand, costs, and lead times, among other input parameters). In this research, a procedure is developed to deal with the stochastic demand in the strategic-tactical model.

Portillo (2008) considered in his multi-criteria mathematical programming model for global location/allocation problems some stochastic input parameters: customer demands, currency exchange rates, operational fixed costs of production lines, and facilities overhead costs at all corresponding echelons. Azaron *et al.* (2008) developed a multi-objective stochastic programming approach for supply chain design under uncertainty. Demands, supplies, processing, transportation, shortage and capacity expansion costs are all considered as the uncertain parameters. Gupta and Maranas (2003) developed a two-stage stochastic programming model to make manufacturing and logistics decisions. In their model, the demand is considered as normally distributed. Guillén *et al.* (2005) developed a multi-objective two-stage stochastic supply chain model that intends to maximize profit and demand satisfaction while minimizing financial risk. They consider demand as a stochastic parameter and use a set of scenarios to deal with this uncertainty.

One common method used to address network design under uncertainty is scenario based stochastic programming (Birge and Louveaux, 1997). Scenario based approaches have their drawbacks, but can be addressed using robust optimization (Ben-Tal and Nemirovski, 1998). Also, robust optimization has been extended to integer programming by Bertsimas and Sim (2003) and Atamtürk (2005) and has been applied to the network design problem by Atamturk and Zhang (2007), Ordoñez and Zhao (2007), and Mudchanatongsuk *et al*. (2008). Mulvey *et al.* (1995) developed a scenario-based robust optimization model with goal programming techniques and considers the conflicting objectives of model robustness (i.e., always being close to feasible) and solution robustness (i.e., always being close to optimal). Also, Solo (2009) developed a flexible, multi-objective optimization tool for supply chain managers in the design and operation of manufacturing-distribution networks under uncertain demand conditions. He considered uncertain, long-term demand forecasts in the form of discrete economic scenarios using mixed-integer robust optimization.

Another major technique used for solving stochastic multicriteria problems is chance-constrained goal programming (CCGP). Chance-constrained programming (CCP) was introduced by Charnes and Cooper (1959) and it allows to have input random parameters while trying to maximize the expected value of the objectives and guaranteeing some probability of occurrence for the different constraints (Aouni *et al*., 2005). Min and Melachrinoudis (1996) determined the locations for manufacturing facilities with uncertain demand and international factors using CCGP. Solo (2009) also used CCGP to provide a useful tool for real-world stochastic production and distribution network optimization problems.

2.4 Conclusions

This chapter presented a summary of the previous research related to the model being developed. The literature review started with the general topic of supply chain modeling, which includes references from as early as 1985. Then, the literature in distribution network design in general was discussed followed by more specific aspects into the design. A summary of previously developed supply chain models was presented and categorized as single-objective models and multi-criteria models. Then, the past research made in adding cross-docking decisions to the supply chain design was discussed. Furthermore, a discussion on integrated models developed by other researchers in the area of supply chain design was included. At last, the previous research in uncertainty in supply chain models was summarized.

This research presents two integrated models. The first model makes strategic and tactical decisions, such as the location and allocation of warehouses, the flow of products, and the transportation modes to consider for distribution. The second model makes tactical and operational decisions, like the flow of products, the transportation modes to use, and replenishment orders decisions. In the past research presented in the previous sections of this chapter, most of these decisions are made individually in separate models. There are some integrated models making several of these decisions but none makes all of the decisions included in these models. Table 2.1 shows the different aspects and decisions considered in this research, and compares it to the most related previous research presented in this chapter. As it can be observed in this table, a large amount of the research does not include multiple criteria, multiple products, cross-docking, transportation modes decisions, direct shipments from the plants, uncertainty in demand, and applications to industry problems. Bachlaus's *et al*. (2008) research is the most similar to the one developed in this dissertation, but they do not consider transportation modes in their model, their material flow design does not include suppliers and direct shipments from the manufacturing plants, and consider cross-docks as locations separate from the warehouse.

Table 2.2. Previous related research

Authors (Year)	Multiple echelons	Multiple criteria	Multiple products	Multiple periods	Location	Distribution (Material flow)	Cross-docking	Direct shipments	Transportation modes	Industry Application	Stochastic Demand
Cohen and Lee (1988)	x			x	x	x				x	
Chandra and Fisher (1994)			x	x		x		x			
Melachrinoudis and Min (2000)	x	x		x	x	x		x		x	
Sabri and Beamon (2000)	x	x	x		x	x					x
Korpela *et al*. (2002)		x				x		x			x
Gupta and Maranas (2003)			x	x							x
Sung and Song (2003)					x	x	x		x		
Gümüs and Bookbinder (2004)	x			x	x	x	x	x			
Guillén *et al.* (2005)	x	x	x	x	x	x				x	x
Wang *et al*. (2005)	x				x	x			x		
Gaur and Ravindran (2006)		x			x	x				x	x
Le Blanc *et al*. (2006)				x		x		x	x	x	
Selim and Ozkarahan (2006)	x	x			x					x	x
Ahire *et al*. (2007)	x			x		x		x		x	x
Cunha and Mutarelli (2007)				x	x	x			x	x	
Jang and Kim (2007)						x				x	x
Azaron *et al.* (2008)		x			x	x				x	x
Bachlaus *et al.* (2008)	x	x	x		x	x	x			x	x
Kreng and Chen (2008)			x	x		x	x			x	
Lee *et al*. (2008)	x			x		x					
Portillo (2008)	x	x	x	x	x	x				x	x
Ross and Jayaraman (2008)					x		x				
Sung and Yang (2008)	x				x	x	x		x		
Ambrosino *et al*. (2009)					x	x			x		
Ding *et al.* (2009)	x	x		x	x	x				x	x
Patel *et al*. (2009)	x		x	x	x	x			x	x	
Solo (2009)	x	x		x	x	x	x			x	x
Tuzkaya and Önüt (2009)	x		x			x				x	
This research	x	x	x	x	x	x	x	x	x	x	x

Chapter 3

MULTI-CRITERIA MODEL FOR DESIGNING THE BASIC DISTRIBUTION NETWORK

3.1 Introduction

A supply chain distribution network design in this chapter refers to the way a company supplies the demand to its customers (i.e., independent distributors and retailers). The network to be studied in this research includes the following components: the manufacturing plants, the customers, and the regional distribution center (DC). The problem presented in this chapter is the basis for the integrated models to be developed in this research. The final design from this chapter will show how the customers will be supplied: from the regional DC, directly from the plants, or from an independent distributor.

Most researchers consider an optimal design as that which minimizes the distribution costs or maximizes profit. However, other criteria that are important in distribution network design are also considered in this study: customer response time, power, credit performance, and distributor reputation. Profit is the most commonly used criterion for decision making. It includes revenue from sales minus the distribution costs. Profit is considered instead of just minimizing the distribution costs because the revenue obtained from sales depends on the way a customer is supplied. Response time is the time in days between the day the order is posted and the day the customer receives it. The response time determines the ability to satisfy customer's demand in a reasonable time. The power criterion is a rating given by the sales team reflecting their desire to keep a customer. A preference for specific customers may be due to their growth potential or relationship with the company. The credit performance criterion is a rating dependent on the customer's credit history. Clearly, clients with a good credit history will be preferred. The distributor's reputation rating is based on the distributor's experience and service to the clients. This criterion considers the distributor's responsiveness, their skills, and their relationship with the clients/company.

This chapter presents a mathematical model to select the best way of configuring the existing customers so that profit is maximized (and hence, distribution costs are reduced) while meeting other key criteria. These costs may be reduced by decreasing the customer demand supplied from the regional DC, and hence supplying more from independent distributors or directly from the plants' warehouses. The model includes several manufacturing plants, where each plant manufactures several products. It is assumed that a mixture of products can be sent directly from a plant to a customer, as long as all the products in the container are manufactured at the specific plant. Actual data from a consumer goods company is used in this study to show the effects of the model in the company's distribution costs. Currently, this company uses two regional DC's located in the same area: a 3PL (third-party-logistics) DC and a company owned DC. However, the model assumes only one DC with infinite capacity. This is to use the results of the model to know how much capacity is really needed to supply the demand to be distributed from the regional DC's. If the demand supplied from the regional DC's decreases significantly, it may be possible to eliminate the 3PL warehouse, which is the highest cost being incurred currently. To make this possible, the resulting demand being distributed from the DC's must be lower than the capacity of the company owned DC. Hence, the model select direct shipments from the manufacturing plants whenever possible.

The next sections of this chapter present more details of the basic model. First, Section 3.2 contains a detailed description of the proposed model. Section 3.3 shows the application of this model in a case study. Finally, Section 3.4 presents some conclusions related to the results obtained from the model in the case study.

3.2 Mathematical Model

This section presents a multi-criteria model that generates the optimal distribution network design for a consumer goods company. The model considers four options that may occur when supplying a customer. These four options are illustrated in Figure 3.1. Let $S = \{1, 2, \ldots, n_S\}$ be the set of manufacturing sites, $J = \{1, 2, \ldots, n_J\}$ be the set of customers or retailers, and $I = \{1, 2, \ldots, n_I\}$ be the set of distributors. The first option represents the situation when plant *s* sends the order to the regional DC, and from there, it is then sent to customer *j*. Option 2 represents a direct shipment from manufacturing plant *s* to customer *j*. In option 3, customer *j* is supplied by distributor *i*, distributor *i* receives the products from the regional DC, which is supplied by manufacturing plant *s*. Option 4 represents the scenario when customer *j* is supplied by distributor *i*, and distributor *i* receives direct shipments from manufacturing plant *s*. Finally, a set $K = \{1, 2, \ldots, n_K\}$ is introduced to identify the different vehicle types (e.g., van or trucks with different container sizes) that can be used to supply the demand from the DC to the customers and distributors. Each vehicle has a different cost and capacity.

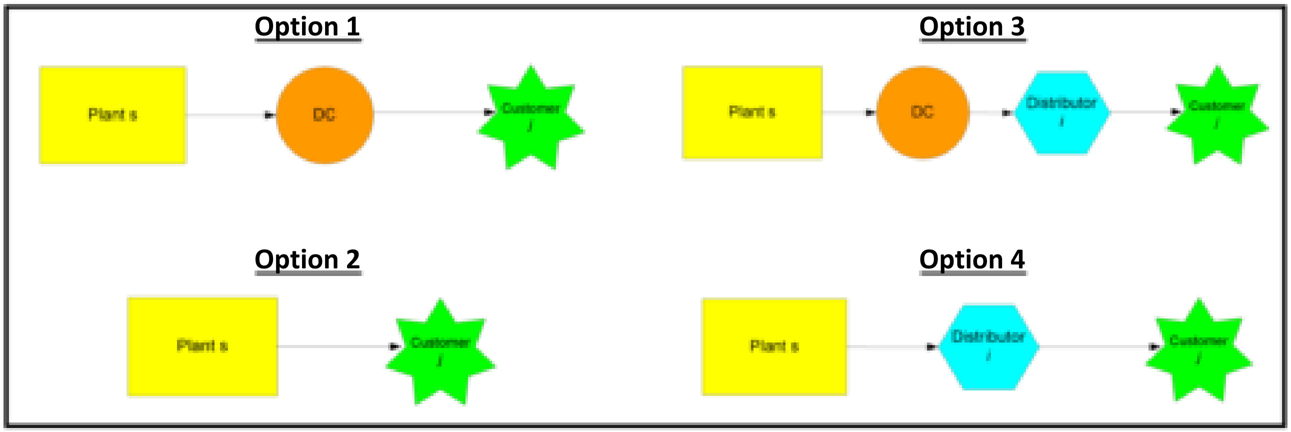

Figure 3.6. Distribution options for each customer

The next sub-sections will present the notation used in the model, the cost and revenue elements needed, the model constraints, and the objective functions.

3.2.1 Relevant Costs and Revenue Factors

One of the objectives or criteria considered in this model is to maximize profit. In this model, the profit is calculated by subtracting the distribution costs from the sales revenue. The revenue can be obtained by multiplying the variable contribution margin (VCM) of an option times the binary variable for that option. The VCM is the revenue obtained from the sales according to how the product is supplied (which option is selected for each customer per plant). If the product is sent directly from the plant or if the product is sold to the independent distributors, the VCM for these demands will have some discount. This is to encourage customers to receive direct shipments and to reward the distributors for storing and distributing the products of several customers.

The distribution costs include: transportation costs, inventory holding costs, storage costs, and "customer service" costs. The transportation costs vary according to the option selected and the demand size. If the product is sent directly from the plant, it will be sent only in containers and the costs will depend on the distance from the port to the customer's city. On the other hand, when the product is supplied locally from the DC, there exist several transportation vehicles (e.g., a van that holds up to 3 pallets or a container truck that holds up to 30 pallets, among others). Hence, the transportation cost will depend on the vehicle used according to the customer's demand and the travel distance between the DC and the customer location. This model assumes that orders from different customers are not consolidated when delivering orders, since the model is used only for tactical decisions. The optimal arrangement of vehicles and routes for local deliveries would require the development of another optimization model for operational decisions.

It is also important to consider other costs that are only incurred when the demand is supplied locally from the DC, such as the inventory holding costs and storage costs. These costs are considered in order to allow the model to select direct shipment whenever possible; that is, it is more costly to store product in the DC for distribution than to ship them directly from a plant. Since the VCM is lower when supplied directly, it is important to show in the model that, when demand is high, the profit is still higher when supplying directly than locally due to storage and inventory holding costs incurred at the DC. Another storage cost considered is the cost per pallet position. This is to "charge" for storing product in the DC. The cost per pallet position is equal to the sum of warehouse storage costs (e.g., rent, salaries, pallets, and wrapping paper) divided by the maximum number of pallets that fit in the DC. Even though costs such as the rent and salaries are constant every month, independent of the size of the demand supplied from the DC, these costs are considered to force the model to use direct shipments. That is, in the future, if less demand is supplied locally, the DC can be replaced by a smaller warehouse in order to lower rental and labor cost.

Finally, the cost of "customer service" is considered. This cost is incurred when customers are supplied from the company, directly or locally, and not from the independent distributors. This is due to the fact that a merchandiser has to go regularly to the customer stores to provide service. Also, a sales representative is needed to negotiate with these customers and prepare customers' orders. Hence, this cost is represented as the cost incurred per customer in the sales team, which is the sum of the salaries of the merchandisers and sales representatives divided by the total number of customers currently supplied by the company, including the distributors. This cost was included in the model to encourage low-demand customers to move to distributors. When a customer has low demand, its revenue or VCM is lower than the distribution costs (including the "customer service" cost), and hence it will be moved to the aggregated demand of distributors.

With the above mentioned revenues and costs, a relative profit function can be obtained. However, this is not an exact accounting value of the company's profit. This function is used to obtain the best arrangement of customers and distributors in the supply chain so that "profit" can be maximized. Hence, this relative profit value is not reported in the results, since it is not a "true profit" value, but a representation of a profit according to the costs and revenue factors that affect the decisions to be made by the model presented in this study.

3.2.2 Notation

Model Parameters

N_j	set that includes all the independent distributors that can supply customer j
M	very large number
cd_{sj}	monthly demand of customer j from plant s (in pallets)
dd_{si}	monthly demand of independent distributor i from plant s (in pallets)
MD	minimum monthly demand to order direct shipment (in pallets)
$LTCC_{kj}$	transportation cost per trip to deliver from the DC to customer j when using vehicle k
$LTCD_{ki}$	transportation cost per trip to deliver from the DC to distributor i when using vehicle k
vc_k	capacity of vehicle type k (in pallets)
CC	vehicle capacity of the containers sent from the plants' warehouses (in pallets)
TCC_{sj}	monthly transportation cost for delivering the demand of customer j directly from plant s
TCD_{si}	monthly transportation cost for delivering to distributor i directly from plant s
VCM_{sj}	monthly VCM of customer j for the demand from plant s
VCM_{si}	monthly VCM of distributor i for the demand from plant s
STC	monthly cost incurred by the sales department per customer (total salaries paid for merchandisers and sales representatives divided by the number of customers)
HCC_{sj}	monthly inventory holding cost per pallet of the demand of customer j from plant s
HCD_{si}	monthly inventory holding cost per pallet of the demand of distributor i from plant s
CPP	cost per pallet position (warehouse storage costs divided by the capacity of the warehouse in pallets)
$DCLT$	lead time from the DC to a customer (in days)
SLT_s	lead time from plant s to a customer (in days)
DLT	lead time from a distributor to a customer (in days)
P_j	power rating for customer j where $P_j \in \{1, 2, \ldots, 10\}$
CP_j	credit performance rating for customer j where $CP_j \in \{1, 2, \ldots, 10\}$
R_i	distributors' reputation rating for distributor i where $R_i \in \{1, 2, \ldots, 10\}$
MP	monthly profit used to normalize the profit goal
MRT	monthly response time used to normalize the customer response time goal
MW	monthly power value used to normalize the power goal
MCP	monthly credit performance value used to normalize the credit performance goal

MR monthly reputation value used to normalize the distributors' reputation goal

Model Variables

y_{sj} 1 if option 1 is selected for customer j when receiving from plant s, and 0 otherwise

t_{sj} 1 if option 2 is selected for customer j when receiving from plant s, and 0 otherwise

x_{sij} 1 if option 3 is selected for customer j when receiving from plant s via distributor i, and 0 otherwise

m_{sij} 1 if option 4 is selected for customer j when receiving from plant s via distributor i, and 0 otherwise

λ_j 1 if customer j receives product from the DC or the plants, and 0 if it receives it from a distributor

β_{si} 1 if distributor i is supplied directly from plant s, and 0 if it is supplied from the DC

α_{ij} 1 if distributor i supplies customer j, and 0 otherwise

γ_{kj} number of vehicles type k (or number of trips) needed to supply the monthly demand of customer j from the DC

δ_{ki} number of vehicle type k (or number of trips) needed to supply the monthly demand of distributor i from the DC

IC_{si} number of containers per month to be sent from plant s to distributor i

3.2.3 Model Constraints

The model is formulated under the assumption that only one option may be selected per customer per plant because the model will be used only to make tactical decisions; the model will identify potential customers or distributors for direct shipment and the arrangement of customers among existing distributors. A set N_j is introduced for each customer, which includes all the independent distributors that can supply customer j. The first set of constraints introduced in the model is that only one option can be selected per customer per plant. Equation (3.1) summarizes this set of constraints:

$$y_{sj} + t_{sj} + \sum_{i \in N_j} x_{sij} + \sum_{i \in N_j} m_{sij} = 1, \qquad s \in S, j \in J. \tag{3.1}$$

Another assumption is that a customer may receive either from the company (i.e., manufacturing plant or company's DC) or from a distributor, but not both. Hence, for each customer, options 3 and 4 may not be selected if options 1 or 2 are selected for a plant. This set of constraints is shown in equations (3.2) and (3.3).

$$\sum_{s\in S} y_{sj} + \sum_{s\in S} t_{sj} \le M\lambda_j, \qquad j \in J, \tag{3.2}$$

$$\sum_{s\in S}\sum_{i\in I} x_{sij} + \sum_{s\in S}\sum_{i\in I} m_{sij} \le M\left(1-\lambda_j\right), \qquad j \in J, \tag{3.3}$$

where λ_j is a binary variable introduced in the model to allow exactly one of the constraints (3.2) or (3.3) to be tight for each customer $j\in J$.

Each independent distributor may be supplied either directly from the plant or locally from the DC. Thus, only one of options 3 and 4 may be selected per distributor for each plant. Equations (3.4) and (3,5) denote these constraints. In these equations, the set of binary variables β_{si} is introduced, so that when $\beta_{si} = 1$, distributor i is supplied directly from plant s, and when it is 0, it is supplied from the regional DC.

$$\sum_{j\in J} x_{sij} \le M(1-\beta_{si}), \qquad s \in S, i \in I, \tag{3.4}$$

$$\sum_{j\in J} m_{sij} \le M\beta_{si}, \qquad s \in S, i \in I. \tag{3.5}$$

It is also important to model that only one distributor may be selected per customer. To represent this, binary variable α_{ij} is introduced, where $\alpha_{ij} = 1$ implies that customer j is supplied by distributor i. These set of constraints are shown in equations (3.6) and (3.7).

$$\left(\sum_{s\in S} x_{sij} + \sum_{s\in S} m_{sij}\right) \le M\alpha_{ij}, \qquad i \in N_j, j \in J, \tag{3.6}$$

$$\sum_{i\in N_j} \alpha_{ij} \le 1, \qquad j \in J. \tag{3.7}$$

In order for a customer or a distributor to be able to receive a direct shipment from the manufacturing plant, the customer must have a demand larger than *MD* pallets for that plant (one full truck-load). This demand may be for the same product or for several products as long as all the products are manufactured at the specific plant (i.e., mixed pallets are allowed). Equations (3.8) and (3.9) express these sets of constraints. In these equations, cd_{sj} is the demand in pallets of customer j from plant s, and dd_{si} is the demand in pallets for distributor i from plant s.

$$cd_{sj} \geq MDt_{sj}, \qquad s \in S, j \in J, \tag{3.8}$$

$$dd_{si} + \sum_{j \in J} cd_{sj} m_{sj} \geq MD\beta_{si}, \qquad s \in S, i \in I. \tag{3.9}$$

In the case study presented in Section 3.4, *MD* is equal to 20 pallets.

Finally, the transportation cost when the customers and distributors are supplied locally depends on the demand size, that is, different vehicles can be used with different capacities and costs. This means that the transportation cost for local supply is a step function. Figure 3.2 illustrates an example of the local transportation cost function, where the *LTC*'s are the costs of using vehicle *k* and the *vc*'s are the vehicle capacities. The model assumes that partial loads are charged at full load capacity of the vehicle.

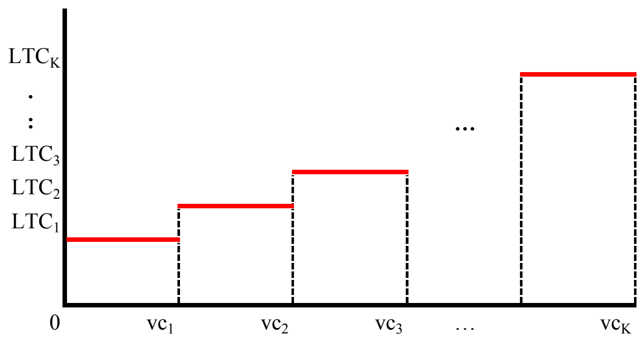

Figure 3.7. Step-wise transportation cost function

Equations (3.10) and (3.11) are the sets of constraints that will select the vehicle(s) to be used for the demand supplied locally to the customers and distributors, respectively.

$$\sum_{s \in S} cd_{sj} y_{sj} \leq \sum_{k \in K} \gamma_{kj} vc_k\,, \qquad j \in J, \tag{3.10}$$

$$\sum_{s \in S} dd_{si}(1 - \beta_{si}) + \sum_{s \in S} \sum_{j \in J} cd_{sj} x_{sij} \leq \sum_{k \in K} \delta_{ki} vc_k\,, \qquad i \in I. \tag{3.11}$$

Finally, two sets of constraints (3.12 and 3.13) must be introduced to determine the number of containers to be sent from each plant to each distributor. A constraint in this set is activated if a distributor receives its demand directly from a plant (option 4). An integer variable is introduced in these constraints to express the demand in containers (rounding-up the division of the demand in pallets over *CC* pallets per container).

$$\frac{\left(dd_{si}\beta_{si} + \sum_j cd_{sj}m_{sij}\right)}{CC} \leq IC_{si} \qquad s \in S, i \in I \tag{3.12}$$

$$\frac{\left(dd_{si}\beta_{si} + \sum_j cd_{sj}m_{sij}\right)}{CC} + 1 \ \geq IC_{si} \qquad s \in S, i \in I \tag{3.13}$$

The containers sent from a manufacturing plant in the case study described in Section 3.4 have capacity of 30 pallets.

3.2.4 Model Objectives

This model considers multiple objectives. The criteria modeled are: profit, customer response time, power, customer's credit performance, and distributor's reputation. Equations (3.14) –(3.18) show the five objectives considered.

- Maximize Profit

$$\begin{aligned}
&\sum_{s\in S}\sum_{j\in J} VCM_{sj}\, y_{sj} + \sum_{s\in S}\sum_{j\in J} VCM_{sj}\, t_{sj} + \sum_{s\in S}\sum_{i\in I}\left[VCM_{si}\,(1-\beta_{si}) + \sum_{j\in J} VCM_{sij}\, x_{sij}\right] \\
&+ \sum_{s\in S}\sum_{i\in I}\left[VCM_{si}\,\beta_{si} + \sum_{j\in J} VCM_{sij}\, m_{sij}\right] - \sum_{k\in K}\sum_{j\in J} LTCC_{kj}\,\gamma_{kj} - \sum_{s\in S}\sum_{j\in J} TCC_{sj}\, t_{sj} \\
&- \sum_{k\in K}\sum_{i\in I} LTCD_{ki}\,\delta_{ki} - \sum_{s\in S}\sum_{i\in I} TCD_{si}\, IC_{si} - STC\left(\sum_{j\in J}\lambda_j + n_I\right) - \sum_{s\in S}\sum_{j\in J} HCC_{sj}\, y_{sj} \\
&- \sum_{s\in S}\sum_{i\in I}\left[HCD_{si}\,(1-\beta_{si}) + \sum_{j\in J} HCD_{sij}\, x_{sij}\right] \\
&- CPP\left[\sum_{s\in S}\sum_{j\in J} cd_{sj}\, y_{sj} + \sum_{s\in S}\sum_{i\in I}\left(dd_{si}\,(1-\beta_{si}) + \sum_{j\in J} cd_{sij}\, x_{sij}\right)\right].
\end{aligned} \tag{14}$$

- Minimize Response Time

$$DCLT\sum_{s\in S}\sum_{j\in J} y_{sj} + \sum_{s\in S}\sum_{j\in J} SLT_s\, t_{sj} + DLT\left(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J} x_{sij} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J} m_{sij}\right). \tag{3.15}$$

- Maximize Power

$$\sum_{j\in J} P_j\lambda_j + \sum_{j\in J}\left(10 - P_j\right)\lambda_j, \tag{3.16}$$

where P_j is a rating (from 1 to 10) assigned to the customers according to their potential to grow or their relationship with the company. Since this rating represents the extent at which the company would like to keep the customer, subtracting it from 10 would be the extent at which the company is willing to give it to a distributor.

- Maximize Credit Performance

$$\sum_{j \in J} CP_j \lambda_j + \sum_{j \in J} (10 - CP_j) \lambda_j, \tag{3.17}$$

where CP_j is a rating (from 1 to 10) assigned to the customers according to their credit history. A high rating for credit score represents a good reason for the company to keep the customer and a low credit score means a good motive for giving the customer away to a distributor. Therefore, as in the power criterion, this rating is subtracted from 10 in the distributors' part of the equation to represent at which extent it is reasonable to give a customer to them.

- Maximize Distributors' Reputation

$$\sum_{s \in S} \sum_{i \in I} \sum_{j \in J} R_i \, x_{sij} + \sum_{s \in S} \sum_{i \in I} \sum_{j \in J} R_i \, m_{sij}, \tag{3.18}$$

where R_i is a rating (from 1 to 10) assigned to the distributors according to their reputation with the company. High ratings are given to distributors with a good relationship with the company and with characteristics, such as good customer service, good distribution skills, and high sales, among others.

3.2.4.1 Non-Preemptive Goal Programming

Non-preemptive weighted goal programming is used to solve the multi-criteria model by modeling the objective functions presented above as goals. Each goal uses a target value that is set by the company. In this case, the ideal values are used as the targets. To get the ideal value of each criterion, a single objective model is solved for each criterion ignoring the other criteria. Equations (3.19) – (3.23) present the goal constraints:

- Profit Goal

$$\sum_{s\in S}\sum_{j\in J} VCM_{sj}y_{sj} + \sum_{s\in S}\sum_{j\in J} VCM_{sj}t_{sj} + \sum_{s\in S}\sum_{i\in I}\left[VCM_{si} * (1-\beta_{si}) + \sum_{j\in J} VCM_{sij}x_{sij}\right]$$

$$+\sum_{s\in S}\sum_{i\in I}\left[VCM_{si}\beta_{si} + \sum_{j\in J} VCM_{sij}m_{sij}\right] - \sum_{k\in K}\sum_{j\in J} LTCC_{kj}\gamma_{kj} - \sum_{s\in S}\sum_{j\in J} TCC_{sj}t_{sj} - \sum_{k\in K}\sum_{i\in I} LTCD_{ki}\delta_{ki}$$

$$-\sum_{s\in S}\sum_{i\in I} TCD_{si}IC_{si} - STC\left(\sum_{j\in J}\lambda_j + n_I\right) - \sum_{s\in S}\sum_{j\in J} HC_{sj}y_{sj} - \sum_{s\in S}\sum_{i\in I}\left[HC_{si}(1-\beta_{si}) + \sum_{j\in J} HC_{sij}x_{sij}\right]$$

$$-CPP\left(\sum_{s\in S}\sum_{j\in J} cd_{sj}y_{sj} + \sum_{s\in S}\sum_{i\in I}\left[dd_{si}(1-\beta_{si}) + \sum_{j\in J} cd_{sij}x_{sij}\right]\right) + d_1^- - d_1^+ = MP, \qquad (3.19)$$

where *MP* is the maximum monthly profit (ideal profit value) and d_1^- is the underachievement of the goal that is to be minimized.

- Response time goal

$$DCLT\sum_{s\in S}\sum_{j\in J} y_{sj} + \sum_{s\in S}\sum_{j\in J} SLT_s t_{sj} + DLT\left(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J} x_{sij} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J} m_{sij}\right) + d_2^- - d_2^+ = MLT, \quad (3.20)$$

where MRT is the minimum of the sum of the lead times for all customers (ideal response time value) and d_2^+ is the violation of the goal that is to be minimized.

- Power goal

$$\sum_{j\in J} P_j\lambda_j + \sum_{j\in J}(10 - P_j)\lambda_j + d_3^- - d_3^+ = MW, \qquad (3.21)$$

where *MW* is the maximum power value (ideal power value) and d_3^- is the underachievement of the goal that is to be minimized.

- Credit performance goal

$$\sum_{j\in J} CP_j\lambda_j + \sum_{j\in J}(10 - CP_j)\lambda_j + d_4^- - d_4^+ = MCP, \qquad (3.22)$$

where *MCP* is the maximum credit performance value (ideal credit performance value) and d_4^- is the underachievement of the goal that is to be minimized.

- <u>Distributor's reputation goal</u>

$$\sum_{s\in S}\sum_{i\in I}\sum_{j\in J} R_i x_{sij} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J} R_i m_{sij} + d_5^- - d_5^+ = MR, \tag{3.23}$$

where *MR* is the maximum value for the distributor's reputation sum (ideal distributor's reputation value) and d_5^- is the underachievement of the goal to be minimized.

Equations (3.19) – (3.23) are then scaled and used as goal constraints in the model. Scaling is very important in non-preemptive goal programs because if the values of some of the goals are much larger compared to others, then they would dominate irrespective to the weights assigned to the various goals in the objective function. To scale each equation, the left-hand-side (LHS) of the equation, excluding the deviation variables, is divided by the right-hand-side (RHS) of the equation, and the RHS is then equal to 1. For example, the scaled equation (3.23) would be

$$\frac{\left(\sum\sum\sum R_i x_{sij} + \sum\sum\sum R_i m_{sij}\right)}{MR} + d_5^- - d_5^+ = 1.$$

The objective function that minimizes the weighted deviations of the goals is shown in Equation (3.24). In this equation, the *w*'s are the weights for each criterion. Section 3.2.4.1.1 shows how these weights are calculated.

$$z = w_1 d_1^- + w_2 d_2^+ + w_3 d_3^- + w_4 d_4^- + w_5 d_5^- \tag{3.24}$$

The non-preemptive goal programming model minimizes equation (3.24) subject to equations (3.1) – (3.13) and equations (3.19) – (3.23) scaled. This model is solved with the GAMS optimization software 12 times (i.e., one for each month for a year of data). Before solving the GP model, the goals are normalized using the ideal values.

3.2.4.1.1 Criteria Weights

The weights for each criterion may be calculated using the Analytical Hierarchy Process (AHP) by Saaty (1980). In this method, the decision makers are asked to do a pairwise comparison of the criteria. Table 3.1 shows an example that can be used for the criteria comparison. In the "More Important" column, the decision makers would write the letter of the criterion that is more important to them in each comparison. In the "Intensity" column, they would write the extent to which it is more important than the other (with a number from 1 to 10, where '10' is extremely more important and '1' is equally important).

Table 3.6. Pairwise Comparisons of Criteria

Criteria		More Important	Intensity
A	B		
Profit	Power		
Profit	Credit Performance		
Profit	Lead Time		
Profit	Distributor's Reputation		
Power	Credit Performance		
Power	Lead Time		
Power	Distributor's Reputation		
Credit Performace	Lead Time		
Credit Performace	Distributor's Reputation		
Lead Time	Distributor's Reputation		

The data from Table 1 is then converted to a matrix as illustrated in Table 3.2. In the matrix, the intensity value will go in the cell of the row of the "more important" criterion with the column of other criterion, and 1/intensity is the value placed in the cell of the "more important" column with the row of the other criterion. For example, in Table 3.2, Profit is more important than Power with an intensity value of 10.

Table 3.7. Pairwise Comparison Matrix Example

	Profit	Power	Cred. Perf.	Lead Time	Dist. Rep.
Profit	1	10	7	8	10
Power	1/10	1	7	1/5	7
Cred. Perf.	1/7	1/7	1	1/5	10
Lead Time	1/8	5	5	1	9
Dist. Rep.	1/10	1/7	1/10	1/9	1
Sum	1.46785714	16.2857143	20.1	9.51111111	37

Following the AHP method, a normalized matrix is calculated by dividing each cell by the column total. Finally, the criteria weights are calculated by taking the average of each row. Table 3.3 shows the normalized matrix with the resulting criteria weights.

Table 3.8. Normalized Matrix with Weights Example

	Profit	Power	Cred. Perf.	Lead Time	Dist. Rep.	Weight
Profit	0.68	0.61	0.35	0.84	0.27	0.55
Power	0.07	0.06	0.35	0.02	0.19	0.14
Cred. Perf.	0.10	0.01	0.05	0.02	0.27	0.09
Lead Time	0.09	0.31	0.25	0.11	0.24	0.20
Dist. Rep.	0.07	0.01	0.00	0.01	0.03	0.02

This is performed for each of the decision makers and the average of the weight results for each criterion is used as the final weight of each criterion in the objective function. The final weights should be discussed with the decision makers to ensure that their preferences are properly represented.

3.3 Case Study

A case study with real data from a specific region of a consumer goods company was used to demonstrate the applicability of the model. The data included 66 customers/retailers, 5 independent distributors, and 4 manufacturing plants. The company currently uses two distribution centers: a 3PL warehouse and a company owned DC. However, the model assumed one DC with infinite capacity, since the company wanted to know from the results how much capacity their owned DC should have in order to eliminate the 3PL warehouse.

Data gathering was one of the most time consuming tasks when solving this problem. The data obtained from the company included customer and distributor demands, transportation costs per customer/distributor to distribute from the DC (stepwise cost function with different vehicle types), the transportation costs per customer/distributor to supply from the manufacturing plants, storage costs (e.g., warehouse rents, salaries, materials, holding cost), sales team costs (merchandisers and sales representatives' salaries), lead times, and ratings for power, credit performance and distributors' reputation. Some of this data was collected from the company's SAP database and some by interviewing the company's personnel. The data from SAP required a considerable large amount of data cleaning. Also, formatting the data of 12 months to allow the optimization program to read from it was very time consuming, especially the transportation costs, since they vary by customer location and demand size.

The multiple-criteria mixed integer program was run in GAMS once for each month in a year (i.e., ran 12 times) with the data for each month to account for the variability in demand. The data was imported into GAMS from an Excel spreadsheet. The GAMS model included 2,790 variables (11 continuous variables and 2,779 discrete variables, from which 2,504 were binary variables) and 893 equations.

3.3.1 Results

The first step before running the goal programming (GP) model was to obtain the criteria weights. Weights were calculated for each criterion according to their importance. The results from the calculation of the weights according to the criteria pairwise comparisons for three decision makers (DM 1, DM 2, DM 3) are shown in Table 3.4. The last column (average of the results of all decision makers) contains the weights used in the multi-criteria model.

Table 3.9. Weights Results

Criteria	DM 1	DM 2	DM 3	Average
Profit	0.53	0.37	0.45	0.45
Power	0.14	0.16	0.28	0.20
Cred. Perf.	0.24	0.25	0.08	0.19
Lead Time	0.03	0.21	0.16	0.13
Dist. Rep.	0.07	0.01	0.02	0.03

The final proposed network was obtained by looking at the results of each month. If the model suggested the use of direct shipment from a plant to a customer for more than 6 months, direct shipment was selected for that customer. However, if it is suggested for exactly 6 months, then it was checked if at least 3 of these months were from the last 6 months (since demand in the last 6 months should be more representative of the actual demand). If most of the results suggested moving to independent distributors, then a distributor was picked for that customer. From the 71 "customers" analyzed (66 retailers and 5 independent distributors), two could receive direct shipments from Plants 1, 2, and 3 and receive the products from plant 4 through the regional DC. Also, there were three customers that could receive the products directly from plants 1 and 2 (the demand from plants 3 and 4 is supplied through the regional DC), and 24 customers could receive directly only from plant 1 and the rest of their demand from the regional DC. No customers could receive directly from Plant 4 since only one product is received from there and there was not enough demand from any customer to fill a container of that product in a month. Furthermore, the model suggested that three customers should be moved to a distributor. And finally, the remaining 39 customers could receive all their demands only from the regional DC.

The results were mostly affected by the profit criterion, since the weight of this criterion was significantly higher than the others (see Table 3.4). However, the other criteria were analyzed to see how they affected the results. The power and credit performance criteria, which were ranked right after the profit criterion, pushed some customers to distributors in some months due to low ratings. This happened also when the profit from these customers was not high enough. Other customers had low ratings in at least one of these two criteria, but since their sales were high and the profit criterion had a considerably higher weight, the model decided to not assign them to the distributors. An interesting result was observed from the customer response time criterion. In some cases, some customers had enough demand to receive direct shipments from Plant 3, but the lead time was so high that the model made them receive their orders locally from the DC or distributors. The lead time from Plant 3 was approximately 34 days, whereas the lead times from Plant 1, 2, and 4, the DC, and distributors were 21, 21, 15, 3, and 2 days, respectively.

The results presented above can be observed in terms of the goal achievements shown in Table 3.5. These results were obtained from the average of the results of the twelve months. It can be observed that the profit goal is almost completely achieved. On the other hand, the customer response time goal had the worst violation from the ideal value. This is because the ideal response time value represents the option when all the customers receive everything from the DC or the distributors, which have a lead time of 2-3 days. However, the profit goal, which has the highest weight, encourages direct shipments which have lead times from 15 to 34 days. The achievements of the power and credit performance goals were close to the ideal values, meaning that the company's desires of keeping or releasing the customers to distributors were almost accomplished. Finally, the distributor's reputation goal was 40% away from its ideal value. This difference occurs because the ideal value assumes that all customers that can receive from a distributor will be supplied by a distributor. Overall, these results were consistent with the decision makers' weights.

Table 3.10. Goal achievements

Goal	Ideal	Achieved	% Difference
Profit	1,879,600	1,872,107	0.40%
Power	1720	1688.67	1.82%
Cred. Perf.	1224	1155.33	5.61%
Lead Time	368	893.5	142.80%
Dist. Rep.	320	190	40.63%

A sensitivity analysis on the weights was performed to observe the change in the results with different weights and the original weight vector (i.e., weights in Table 3.4). These changes were observed in the deviation variables (e.g., d_1^-, d_2^+, etc.) to be minimized. The different weight vectors to be evaluated were obtained using Steuer's (1986) technique in the interval criterion weights algorithm. According to this method, eleven weight vectors (2k + 1 = 2(5) + 1, where k = # of objectives) were evaluated. The first five weight vectors to be evaluated were the extreme points, where each objective/goal was evaluated as a single objective. The results of these five extreme points were clearly different from the results obtained from the actual weights used to solve the problem. In four of these extreme points, the profit had a weight of zero resulting in the profit being negative, meaning that money loss could occur if profit is not considered. Weight vector (0.04, 0.24, 0.24, 0.24, 0.24) yielded a slightly different result from the original vector, where the profit was $205 less but all the other goal results stay the same. The other five weight vectors yielded the same results as the original weight vector. Hence, according to these results, this model showed robustness in terms of the weight selection for the criteria.

3.3.2 Managerial Implications

The company's motivation to use this model was to reduce the distribution costs by supplying most of their demand directly from the plants. By following this proposed network the ratio of "from plants"/"from DC" orders would change from 33%/67% to 83%/17%. This ratio was obtained from the demand in cases supplied in one month from the plants' warehouses and the regional DC. Figures 3.3 and 3.4 illustrate these results. In addition, the distribution costs will decrease from 12% to 3% of the Net Sales (the average monthly net sales for this region of the company is $6.5 million). Costs decrease due to two main reasons: 1) transportation costs decrease due to aggregation of demand (either with a distributor, or aggregating individual stores' demand to receive at the customer's DC, or aggregating orders to fill a container for direct shipments from the plants) and 2) storage costs decrease because only one of the DC's is needed. With the resulting demand being supplied locally, the maximum amount of pallets to be supplied in a month is 2,161. Actually, the company's DC can fit approximately 4,000 pallets, meaning that the 3PL warehouse would not be needed. Eliminating the 3PL warehouse's rent and personnel reduces the cost significantly.

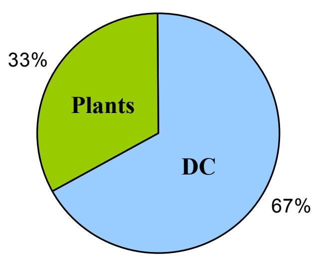

Figure 3.8. Actual Network Orders' Ratio

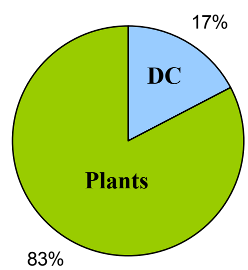

Figure 3.9. Proposed Network Orders' Ratio

However, achieving this proposed network will take time and effort. This is so because it may take a long time to convince some customers to consider receiving directly from the manufacturing plants. To receive direct shipments from the plants, customers may need to change their review policies if they were used to submitting small orders. Also, they need to make space in their warehouses to fit the amount of products received in one full container. For this reason, an analysis was made to determine to what extent the ratio of the actual network must change to still be able to eliminate the 3PL warehouse. This could happen if the maximum amount of pallets to be supplied in a month locally was up to 4,000 pallets. The DS/Local orders ratio would have to change to at least 69%/31% (approximately flipping over the graph in Figure 3.3). Figure 3.5 shows the ratio needed to be able to eliminate the 3PL warehouse without having to switch completely to the proposed network.

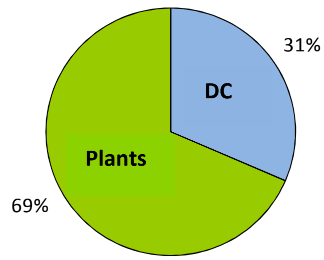

Figure 3.10. Ratio needed to eliminate the 3PL warehouse

3.4 Conclusions

A mathematical model was developed to make tactical decisions in the design of a supply chain distribution network. The model proposed an optimal arrangement of customers and distributors in the supply chain network according to the following multiple-criteria: profit, customer response time, power, credit performance, distributors' reputation. A case study was used to show the feasibility of this model. This application used real data from the Small Island region of the Anonymous consumer goods company. The model was solved with GAMS for each of the 12 months analyzed. Results showed a proposed network, where two customers receive directly from three of the plants, three customers would receive directly from only two of the plants, 24 customers may receive only from one plant, three customers should be supplied by a distributor, and the other 39 customers receive everything from the DC. This suggested network will make the "from plants"/"from DC" ratio to be 83%/17%, which conforms with the company's objective of moving to mostly direct shipments from the plants. It was proved that moving to direct shipment from plants could reduce the distribution costs, from 12% to 3% of the Net Sales (approximately $574,000 in monthly savings). This reduction was mostly due to the elimination of a 3PL warehouse. Since implementing the whole proposed network would take a long time, a large reduction in costs (approximately $467,000) could be obtained immediately by eliminating the 3PL warehouse. To eliminate this warehouse, the demand supplied from the DC must be reduced to a maximum of 4,000 pallets (i.e., the capacity of the company's owned DC). For this demand to be approximately 4,000 pallets, the "from plants"/"from DC" ratio must change to at least 69%/31%. Therefore, to obtain potential savings, the company's sales team should start using their best efforts to encourage potential customers to receive their orders through direct shipment.

This model is the first step or basis for constructing other integrated supply chain models. The next chapters present the two integrated models developed from modifications made to this base model.

Chapter 4

STRATEGIC-TACTICAL MULTI-CRITERIA INTEGRATED MODEL

4.1 Introduction

In the previous chapter, a basic distribution network program that will lead to the desired integrated models was presented. In Chapter 3 it was assumed that the company owns only one DC with infinite capacity. This chapter presents a model similar to the one in the previous chapter but includes the option of having multiple DC's in different locations and considers multiple time periods.

As in the previous chapter, this chapter presents a mathematical model to select the best way of configuring the existing customers so that profit is maximized while meeting other key criteria. However, the distribution network design resulting from this model includes the location and capacity of warehouses. This is a major decision that companies have to make when they start or as they grow into new or larger markets. This decision significantly influences the profit and customer response time objectives. In the profit criterion the warehouse leasing cost depends on the DC locations. Also, depending on the location of the DC in relation with the customers, the transportation costs and response times will be affected.

The proposed strategic-tactical model also considers multiple time periods. This allows the company to plan for actions to be taken in future periods. That is, the model results show the time period when a DC should be opened, its location, and capacity. It also allows for expanding capacity of an already opened DC in the future. Adding this type of dynamic decisions makes the model more realistic and useful for companies.

Even though similar problems have been studied in the past, they do not take into account all aspects and decisions considered in the model presented in this chapter. The main aspects studied in this model are: multiple criteria, multiple periods, multiple products, multiple echelons, DC locations and size selection, distribution network flow decisions, and vehicle (transportation mode) selection. No research has been found with all these considerations in one integrated model. Most models that include DC locations do not consider multiple periods as they are considered strategic static models. Examples of such work are Jayaraman and Pirkul (1999), Sung and Song (2003), Wang *et al.* (2005), Bachlaus *et al*. (2008), Elhedhli and Gzara (2008), and Bidhandi *et al.* (2009), among others. Making the model dynamic allows for better future planning and decision making as to when would be the best time to open or expand DC's.

On the other hand, researchers such as Cohen and Lee (1988), Melachrinoudis and Min (2000), Guillén *et al.* (2005), Cunha and Mutarelli (2007), and Portillo (2008) consider the facility location problem as a dynamic model. Dynamic location/allocation models commonly include flow conservation constraints for DC's or warehouses, where the orders that enter the warehouse plus the inventory that was already in it must be equal to the customer orders or demand plus the inventory of the next period. All the researchers mentioned above include these inventory considerations in their models, and some even consider inventory review policies (Cohen and Lee, 1988). In the strategic-tactical model presented in this research inventory levels are not considered in the same way. Since the model is meant for making strategic and tactical decisions, the specific flow of orders is not included since that is an operational decision. This model recommends the best locations for DC's and how each customer should be supplied according to their demands but does not consider specific orders from the customers or replenishments for the DC's. This is justified because the period lengths in strategic and tactical models are long, and thus multiple replenishments may occur in one period and the demand is an aggregate of multiple orders from a customer. For this reason, the decision variables in this model are binary instead of integer flow variables. However, these inventory considerations and replenishment and customer orders are taken into account in the tactical-operational integrated model presented later in Chapter 6.

Another feature of the strategic-tactical integrated model presented in this research is the use of multiple criteria. Most models use maximizing profit or minimizing cost as the only objective. A few researchers that incorporated multiple criteria in their location/allocation models are Melachrinoudis and Min (2000), Sabri and Beamon (2000), Korpela *et al*. (2002), Guillén *et al.* (2005), Gaur and Ravindran (2006), Azaron *et al.* (2008), Bachlaus *et al*. (2008), Portillo (2008), Ding *et al*. (2009), and Solo (2009). Some of the most common criteria considered in these models are minimizing lead time and minimizing risks. The criteria considered in the model presented in this chapter are: profit, customer response time, power, credit performance, and distributor's reputation (see Chapter 3 for descriptions). Using multiple objectives allows tradeoff between the two key aspects of a supply chain: efficiency and responsiveness. The work done by the researchers mentioned above use multiple criteria in location/allocation models, but do not consider other important aspects that are taken into account in the model presented in this chapter, such as multiple periods, multiple products, or vehicle selection.

Finally, the applicability of the model presented in this research is shown using a real life case study. The model becomes fairly large for the case study but it is shown that it can be solved in a reasonable time with an optimization software. Demonstrating the applicability of this model with a case study helps companies understand the solutions that can be obtained from it in order to make important decisions.

This chapter includes several sections discussing the strategic-tactical model. Section 4.2 contains a detailed description of the deterministic strategic-tactical model. Then, Section 4.3 summarizes the applicability of this model using the case study described in Section 1.4. Finally, Section 4.4 discusses the sensitivity in demand and how to deal with this in the case study presented in this research.

4.2 Mathematical Model

The model introduced in this chapter is similar to the one presented in Chapter 3, but adds more parameters, variables and constraints. The same four distribution options are considered in this model, but the DC stage or echelon includes more than one DC (Figure 4.1). Three more sets are introduced for the strategic-tactical model. Let $R = \{1, 2, \ldots, n_R\}$ be the set of possible DC locations, $C = \{1, 2, \ldots, n_C\}$ be the set of possible DC capacities, and $P = \{1, 2, \ldots, n_P\}$ be the set of time periods. The next sub-sections present the notation, constraints, and objective functions used in the strategic-tactical model, as well as a case study showing the model's applicability.

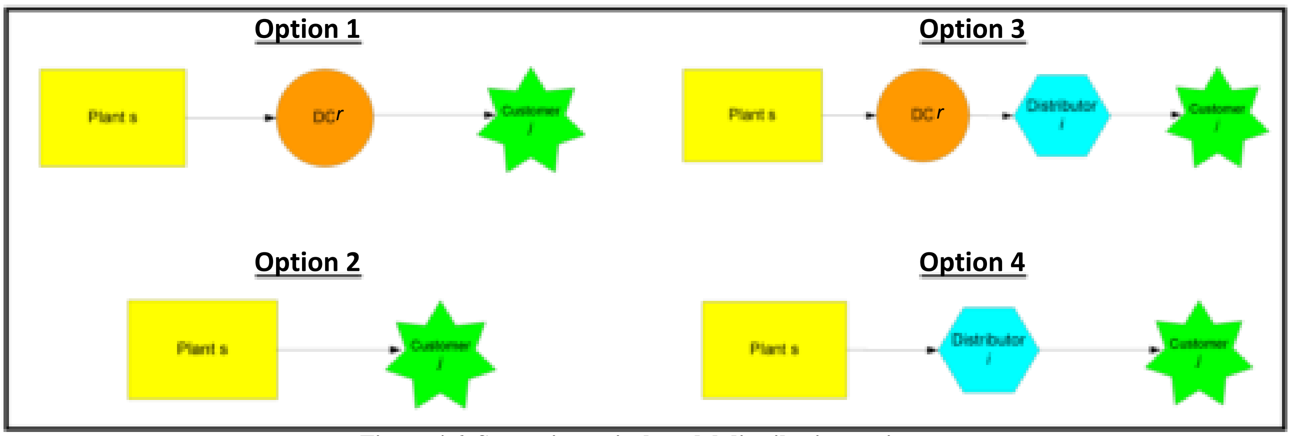

Figure 4.6. Strategic-tactical model distribution options

4.2.1 Notation

Model Parameters

N_j	set of independent distributors that can supply customer *j*
M	very large number
cd_{sjp}	demand of customer *j* from plant *s* in period *p* (in pallets)
dd_{sip}	demand of independent distributor *i* from plant *s* in period *p* (in pallets)
MD	minimum demand to order direct shipment (in pallets)

CAP_{rc}	capacity c of DC r (in pallets)
$LTCC_{krj}$	transportation cost per trip to deliver from DC r to customer j when using vehicle type k
$LTCD_{kri}$	transportation cost per trip to supply from DC r to distributor i when using vehicle type k
vc_k	capacity of vehicle type k (in pallets)
CC	vehicle capacity of the containers sent from the plants' warehouses (in pallets)
TCC_{sjp}	transportation cost for delivering the demand of customer j directly from plant s in period p
TCD_{sip}	transportation cost for delivering the demand of independent distributor i directly from plant s in period p
VCM_{sjp}	Variable contribution margin (revenue) of customer j for the demand from plant s in period p
VCM_{sip}	Variable contribution margin (revenue) of distributor i for the demand from plant s in period p
STC	cost per customer incurred by the sales department (total salaries paid for merchandisers and sales representatives divided by the number of customers)
HCC_{sjp}	inventory holding cost per pallet of the demand of customer j from plant s in period p
HCD_{sip}	inventory holding cost per pallet of the demand of independent distributor i from plant s in period p
CPP	cost per pallet position (warehouse storage costs divided by the capacity of the warehouse in pallets)
$WLOC_{rcp}$	cost of operating a DC at location r with capacity c in period p (e.g., annualized cost divided by 12 months since the periods are months)
ILF	inventory level factor – fraction of demand (rate) withheld as average inventory
RC	utilization level at which the DC is intended to be run ($0 < RC \leq 1$)
$DCLT_{rj}$	lead time from the DC r to customer j (in days)
SLT_{sj}	lead time from plant s to customer j (in days)
DLT_{ij}	lead time from distributor i to customer j (in days)
P_j	power rating for customer j, where $P_j \in \{1, 2, \ldots, 10\}$
CP_j	credit performance rating for customer j, where $CP_j \in \{1, 2, \ldots, 10\}$
DR_i	Reputation rating for distributor i, where $DR_i \in \{1, 2, \ldots, 10\}$
MP	maximum profit used to normalize the profit goal
MRT	minimum response time used to normalize the response time goal
MW	maximum power value used to normalize the power goal
MCP	maximum credit performance value used to normalize the credit performance goal

MDR maximum reputation value used to normalize the distributors' reputation goal

Model Variables

y_{srjp} 1 if option 1 is selected for customer *j* when receiving from plant *s* via DC *r* in period *p,* and 0 otherwise

t_{sjp} 1 if option 2 is selected for customer *j* when receiving from plant *s* in period *p,* and 0 otherwise

x_{srijp} 1 if option 3 is selected for customer *j* when receiving from plant *s* via distributor *i*, who is distributed from DC *r* in period *p,* and 0 otherwise

m_{sijp} 1 if option 4 is selected for customer *j* when receiving from plant *s* via distributor *i* in period *p,* and 0 otherwise

λ_j 1 if customer *j* receives product from a DC or the plants, and 0 if it receives it from a distributor

β_{sip} 1 if distributor *i* is supplied directly from plant *s* in period *p,* and 0 if it is supplied from a DC

α_{ij} 1 if distributor *i* supplies customer *j,* and 0 otherwise

γ_{krjp} number of vehicles type *k* (or number of trips) needed to supply the demand of customer *j* from DC *r* in period *p*

δ_{krip} number of vehicles type *k* (or number of trips) needed to supply the demand of distributor *i* from DC *r* in period *p*

IC_{sip} number of containers to be sent from plant *s* to distributor *i* in period *p*

τ_{srip} 1 if distributor *i* receives the demand from plant *s* through DC *r* in period *p*, and 0 otherwise

ω_{rcp} 1 if DC *r* with capacity *c* is opened during period *p*, and 0 otherwise

4.2.2 Model Constraints

The strategic-tactical model includes all the constraints from Chapter 3, and in addition, considers other constraints for DC location and capacity. Also, all the constraints from Chapter 3 were adjusted according to the three added sets. Constraints 4.1 to 4.13 are the modified constraints from Chapter 3.

First, the model considers the assumption that only one option may be selected per customer per plant for each period. Again, set N_j is introduced for each customer, which includes all the independent distributors that can supply customer *j*. Equation (4.1) summarizes the set of constraints that considers this assumption:

$$\sum_{r\in R} y_{srjp} + t_{sjp} + \sum_{r\in R}\sum_{i\in N_j} x_{srijp} + \sum_{i\in N_j} m_{sijp} = 1, \qquad s\in S, j\in J. p\in P. \tag{4.1}$$

Another important assumption is that a customer may be distributed either from the company (i.e., a manufacturing plant or a DC) or from an independent distributor, but not both. Therefore, for each customer, options 3 and 4 may not be selected if options 1 or 2 are selected for a plant. This set of constraints is shown in equations (4.2) and (4.3).

$$\sum_{s\in S}\sum_{r\in R}\sum_{p\in P} y_{srjp} + \sum_{s\in S}\sum_{p\in P} t_{sjp} \le M\lambda_j, \qquad j\in J, \tag{4.2}$$

$$\sum_{s\in S}\sum_{r\in R}\sum_{i\in I}\sum_{p\in P} x_{srijp} + \sum_{s\in S}\sum_{i\in I}\sum_{p\in P} m_{sijp} \le M(1-\lambda_j), \qquad j\in J, \tag{4.3}$$

where λ_j is a binary variable introduced to allow exactly one of the constraints (4.2) or (4.3) to be true for each customer $j\in J$.

In each period, each independent distributor may be supplied either directly from the plant or locally from a DC. Hence, only one of options 3 and 4 may be selected per distributor for each plant in each period. Equations (4.4) and (4.5) represent these constraints. The set of binary variables β_{sip} is introduced in these constraints, so that when $\beta_{sip} = 1$, distributor i is supplied directly from plant s in period p, and when it is 0, it is supplied from one of the regional DC's.

$$\sum_{r\in R}\sum_{j\in J} x_{srijp} \le M(1-\beta_{sip}), \qquad s\in S, i\in I, p\in P, \tag{4.4}$$

$$\sum_{j\in J} m_{sijp} \le M\beta_{sip}, \qquad s\in S, i\in I, p\in P. \tag{4.5}$$

Also, a variable τ_{srip} is introduced to identify when a distributor is supplied from a DC. When τ_{srip} = 1, it means that distributor i receives the demand from plant s via DC r in period p. Equation (4.6) indicates that only one τ_{srip} and β_{sip} can be equal to 1 for each period, plant, and distributor, since at each period, a distributor may receive the demand from a specific plant either directly from the plant or from only one of the DC's.

$$\sum_{r \in R} \tau_{srip} + \beta_{sip} = 1, \qquad s \in S, i \in I, p \in P. \tag{4.6}$$

After identifying from which DC a distributor is being supplied, a constraint has to be introduced to relate this variable to the one related with option 3 (x_{srijp}). That is, equation (4.7) makes the r value in the index to be the same in both x and τ.

$$\sum_{s \in S} \sum_{j \in J} x_{srijp} \leq M \sum_{s \in S} \tau_{srip}, \qquad r \in R, i \in I, p \in P. \tag{4.7}$$

Another important assumption is that, in all periods, only one distributor may be selected per customer. This is because, as in Chapter 3, the decision of moving a customer to an independent distributor is a strategic decision. This means that if a customer is to be given to an independent distributor, it will stay with that independent distributor forever and cannot be a direct customer of the company anymore or moved to another distributor. To represent this, binary variable α_{ij} is introduced, where $\alpha_{ij} = 1$ implies that customer j is supplied by distributor i. Equations (4.8) and (4.9) denote these constraints.

$$\left(\sum_{s \in S} \sum_{r \in R} \sum_{p \in P} x_{srijp} + \sum_{s \in S} \sum_{p \in P} m_{sijp} \right) \leq M \alpha_{ij}, \qquad i \in N_j, j \in J, \tag{4.8}$$

$$\sum_{i \in N_j} \alpha_{ij} \leq 1, \qquad j \in J. \tag{4.9}$$

The next constraints consider the minimum demand needed for a customer or a distributor to receive direct shipments from the plants. Customers/distributors must have a demand larger than MD pallets for the specific plant. These sets of constraints are shown in equations (4.10) and (4.11).

$$cd_{sjp} \geq MD t_{sjp}, \qquad s \in S, j \in J, p \in P, \tag{4.10}$$

$$dd_{sip} + \sum_{j \in J} cd_{sjp} m_{sijp} \geq MD \beta_{sip}, \qquad s \in S, i \in I, p \in P. \tag{4.11}$$

To distribute the demand from the DC's different vehicles can be used with different capacities and costs. The next set of constraints selects the best vehicle selection from each DC to each customer and distributor for each period so that the transportation costs are minimized. As described in Chapter 3, the transportation cost for supplying from the DC's is a step function (Figure 3.2). Equations (4.12) and (4.13) represent the set of constraints for vehicle arrangements.

$$\sum_{s\in S} cd_{sjp} y_{srjp} \leq \sum_{k\in K} \gamma_{krjp} vc_k\,, \qquad r \in, R, j \in J, p \in P, \tag{4.12}$$

$$\sum_{s\in S} dd_{sip}\tau_{srip} + \sum_{s\in S}\sum_{j\in J} cd_{sjp}x_{srijp} \leq \sum_{k\in K} \delta_{krip} vc_k\,, \qquad r \in R, i \in I, p \in P. \tag{4.13}$$

For the distributors that receive demand directly from a plant, two sets of constraints (4.14 and 4.15) must be introduced. These constraints determine the number of containers to be sent from each plant to each distributor in each period. A constraint in this set is only true if a distributor receives its demand directly from a plant (option 4). An integer variable is introduced to obtain the demand in containers by rounding-up the division of the demand in pallets over the number of pallets per container (*CC*).

$$\frac{\left(dd_{sip}\beta_{sip} + \sum_j cd_{sjp}m_{sijp}\right)}{CC} \leq IC_{sip}, \qquad s \in S, i \in I, p \in P, \tag{4.14}$$

$$\frac{\left(dd_{sip}\beta_{sip} + \sum_j cd_{sjp}m_{sijp}\right)}{CC} + 1 \geq IC_{sip}, \qquad s \in S, i \in I, p \in P. \tag{4.15}$$

Finally, to have the DC's opened additional constraints are introduced. First, two sets of constraints are used to show that for a customer or a distributor to receive from a DC, this DC must be open. Variable ω_{rcp} is introduced in equations (4.16) and (4.17) to activate τ_{srip} or y_{srjp} only if the corresponding ω_{rcp} is equal to 1 for each location and period.

$$\sum_{s\in S}\sum_{i\in I} \tau_{srip} \leq M \sum_{c\in C} \omega_{rcp}\,, \qquad r \in R, p \in P, \tag{4.16}$$

$$\sum_{s\in S}\sum_{j\in J} y_{srjp} \leq M \sum_{c\in C} \omega_{rcp}\,, \qquad r \in R, p \in P. \tag{4.17}$$

Then, a set of constraints is introduced to select the capacity needed for each DC. If a DC with capacity CAP_{rc} is opened, capacity CAP_{rc} must be greater than or equal to the average inventory at that DC divided by the capacity at which the DC is run. The average amount stored in inventory at a DC can be expressed as the *ILF* (Inventory Level Factor) times the demand in that period. The ILF is the fraction of a period that is planned to be the average inventory level in the Inventory Review Policy. This model assumes that the average inventory level used in the Inventory Review Policy will remain the same through the entire time horizon. If the average inventory or *ILF* is changed, especially increased, the model results may change. The other factor considered at the moment of selecting the size of a DC is the capacity at which it will be run (*RC*). A DC should not be ran at 100% since, if changes in demand occur some space should be available to take care of these sudden changes. For this reason, the average inventory is divided by a factor *RC* in the capacity equation to make sure that the size of the DC considers the capacity at which it will be ran. Equations (4.18) and (4.19) denote the capacity constraints for each DC location, allowing only one capacity or less to be opened for each location at each period.

$$\frac{ILF}{RC}\left(\sum_{s\in S}\sum_{j\in J} cd_{sjp}y_{srjp} + \sum_{s\in S}\sum_{i\in I} dd_{sip}\tau_{srip} + \sum_{s\in S}\sum_{j\in J} cd_{sjp}\sum_{i\in I} x_{srijp}\right) \leq \sum_{c\in C} CAP_{rc}\omega_{rcp}\,, r \in R, p \in P, \tag{4.18}$$

$$\sum_{c\in C}\omega_{rcp} \leq 1 \qquad r \in R, p \in P. \tag{4.19}$$

Finally, it is important to consider that after a DC at a specific location is opened, it must remain open or be expanded during the remaining time horizon or planning period considered in the model, but it cannot be closed. Equation (4.20) forces a DC to remain open or be expanded at period p if it was already opened during the previous period.

$$\sum_{c\in C} CAP_{rc}\omega_{rcp} \geq \sum_{c\in C} CAP_{rc}\omega_{rcp-1} \qquad r \in R, p \in P\{1\}. \tag{4.20}$$

4.2.3 Objective Functions

This model considers the same multiple objectives as those used in Chapter 3: profit, customer response time, power, customer's credit performance, and distributor's reputation. Equations (4.21) – (4.25) present these five objectives modified with the new variables introduced for the strategic-tactical model.

- <u>Maximize Profit</u>

$$\sum_{s\in S}\sum_{j\in J}\sum_{p\in P} VCM_{sjp}\sum_{r\in R} y_{srjp} + \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} VCM_{sjp}t_{sjp} + \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[VCM_{sip} * (1-\beta_{sip}) + \sum_{j\in J} VCM_{sijp}\sum_{r\in R} x_{srijp}\right]$$
$$+\sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[VCM_{sip}\beta_{sip} + \sum_{j\in J} VCM_{sijp}m_{sijp}\right] - \sum_{k\in K}\sum_{r\in R}\sum_{j\in J} LTCC_{krj}\sum_{p\in P}\gamma_{krjp} - \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} TCC_{sjp}t_{sjp}$$
$$-\sum_{k\in K}\sum_{r\in R}\sum_{i\in I} LTCD_{kri}\sum_{p\in P}\delta_{krip} - \sum_{s\in S}\sum_{i\in I} TCD_{si}\sum_{p\in P} IC_{sip} - STC\left(\sum_{j\in J}\lambda_j + n_I\right) - \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} ILF * HC_{sjp}\sum_{r\in R} y_{srjp}$$
$$-\sum_{r\in R}\sum_{c\in C}\sum_{p\in P} WLOC_{rcp}\omega_{rcp} - \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[ILF * HC_{sip}(1-\beta_{sip}) + \sum_{j\in J} ILF * HC_{sijp}\sum_{r\in R} x_{srijp}\right]$$
$$-CPP\left(\sum_{s\in S}\sum_{j\in J}\sum_{p\in P} cd_{sjp}\sum_{r\in R} y_{srjp} + \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[dd_{sip}(1-\beta_{sip}) + \sum_{j\in J} cd_{sijp}x_{sijp}\right]\right), \tag{4.21}$$

- <u>Minimize Response Time</u>

$$\left[\sum_{r\in R}\sum_{j\in J} DCLT_{rj}\sum_{s\in S}\sum_{p\in P} y_{srjp} + \sum_{s\in S}\sum_{j\in J} SLT_{sj}\sum_{p\in P} t_{sjp}\right.$$
$$\left. +DLT\left(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\sum_{p\in P} x_{srijp} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{p\in P} m_{sijp}\right)\right], \tag{4.22}$$

- <u>Maximize Power</u>

$$\sum_{j\in J} P_j\lambda_j + \sum_{j\in J}(10 - P_j)(1-\lambda_j), \tag{4.23}$$

- <u>Maximize Credit Performance</u>

$$\sum_{j\in J} CP_j\lambda_j + \sum_{j\in J}(10 - CP_j)(1-\lambda_j), \tag{4.24}$$

- <u>Maximize Distributor's Reputation</u>

$$\frac{\left(\sum_{s\in S}\sum_{r\in R}\sum_{i\in N_J}\sum_{j\in J}\sum_{p\in P} DR_i x_{srijp} + \sum_{s\in S}\sum_{i\in N_J}\sum_{j\in J}\sum_{p\in P} DR_i m_{sijp}\right)}{MDR}. \tag{4.25}$$

4.2.3.1 Non-Preemptive Goal Programming

The model in Chapter 3 was solved using non-preemptive weighted goal programming. Since the strategic-tactical model is similar to the basic one and non-preemptive weighted goal programming seemed to represent well the decision makers' preferences in the basic model, this procedure is also used to solve the strategic-tactical model. Non-preemptive goal programming allows for tradeoffs between goals or objectives and allows the decision makers to reconsider their preferences easily (i.e., the decision makers' preferences can be easily changed by just changing the weights). As in the basic model, the objective functions presented above are modeled as goals and ideal values are used as the targets. To get the ideal value of each criterion, a single objective model is solved for each criterion ignoring the other criteria (e.g., maximum profit, minimum response time, maximum power, etc.). Equations (4.26) – (4.30) present the goal constraints of the multi-period deterministic strategic-tactical model. The goal constraints are scaled using their ideal values.

- Profit goal

$$\Bigg(\sum_{s\in S}\sum_{j\in J}\sum_{p\in P} VCM_{sjp}\sum_{r\in R} y_{srjp} + \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} VCM_{sjp}t_{sjp} + \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[VCM_{sip} * (1-\beta_{sip}) + \sum_{j\in J} VCM_{sijp}\sum_{r\in R} x_{srijp}\right]$$
$$+\sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[VCM_{sip}\beta_{sip} + \sum_{j\in J} VCM_{sijp}m_{sijp}\right] - \sum_{k\in K}\sum_{r\in R}\sum_{j\in J} LTCC_{krj}\sum_{p\in P}\gamma_{krjp} - \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} TCC_{sjp}t_{sjp}$$
$$-\sum_{k\in K}\sum_{r\in R}\sum_{i\in I} LTCD_{kri}\sum_{p\in P}\delta_{krip} - \sum_{s\in S}\sum_{i\in I} TCD_{si}\sum_{p\in P} IC_{sip} - STC\left(\sum_{j\in J}\lambda_j + n_I\right) - \sum_{s\in S}\sum_{j\in J}\sum_{p\in P} ILF * HC_{sjp}\sum_{r\in R} y_{srjp}$$
$$-\sum_{r\in R}\sum_{c\in C}\sum_{p\in P} WLOC_{rcp}\omega_{rcp} - \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[ILF * HC_{sip}(1-\beta_{sip}) + \sum_{j\in J} ILF * HC_{sijp}\sum_{r\in R} x_{srijp}\right]$$
$$-CPP\left(\sum_{s\in S}\sum_{j\in J}\sum_{p\in P} cd_{sjp}\sum_{r\in R} y_{srjp} + \sum_{s\in S}\sum_{i\in I}\sum_{p\in P}\left[dd_{sip}(1-\beta_{sip}) + \sum_{j\in J} cd_{sijp}x_{sijp}\right]\right)\Bigg)/MP + d_1^- - d_1^+ = 1, \quad (4.26)$$

- Response time goal

$$\left[\sum_{r\in R}\sum_{j\in J} DCLT_{rj}\sum_{s\in S}\sum_{p\in P} y_{srjp} + \sum_{s\in S}\sum_{j\in J} SLT_{sj}\sum_{p\in P} t_{sjp}\right.$$
$$\left.+DLT\left(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{r\in R}\sum_{p\in P} x_{srijp} + \sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{p\in P} m_{sijp}\right)\right]/MRT + d_2^- - d_2^+ = 1, \tag{4.27}$$

- Power goal

$$\left(\sum_{j\in J} P_j\lambda_j + \sum_{j\in J}(10 - P_j)(1-\lambda_j)\right)/MCP + d_3^- - d_3^+ = 1, \tag{4.28}$$

- Credit performance goal

$$\left(\sum_{j\in J} CP_j\lambda_j + \sum_{j\in J}(10 - CP_j)(1-\lambda_j)\right)/MCP + d_4^- - d_4^+ = 1, \tag{4.29}$$

- Distributor's Reputation goal

$$\frac{\left(\sum_{s\in S}\sum_{r\in R}\sum_{i\in N_J}\sum_{j\in J}\sum_{p\in P} DR_i x_{srijp} + \sum_{s\in S}\sum_{i\in N_J}\sum_{j\in J}\sum_{p\in P} DR_i m_{sijp}\right)}{MDR} + d_5^- - d_5^+ = 1. \tag{4.30}$$

With non-preemptive goal programming the model minimizes objective function (4.31), which is a weighted sum of the deviations of the goals. The *w*'s in this equation are the weights for each criterion.

$$z = w_1 d_1^- + w_2 d_2^+ + w_3 d_3^- + w_4 d_4^- + w_5 d_5^-. \tag{4.31}$$

Finally, the strategic-tactical non-preemptive goal programming model minimizes equation (4.31) subject to equations (4.1) – (4.20) and equations (4.26) – (4.30). As it was described in the previous chapter, the goals are normalized using the ideal values obtained from solving the model with each criterion as a single objective.

4.3 Case Study

The case study described in Section 1.4 was used to view the functionality of this deterministic strategic-tactical model. For this model, some warehousing and transportation costs were added due to the different DC locations. The warehouse leasing and operating costs are considered and they depend on the location and size of the DC.

The case study considers 24 periods and each period is one month. The demand data used for this model were approximate monthly forecasts for each period. The average inventory to be kept on the DC's is 2 weeks; hence, the *ILF* is equal to 0.5 in this model. Also, each DC is to be run at 85% (i.e., *RC* = 0.85) of its capacity to keep a 15% of capacity available for emergencies.

Three DC locations were considered and three different sizes (capacities) were possible at each location. The three different capacities considered at each location were: 500, 1000, and 2000 pallets. The DC costs according to its location and size are shown in Table 4.1. The costs shown in this table are a sum of the General Overhead Costs and Labor Costs. The General Overhead Costs include: rent (or mortgage), property taxes, utilities, equipment (e.g., pallets, racks, material handling equipment, etc.), and security devices, among others (Gluckman, 2006).

Table 4.10. Cost of each distribution center

		Capacity (Pallets)		
		500 (Small)	1000 (Medium)	2000 (Large)
Location	1	$210,000	$250,000	$300,000
	2	$200,000	$240,000	$290,000
	3	$180,000	$210,000	$250,000

This case study was run with GAMS optimization software. Table 4.2 shows the model statistics (e.g., number of equations and different variables) to show the problem size. It took approximately 6 hours to run this model with an Intel Pentium Dual Core, 2 GHz processor with 4 GB memory, when using the actual data from the company. However, some parameters were changed for validating the model (e.g., weights, DC capacities and costs, and demand data) and the running time may vary according to the data. Depending on the data used when running the model, it could take from 15 minutes to up to 8 hours to run this model. The next section summarizes the results obtained from the case study.

Table 4.11. Problem Size

Model Statistics	
Equations	**21,915**
Objective Function	1
Goal Constraints	5
Hard Constraints	21,909
Variables	**180,647**
Continuous	11
Discrete	180,636
Binary	*156,036*
Integer	*24,600*

4.3.1 Results

The results obtained from this model represent a different scenario than the results from Chapter 3. That is, the results obtained here are more reasonable since more realistic constraints are being considered. The decisions made in Chapter 3 have been very strategic, while in this chapter strategic and tactical decisions are taken. More specifically, in the previous chapter, the distribution decisions for each customer have been made assuming that the selected distribution option is the one that the customer will always use since the decisions for the model are meant to be used for negotiation purposes. On the other hand, in the model presented in this chapter, these decisions are made for each month since they are considered as tactical decisions used for planning. These planning decisions aid in making the strategic decisions of location and size of the DC's, since the model decides which DC's take care of which customers.

Several scenarios, by varying the non-preemptive weights, were evaluated to show the multiple results to the decision makers. Tables 4.3 and 4.4 present solutions different scenarios with their weights, goal achievements, and DC locations and their size. These results are shown to the decision makers so that they can decide which scenario represents the best strategy for implementation. Table 4.3 shows the results from the single objective models with 100% weight in one objective and zeros on the others (the highlighted cells are the ideal or optimal values for the respective objectives). Table 4.4 presents four more scenarios with different weights on the objectives.

Table 4.12. Results of the single objective models and their impact to all criteria

	Weights (Profit, Power, Credit Performance, Response Time, Distributors' Reputation)				
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
	(1,0,0,0,0)	(0,1,0,0,0)	(0,0,1,0,0)	(0,0,0,1,0)	(0,0,0,0,1)
Profit Goal	$52,680,802	$43,388,000	$42,087,000	$34,439,240	$38,771,000
Power Goal	624	630	610	624	566
Credit Perf. Goal	502	496	506	502	476
Response Time Goal	30,334	30,320	28,839	6,375	26,755
Dist. Rep. Goal	0	1,920	1,920	0	12,480
DC 1 Size	500 for periods 23 and 24	500 for perios 1-5 1,000 for periods 6-8 2,000 for periods 9-24	500 for periods 1-3 1,000 for periods 4-6 2,000 for periods 7-24	2000 for all periods	500 for period 1 1,000 for periods 2-3 2,000 for periods 4-24
DC 2 Size	500 for all periods	500 for periods 1-12 1,000 for periods 13-24	500 for periods 1-14 1,000 for periods 15-24	2000 for all periods	500 for period 1 2,000 for periods 2-24
DC 3 Size	500 for all periods	500 for periods 1-5 2,000 for periods 6-24	500 for period 1 1,000 for periods 2-8 2,000 for periods 9-24	500 for periods 1-12 2,000 for periods 13-24	500 for periods 1-5 2,000 for perids 6-24

Table 4.13. Results of the multi-criteria model for some scenarios

	Weights (Profit, Power, Credit Performance, Response Time, Distributors' Reputation)			
	Scenario 6	Scenario 7	Scenario 8	Scenario 9
	(0.45,0.2,0.19,0.13,0.03)	(0.63,0.05,0.05,0.25,0.02)	(0.72,0.05,0.05,0.15,0.03)	(0.62,0.05,0.15,0.15,0.03)
Profit Goal	$46,043,021	$41,249,068	$51,416,463	$45,990,340
Power Goal	618	620	618	612
Credit Perf. Goal	425	504	425	498
Response Time Goal	9,148	7,223	11,883	9,051
Dist. Rep. Goal	1,920	1,920	1,920	1,920
DC 1 Size	1,000 for period 1 2,000 periods 2-24	2,000 for all periods	1,000 for all periods	2,000 for all periods
DC 2 Size	500 for all periods	500 for all periods	500 for periods 1-4 1,000 for periods 5-24	500 for period 24
DC 3 Size	500 for period 24	500 for all periods	0	0

It can be observed in these tables that changes to the weights affect the results. In Scenario 1, where profit is the only goal considered, the power and credit performance goals are close to the ideal values, but the response time and distributor reputation goals are not. This happens because only four out of 66 customers had power and credit performance ratings lower than 5 (two for power and two for credit performance), and no customers were moved to an independent distributor. Hence, the solution does not affect the power and credit performance goals significantly, but makes the value of the distributors' reputation goal zero. On the other hand, the customer response time is drastically affected in Scenario 1, because every direct shipment from the plant, that is possible and profitable, is selected, which have really large lead times. In Scenarios 2 and 3, where power and credit performance are the only goals considered, respectively, all the goals, except for the credit performance and power ones, seem to be affected. This is because when the other goals are not taken into account, the model selects the distribution randomly as long as the customers with power and credit performance ratings lower than 5 are moved to an independent distributor. When response time is the only objective considered (Scenario 4) it can be observed that the profit and distributors' reputation goals are the most affected ones. This is attributed to the fact that everything is being supplied by the DC closer to each customer. Scenario 5 in Table 4.3, considers only the distributors' reputation goal. In this situation, the model selects all the customers that can receive from a distributor (e.g., customers in the N_j sets) and moves them to an independent distributor. This affects all the other goals, even the power and credit performance goals, since customers with high ratings are moved to independent distributors only because they are allowed to receive from them.

In Table 4.4, it can be observed that, even though all the criteria are considered, the weight distribution affects the different goal achievements significantly. Scenario 6 represents the weights given by the decision makers initially. These weights were changed in Scenarios 7, 8, and 9, so that the impact of weights can be demonstrated to the decision makers in terms of the actual solutions. Figure 4.2 is a Value Path Graph that shows the achievements of each goal under scenarios 6, 7, 8, and 9 and allows viewing graphically the tradeoff between objectives (a graphical illustration of Table 4.4). To construct this graph, the objective function values from Table 4.4 were scaled using the ideal values. That is, for the maximization goals (e.g., profit, power, credit performance, and distributors' reputation), the objective function values were divided by the ideal ones, and for the minimization goal (e.g., customer response time), the ideal value was divided by the objective function result. This converts all the values to numbers between 0 and 1 (with 1 being the ideal value), and hence, the higher the number the closer the solution is to achieving the ideal value (even for the minimization goals). These values were then plotted in the graph and then connected by lines, for clarity, representing each scenario.

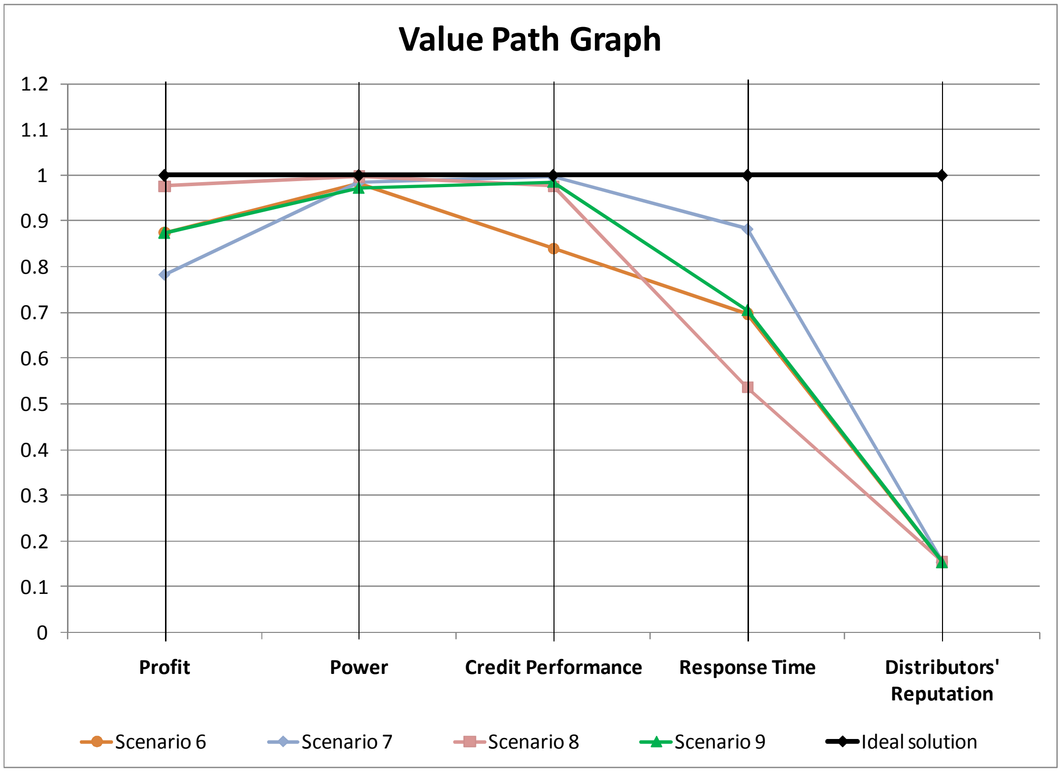

Figure 4.7. Value Path Graph of the scenarios in Table 4.4

This graph helps to identify if a scenario dominates another. That is, if one line has all its values higher than another line, it means that first line (solution or scenario) dominates the other. In Figure 4.2, no scenario dominates another because all the lines intersect with each other. Also, it can be observed that the five criteria are conflicting, especially profit and response time. The conflict between profit and customer response time can be easily identified by seeing that Scenario 8 has the highest profit but the lowest customer response time achievement, whereas Scenario 7 has the lowest profit but the highest response time achievement.

Also, from Table 4.4 and Figure 4.2, more detailed results and comparisons can be obtained about each scenario's goal achievements. In Scenario 6, the profit weight is higher than those of the other criteria but not significantly, the profit and credit performance weights are almost the same, and the customer response time weight is not too far from the latter. The distributors' reputation goal has a significantly lower weight in all the scenarios, based on the decision makers' preferences. Scenario 7 has slightly higher weights for profit and customer response time, but lower weights for power and credit performance. Scenario 8 includes a significantly higher weight for profit, a somewhat lower weight for response time, and significantly lower weights for profit, credit performance, and distributors' reputation. Finally, Scenario 9 is similar to Scenario 7 but it reduces the response time weight and increases the credit performance weight. From these scenarios, it can be observed that if the profit weight is not significantly high, the profit goal will be notably affected. The profit decreases by 10.5% from Scenario 8 to Scenarios 6 and 9 and by 20% compared to Scenario 7. In Scenario 7, the profit was also affected by the weight increase in the customer response time. Similarly, Scenario 7 shows the best customer response time among the four scenarios, but it affects the profit the most. It seems that these two criteria (profit and response time) are the most conflicting with each other. The power and credit performance criteria were never highly affected since, in all the cases, one of the two customers with low ratings for each criterion was selected. The distributors' reputation obtained the same value in all scenarios, which was that of moving two customers to an independent distributor. This criterion does not make any difference in this case study since the reputation ratings were the same for all distributors. Thus, the Value Path Graph is a good way for the decision makers to look at trade-off among the conflicting criteria visually.

Scenario 1, 6, and 8 were selected for detailed discussion in order to compare their solutions. Scenario 1 represents the model that most companies use, where only profit is considered as the objective function. Scenario 6 uses the weights that were selected by the decision makers initially in Chapter 3 to show the changes in the results when more decisions are added to the basic model. Scenario 8 is also discussed since it shows a "most likely to be selected" solution where the profit is close to the ideal while the response time does not increase that much compared to Scenario 1. When the decision makers selected the weights used in Scenario 6, they were looking at the criteria only and their relative importance, without knowing how they would impact the final solution. However, when looking at the results of Scenarios 6 and 8, Scenario 8 will most likely be selected by the decision makers, since they would probably not want to give up as much in profit for a small increase in the response time.

The distribution plans obtained from the (profit maximizing) single objective model (Scenario 1) and the multi-criteria models in Scenarios 6 and 8 are shown in Figures 4.3, 4.4, and 4.5, respectively. The results shown in the figures are the averages (in %) for each distribution among all periods. Each customer may have a different distribution option in every period. To construct these figures, the total demand in pallets from all customers was obtained for each period and the corresponding distribution option. Then, the average demand of all periods for each distribution option was obtained and the four averages (for four different distribution options) are converted to percentages.

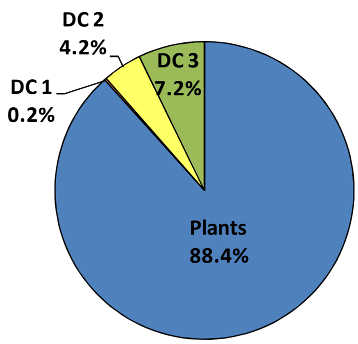

Figure 4.8. Scenario 1 model results (weights – 1,0,0,0,0)

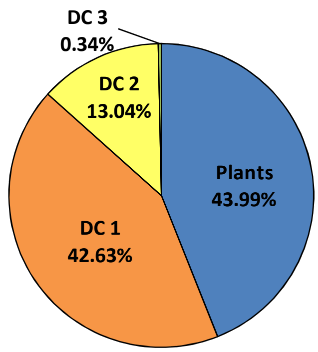

Figure 4.9. Scenario 6 model results (weights – 0.45,0.2,0.19,0.13,0.03)

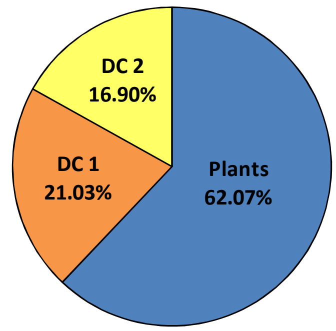

Figure 4.10. Scenario 8 model results (weights – 0.72,0.05,0.05,0.15,0.03)

Some interesting results can be observed from these figures. First, it can be observed in Figure 4.4 that, on the average, only 44% of the demand is to be sent directly from the plants to the customers each month. In the basic model (Chapter 3), it was recommended to supply directly from the plants about 80% of the monthly demand. This difference may be attributed to the fact that having multiple periods makes the ideal values very large, and hence, trying to achieve them becomes challenging. That is, the profit ideal value from the basic model in Chapter 3 was small in comparison to the one in this model because it represented only one period, and hence, making it easier for the multi-criteria model to get closer to achieving the goal. This can be observed more clearly when comparing the results from the multi-criteria model to those from the single objective profit model. The profit maximizing single objective model yields similar results as the basic model from Chapter 3 (88% of demand is direct shipments from the plants). On the other hand, the direct shipments from the plants suggested in Scenario 8 are closer to the profit maximizing model results (Scenario 1) and the recommendations from the basic model in Chapter 3. In Scenario 8, the DC at location 3 is always closed and the DC at location 1 never expands to the largest size (see Table 4.4). This is explained by the fact that more direct shipments from the plants are recommended and hence, there is no need to have so much storage space at the DC’s. However, because of the larger amounts of direct shipments from the plant, Scenario 8 has a higher profit than Scenario 6 at the expense of higher response time.

Table 4.14. Comparison of Scenarios 1, 6, and 8

	Scenario 1	Scenario 6	Scenario 8
	(1,0,0,0,0)	(0.45,0.2,0.19,0.13,0.03)	(0.72,0.05,0.05,0.15,0.03)
Profit Goal	$52,680,802	$46,043,021	$51,416,463
Power Goal	624	618	618
Credit Perf. Goal	502	425	425
Response Time Goal	30,334	9,148	11,883
Dist. Rep. Goal	0	1,920	1,920
DC 1 Size	500 for periods 23 and 24	1,000 for period 1 2,000 periods 2-24	1,000 for all periods
DC 2 Size	500 for all periods	500 for all periods	500 for periods 1-4 1,000 for periods 5-24
DC 3 Size	500 for all periods	500 for period 24	0
Distribution from plants	88.4%	43.41%	62.07%
Distribution from DC 1	0.2%	43.21%	21.03%
Distribution from DC 2	4.2%	13.04%	16.90%
Distribution from DC 3	7.2%	0.34%	0.00%
# of customers moved to distributors	0	2	2

A comparison of the optimal distribution plans for Scenarios 1, 6, and 8 are shown in Table 4.5. In the model with profit as the only objective (Scenario 1), the results suggest to open only two DC's with the lowest cost at the beginning (locations 2 and 3 at the lowest capacity), and for the last two periods, to also open the location with the highest cost (location 1 at the lowest capacity). On the other hand, the multi-criteria model for Scenario 6 opens DC's at locations 1 and 2 from the beginning (location 1 at the second capacity for the first period and the highest capacity for the rest, and location 2 at the lowest capacity) and a DC at location 3 during the last period (at the lowest capacity). Similarly, the model for Scenario 8 opens DC's at locations 1 and 2 (location 1 at medium capacity for all periods and location 2 at the lowest capacity in the first 4 periods and at the medium capacity for the rest), and does not suggest opening a DC at location 3 at all. This difference in results occurs because the multi-criteria models consider customer response time as another objective, whereas the profit maximizing single objective model does not. Direct shipments from the plants have a significantly larger lead times (15-34 days) compared to those from a DC (1-2 days). Hence, when response times (and the other criteria) are included, the multi-criteria models seem to obtain a better objective function value (weighted sum of the deviations) by opening the DC's that are closer to the high demand points and delivering less from the plants, as compared to opening the less costly DC's and also supplying more product directly from the plants. This makes the profit in Scenario 6 decrease by 13% (representing about $6.6 million) and the profit in Scenario 8 to reduce by 2% (representing $1.3 million). Note that the profit calculated from this model is not an actual profit but an approximate representation of the revenues and costs that affect the supply chain. In other words, the profit numbers obtained from this model are not the ones reported in the P&L statements.

Another difference, observed from Table 4.5, is that the single objective model does not recommend moving any customers to a distributor, whereas the multi-criteria models suggest doing this for two customers. This difference must be attributed to the power and credit performance criteria. These two criteria have the second and third highest weights, giving them a higher chance to have an impact on the results.

The objectives considered in the multi-criteria model were conflicting with one another. Non-preemptive goal programming with ideal values as targets was used to get the best possible solution that represented the decision makers' preferences. Since the criteria were conflicting, it was not possible to achieve any of the ideal values. Table 4.6 shows how much of each criterion was achieved and the percent difference from the ideal values for Scenarios 6 and 8. As it can be observed, in both scenarios the power objective was almost fully met and the credit performance was not too far. This happened because very few customers had low ratings (two customers had power ratings below 5 out of 10 and two had credit performance ratings below 5 as well) and two of them were selected.

Table 4.15. Goal achievements for Scenario 6

Goal	Ideal	Scenario 6		Scenario 8	
		Achieved	% Difference	Achieved	% Difference
Profit	$52,680,802	$46,043,021	13%	$51,416,463	2%
Power	630	618	2%	618	2%
Cred. Perf.	506	425	16%	425	16%
Resp. Time	6,375	9,148	43%	11,883	86%
Dist. Rep.	12,480	1,920	85%	1,920	85%

The profit goal in Scenario 6 did not seem to have such a high % difference, but in dollar terms it was a large amount. Even though the profit criterion had the largest weight in this scenario, the profit values were significantly larger in magnitude than the other criteria's values, and hence the large difference in the amounts. Also, in order to consider other objectives, the model recommended opening more expensive DC's and supplying less from the plants, which resulted in a large drop in profit. On the other hand, Scenario 8 used a much higher weight for profit, and hence, the difference from the ideal profit value was not significant.

The customer response time criterion was affected by those customers receiving direct shipments from the plant. The ideal value for response time would be achieved if every customer receives everything from their closest DC which would have a response time of one day. However, the profit objective forces some direct shipments from the plant, which affects the response time to customers (21 days compared to one day from a DC). In Scenario 6, the response time goal was not affected too much, compared to Scenario 8, since the model suggested opening more and/or larger DC's to supply more demands from the DC's than from the plants. However, Scenario 8 recommended using more direct shipments from the plants and opening less and/or smaller DC's, and hence the response time goal was affected more.

Finally, the distributor's reputation goal was not close to being satisfied in either Scenario 6 or 8, because the ideal assumed that all customers would be supplied by a distributor. Since this goal had a significantly lower weight, it did not have much impact on the multi-criteria model results. If the weights were changed these results may change as well.

The discussion of results of Scenario with weights (0.45, 0.20, 0.19, 0.13, and 0.03 for profit, power, credit performance, customer response time, and distributors' reputation, respectively) is done primarily for comparison. These weights are not necessarily the preferred solution for all decision makers, but represented the initial preferences of the company's decision makers. Most likely, decision makers may not sacrifice so much profit ($6.6 million) and may pick one of the solutions with higher profit, such as the one for Scenario 8 with the (0.72, 0.05, 0.05, 0.15, 0.03) weight vector (see Table 4.4). It is clear that the customer response time objective affects the profit significantly. However, in this case study, the company is interested in maintaining good customer responsiveness, and hence, it plays an important role in the model as an objective. In some cases, differential weights could also be applied, where the criteria weights could be assigned by customer. With this method, responsiveness could be considered as important as profit for major customers and not as important for minor customers.

4.4 Demand Sensitivity

This model is more useful to the decision makers than the basic model presented in Chapter 3. However, changes in the demand forecast over the planning horizon can easily result in changes in the model solution (and execution time). That is, this model is more sensitive to changes in the data or criteria weights. The next sub-sections show how a sensitivity analysis and scenario modeling can be used to study solution robustness.

4.4.1 Sensitivity analysis

The demand forecasts in this case study show a somewhat increasing pattern. From period to period the forecasts increase slightly, sometimes not changing much, but by the end of the time horizon, large increments in demand can be observed, compared to the starting time periods' forecasts. A sensitivity analysis was performed, where the order of the demand data over 24 months was changed several times to observe how sensitive the model was to opening the different DC's according to different periods' demand. For example, one of the scenarios moved the demand data for the last 12 months to the beginning of the horizon and the one of the first 12 months to the end. Table 4.7 shows some of the results from the different demand data patterns. It can be observed that the same DC's opened in all four scenarios but in different periods, according to where the high demands were. The only difference was in the third scenario, which suggests opening a DC with medium capacity at location 3 for the last four periods. This expansion seems to occur because the last four periods have large demands, and since it is at the end of the time horizon, it is more profitable and responsive to pay higher leasing costs for four periods to expand the DC and supply some large orders from it, than sending all direct shipments from the plant. It can also be observed that the profit values are all very close, meaning that the optimal solutions are very close. The profit of the scenario with the actual forecast is higher because it does not start with the largest DC at location 1 and opens the DC at location 3 later in the horizon. This is due to the fact that the actual demand from periods 1 through 6 is the lowest, and hence there is no need to have so much capacity to store products during these periods. On the other hand, the other scenarios have the actual data of periods 1 through 6 later in the horizon, and hence larger demands are distributed in the earlier periods, needing larger DC capacities from the beginning of the horizon.

Table 4.16. Sensitivity analysis for switching the periods' demands using the weights from Scenario 6

	Actual forecast	Last 12 months at the beginning	Demand periods 7-12 and 19-24 in front of 1-6 and 13-18, respectively	Order of the periods of actual demands: 19-24, 13-18, 7-12, 1-6
DC 1 Size	1,000 for the 1st period 2,000 for the rest	2,000 for all periods	2,000 for all periods	2,000 for all periods
DC 2 Size	500 for all periods	500 for all periods	500 for all periods	500 for all periods
DC 3 Size	500 for period 24	500 for all periods	500 for the 1st 20 periods 1,000 for the last 4 periods	500 for all periods
Profit	$46,043,021.00	$41,775,875.99	$41,723,195.18	$41,723,195.18

The same sensitivity analysis was performed to the single objective profit model (Table 4.8). In this case, DC's in locations 2 and 3 are always opened. Also, the DC in location 1 is closed in two of the scenarios and in the other two, it is only opened for the last two periods. This DC is closed in the second and third scenarios because these include the larger demands at the beginning of the period and opening this DC for all the periods is not profitable. However, in the scenarios where these demands are at the end of the time horizon, it opens it at the end because it is more profitable to incur in the warehouse costs for this location and supply more demand from here than directly from the plant.

Table 4.17. Sensitivity analysis for switching the periods' demand for Scenario 1 (profit as single objective)

	Actual forecast	Last 12 months at the beginning	Demand periods 7-12 and 19-24 in front of 1-6 and 13-18, respectively	Order of the periods of actual demands: 19-24, 13-18, 7-12, 1-6
DC 1 Size	500 for periods 23-24	Closed	500 for periods 23-24	Closed
DC 2 Size	500 for periods 3-24	500 for all periods	500 for periods 2-24	500 for periods 17-24
DC 3 Size	500 for all periods	500 for all periods	500 for all periods	500 for all periods
Profit	$52,680,802.45	$52,748,563.96	$52,571,062.02	$53,832,834.07

The sensitivity analyses show that, the opening of the DC's and their sizes depend on when the large demands happen. That is, if the larger demands are at the beginning of the time horizon, the model suggests using more direct shipments and opens fewer or smaller DC's. However, if these larger demands are at the end, then the model suggests opening more or bigger DC's later in the horizon. This happens because incurring in more or bigger DC's for a short time horizon gives a better solution to the multi-criteria and profit objective functions than making many direct shipments from the plant, but spending on these DC's for a long time horizon is not profitable and is not justified by the multi-criteria objective function.

Because of the changes in the DC opening results due to the alterations in the data, the model should be run several times and the results of all these runs should be analyzed in order to make the final decisions. One way to analyze the results would be similar to the procedure used in Chapter 3 to select the best distribution for each customer. After the model is run several times, the combination of DC's openings and sizes that was suggested the most could be selected. However, in this case, several other factors should be taken into consideration, like the quantity of demand that could be supplied directly from the plant but was not, because sending it from a DC had a faster response time. That is, if opening a DC of a smaller size is suggested several times, and during the periods it is suggested there are several potential direct shipments from the plants that could be made but the model did not suggest it in the run with the actual order data, then it may be better to open this DC and then expand if necessary. However, when the bigger DC's are suggested by a large number of runs, then that should be the final decision for those DC's. The decisions of opening and expanding DC's are very important and costly, and for this reason the results from the model should be analyzed thoroughly before implementing the decisions. For clarity, a step-by-step procedure is presented below.

STEP 0. Initialization – Select the number of runs or demand pattern changes to be made. The decision concerning the number of runs should be made according to the known accuracy in the history of the forecasts. That is, if the forecasts are known to be somewhat accurate, a low number of runs would be needed, as compared to a history of forecasts with large errors.

STEP 1. **Define the patterns** – The demand patterns should be created, having the first pattern as the actual forecast. The other patterns will be created by switching the demands between the periods (e.g., move the last half of the time periods' demands to the beginning of the horizon and the first half to the end). However, it must also be considered that the first quarter's demand should be a more reliable forecast, and maybe, it should always stay at the beginning of the horizon and not be moved.

STEP 2. **Run the model** – The model is then run for each pattern created and the results concerning DC openings and sizes will be obtained from each run.

STEP 3. **Analyze results** – The final solution of opening a DC, including its size, is obtained from analyzing the results of all the runs. Some guidelines for selecting the DC's to open, their size, and when to open them are the following:

- If a specific location and size of a DC is selected in more than 50% of the runs, then open it.
- If the solution is not obvious (e.g., for a location, not one size is opened in more than 50% of the runs), use a rolling horizon approach. (See Yang and Chang, 2010, Schönberger and Kopfer, 2009, and Boulaksil *et al*., 2009 for examples of models using a rolling horizon approach.) First, implement the results for the first quarter, by either using the results from the actual forecast for this quarter or by opening the least costly DC's suggested from the different solutions. Then, at the end of this quarter, re-run the model for the next 24 periods with updated forecasts to see if the results changed.
- Also, if it is suggested to expand or open a DC later in the horizon, re-run the model in the period before this decision to make sure that this is still the best option (see STEP 4).

STEP 4. Re-run the model – The model should be run again in the following periods:

- Half-way of the time horizon (e.g., in period 12 when there are 24 periods). This is to verify the results with updated forecasts.
- The time period before a DC is supposed to be opened or expanded. The forecasts should be updated and the model should be run every time a change will occur with a DC to make sure that it is still the best option according to more reliable forecasts.

- When the solution in STEP 3 was not obvious and the least costly DC suggested from the results was opened at a location, the model should be run 2 or 3 periods later, or at the latest, at the end of the quarter, to observe if more obvious results are obtained with the updated forecasts and if any changes are needed.

Scenario 6 was used to illustrate the decision making process of opening DC's using the above procedure. First, four demand patterns were created as can be observed in Table 4.7. The first pattern is the actual forecast. The second pattern was obtained by switching the demands of the last 12 periods to the beginning of the horizon and the first 12 to the end. For the third pattern, the demands of the second half of the first year (periods 7 – 12) were switched with the demands from the first half of that year (periods 1 – 6), and the demands of the second half of the second year (periods 19 – 24) were switched with the demands from the first half of that second year (periods 13 – 18). The last demand pattern was created by placing the demands of the last six periods (periods 19 – 24) at the beginning of the time horizon, then placing the demands of the second to last six periods (13 – 18) after these, then inserting the demands of periods 7 – 12 after the ones of periods 13 – 18, and then placing the first periods' demands (1 – 6) at the end. The results obtained from STEP 2 are shown in Table 4.7.

It can be observed in Table 4.7, that for Scenario 6 the results seem to be obvious; that is, each of the DC's obtained a solution in more than 50% of the runs. The final solution in this case should be opening a large DC in location 1 and small DC's in locations 2 and 3 since the beginning for all 24 periods (no expansions in this time horizon). However, in the first pattern (actual forecast), it is suggested to open a medium size DC at location 1 for the first period and then expand it to the large size in the second period. Even though this result is for the first quarter, which has the most reliable forecast, it might be costly to have the smaller DC for just one period and then go through an expansion process right away. Instead, the large DC could be opened from the beginning as suggested in most of the demand pattern scenarios. After implementing the results, the model should be run again in period 12 for the next 24 months as suggested in STEP 4, and then before any other period where an expansion is suggested.

4.4.2 Demand uncertainty

Similar to the sensitivity analysis for the different demand patterns discussed above, the model should be analyzed for variations in demand. The demand used in the strategic-tactical integrated model was based on monthly forecasts. The reality is that demand forecasts are uncertain, and hence, not completely reliable. According to Portillo (2008), each forecast is exposed to uncertainty from both, the uncertainty in the development of exogenous variables and that from errors resulting from the model used in preparing the projection. For this reason, a methodology should be used to deal with this demand uncertainty.

The procedure to be used to manage uncertainty depends on the data available. Gupta and Maranas (2003) mention that there are two different methodologies to represent uncertainty in stochastic programming: distribution-based and scenario-based approaches. However, in the case, as well as in most cases, the demand probability distribution is not available. Thus, a scenario-based analysis can be used to analyze the results of this model.

In Chapter 3, a type of scenario analysis was performed. The basic model was run several times with different demands, one run for each of the twelve months in the year. However, the strategic-tactical model developed in this chapter is a multi-period model and contains all the different monthly demands in the model. Hence, the scenario analysis in this chapter should be performed differently, by using distinct discrete economic scenarios (e.g., worst-case scenario, best-case scenario, most-likely-to-happen scenario, etc.). The scenarios can be catalogued according to their demand, from the best case to the worst. Table 4.9 shows an example of how the data could be arranged when doing a scenario analysis with discrete economic scenarios using the data from the case study. The table contains the data for one customer from all the manufacturing plants (s) for the first three periods (p). In this case, the forecast demand used in the model is catalogued as *fair*. This table should be constructed by the decision makers, using the forecasts as a reference. These forecasts can be obtained using analytical methods (e.g., regression models, moving average method, Holt's technique, etc.) or consensus techniques (e.g., surveys, Delphi method, experts' opinions). Chopra and Meindl (2007) describe in detail all of the forecasting analytical methods, as well as the Delphi method and other consensus techniques.

Table 4.18. Scenario analysis sample data for customer 1

		Scenario				
s	p	Best	Good	Fair	Bad	Worst
1	1	602	551	501	451	401
2	1	195	178	162	146	130
3	1	16	15	13	12	11
4	1	6	5	4	3	2
1	2	641	588	534	481	427
2	2	90	83	75	68	60
3	2	15	14	12	11	10
4	2	5	4	3	2	1.5
1	3	551	505	459	413	367
2	3	111	102	92	83	74
3	3	18	16	15	13	12
4	3	2	1.5	1	0.75	0.5

In this research, it is suggested to use consensus to obtain the different scenarios. The decision makers should meet to discuss the forecasts and select the possible scenarios. There can be *n* different scenarios, depending on the amount of data available and the decision makers' preferences. In Table 4.9, we have used $n = 5$ for illustrative purposes, to show an example of the procedure and how the data should be collected. The five scenarios (or *n* scenarios for the general case) for each of the 66 customers and 5 independent distributors have to be obtained and the model should be run five times, one for each scenario. Similar to the sensitivity analysis for the demand patterns, five different sets of results would be obtained and the decision makers should select the one that represents the present reality the best or the one that was obtained the most. The results obtained from this analysis and the ones from the sensitivity analysis should be compared when making the final decision.

4.5 Conclusions

This chapter presented an extension to the basic model developed and analyzed in Chapter 3. The model developed in this chapter integrates strategic and tactical decisions when designing a distribution network. The strategic decisions are the location and size of the DC's to be opened in specific time periods. The tactical decisions, made by the model, are the selection or planning of the distribution options to be used for each customer in each period. This strategic-tactical model considers the same conflicting criteria as in Chapter 3, namely, profit, customer response time, power, credit performance, and distributor's reputation. In addition, this model also considers multiple time periods to the basic model to make decisions for a given planning horizon.

The case study involving a consumer goods company, described in Chapters 1 and 3, was used again to show the applicability of this model. The model was run in GAMS and took approximately 6 - 8 hours to obtain optimal results with an Intel Pentium Dual Core, 2 GHz processor with 4 GB memory. It was shown that, when multiple criteria are considered in long term decision making models, direct shipments from the plant are not always the best supplying option even if the demand is sufficient. However, this will depend on the importance of each criterion. In this Scenario 6, the profit criterion weight was not high enough to manipulate the decision of increasing the number of direct shipments from the plants. It could be observed that the multi-criteria model suggested that only 44% (in average) of the monthly demand should be supplied directly from the plants, whereas the model that only considered profit (Scenario 1) recommended direct shipments from the plants for 88% of the monthly demand. On the other hand, Scenario 8 used a significantly higher profit weight, resulting in supplying 62% of the demand directly from the plants. Also, the model considering only the profit, does not propose moving any customers to the distributors, whereas the multi-criteria models do it for two customers. The latter decision in the multi-criteria models is influenced by the power, credit performance, and customer responsiveness criteria.

The different results obtained from this case study showed the importance of considering multiple criteria when designing and analyzing supply chains. To have an effective supply chain, several factors and criteria must be considered. Many researchers consider cost or profit as their only objective and fail to consider that response time and other factors (e.g, like dealing with irresponsible customers that represent problems and implicit costs to the company). Also, using weighted non-preemptive goal programming allows changing the priorities of each objective according to the situation at the moment (e.g., in most cases, profit has a significantly higher weight, but in case of an emergency, customer response time may end up as the most important criterion). The criteria weights can also be adjusted by customer. For example, for important customers response time could be as important as profit.

A weakness or concern in having a multi-period strategic-tactical model is that profit and the other criteria values are considered only for a specific number of periods, and that the decisions to be made depend on the demands of each period. To take care of this, this research presented an approach to generate the final decisions when dealing with this sensitivity in demand. A step-by-step procedure was presented to select the final decisions on opening DC's according to different demand patterns. This is necessary because the DC opening decisions were very dependent on when the large demands occurred. Also, a scenario approach that deals with the demand uncertainty (e.g., actual changes in demand, not changes in the demand pattern) was discussed. A procedure that uses discrete economic scenarios was described, but the model was not illustrated. The solution procedure in both approaches is similar to the one used in Chapter 3 to select the final solution, where the model is run several times to select the solution that occurs the most.

The multi-criteria deterministic strategic-tactical model showed how effective it can be when making practical decisions in the marketplace. The model was developed to generate realistic planning decisions that consider the decision makers' preferences. Based on the results obtained for the case study, this model can be very helpful when designing a distribution network. It was shown that the model serves as a support tool for the managers to make the important strategic decisions of opening new DC's and giving up customers to distributors. The model makes the strategic decision of opening DC's, but these decisions can also be considered tactical since, for the opening of DC's in future periods, the model should be run again before that period to make sure that it is still optimal to open it at that moment.

After the results from strategic-tactical model are implemented, a tactical-operational integrated model is used to make daily distribution decisions. The next chapter describes this tactical-operational model in detail.

Chapter 5

TACTICAL-OPERATIONAL MULTI-CRITERIA INTEGRATED MODEL

5.1 Introduction

The research presented in this dissertation so far has focused on strategic and tactical decisions. These decisions are to be used for planning purposes in the long run. However, the results from these models can be used as input for models that make operational decisions. That is, after knowing which DC's are operating and who the final customers are, the logistics to supply the daily orders from the customers need to be determined. This chapter presents a tactical-operational model that helps the logistics team in making these day-to-day decisions.

The tactical-operational model is a distribution model that considers DC's in several locations and decides when to place replenishment orders for these DC's, and when and from where to distribute the customer orders. That is, the model considers the customer demands or orders for each day and decides if it should be sent directly from the plant or from a DC and in which period. Since the model considers day-to-day operations, these decisions are considered to be operational. However, this model is expected to be run for multiple periods for a time horizon larger than a month, in order to plan well for the future orders (e.g., to have an idea of what is needed for future replenishments because the lead times from the plants to the customers and DC's might be high in some cases). Since the time horizon is not small and the decisions for the orders at the later periods may be used for planning, this model is also considered tactical. The decisions for the later time periods are used for planning, because these are not meant to be implemented. That is, solutions for this model are implemented in a rolling horizon every few periods. This is because the results for the later periods may change due to different situations, such as the arrival of new customer orders, changes to the already placed customer orders, additional DC capacities needed, or considerations in the amount of vehicles available.

The results obtained from the tactical-operational model can be used to make other logistics decisions, such as cross-docking. For example, if a replenishment order is expected to arrive to a DC the same day that a customer order from that DC is to be sent, then cross-docking can be planned for that day for that order. Cross-docking can reduce costs significantly, since no holding cost at the DC is incurred, the warehouse space can be used for other products, and the labor cost is reduced since the workers do not have to store the product and then pick it up later (the number of handling steps are reduced).

This type of operational model has been used very often in the past. It is very common for these models to be dynamic. Chandra and Fisher (1994) develop a model similar to the one presented in this chapter. Their model makes decisions for the quantity that should be sent to a customer in a specific time period and how many vehicles are needed to serve these orders. Also, they take into consideration the inventory at the DC's and the amount of product to be sent to them at each period (they consider the amount produced at a plant to store at the DC). However, they consider only one type of vehicle, whereas the model presented in this chapter considers multiple types. A similar model has been developed by Bolduc *et al*. (2006) considering several vehicle types. Still, the model developed in this chapter has multiple DC's and objectives, while both of these models consider only one DC and a single objective. Also, the tactical-operational model presented in this chapter considers direct shipments from the plant as one of the distribution options, which are not considered by these scholars, as well as by most other researchers.

Similarly, Kreng and Chen (2008) consider the distribution network problem of delivering products from the plant to a DC and from this DC to the retailers. In their work they analyze the advantages of cross-docking and use two distribution options: cross-docking at the DC and no cross-docking or "normal" distribution from the DC. Also, they consider only one type of vehicle but with two different costs – Full-Truck-Load and Half-Truck-Load – which can then be considered as two types of vehicles with different capacities. However, they also do not consider more than one DC and multiple objectives.

Lee *et al*. (2008) develop a mixed integer program (MIP) for distribution planning (i.e., multiple plant warehouses supply multiple DC which supply multiple customers) but consider neither direct shipments from the plants nor different vehicle types nor multiple criteria. The way their model is formulated is very similar to the one developed in this chapter in the sense that, the distribution variables consider the lead time (LT) and show the amount to deliver at period, $p\text{-}LT$, to be received by the customer at period p to serve their demand for that period. The same concept is used for the replenishment orders from the plants' warehouses to the DC's.

On the other hand, Le Blanc *et al*. (2006) consider a similar approach to the direct shipments from the plant included in the models presented in this dissertation. They introduce the term of Factory Gate Pricing (FGP) which means that the retailer buys the product directly with the manufacturing plant and the product does not go through a consolidation hub or DC. However, in their approach, the retailer takes care of the transportation costs from the plant when this option is used, whereas, in the models presented in this dissertation, these costs are incurred by the company or supplier and not the retailer. Also, Le Blanc *et al*. (2006) only consider one DC or hub, one objective, and one vehicle type for the trips from the DC.

Finally, Tuzkaya and Önüt (2009) present a distribution network where the echelons are raw material suppliers, a DC, and the manufacturing plants. In this case, the manufacturers can be compared to the customers in this chapter's model and the suppliers to the manufacturing plants. This model, as most of the previous ones, does not consider different vehicle types, direct shipments from the plants (suppliers), nor multiple objectives.

The review discussed above presents the models that mostly relate to the research presented in this chapter. As it could be observed, none of them included multiple criteria. The closest multi-criteria models are those developed by Liang (2006), Liang (2008), and Liang and Cheng (2009), where a production/distribution model is presented with similar distribution decisions, but do not consider direct shipments from the plants nor different vehicle types to supply the demand from the warehouses. Also, Porkharel (2008) consider multiple criteria in making distribution decisions with a system very similar to the one described by the above researchers, but instead of a plant there is an assembler.

The model developed in this chapter includes three criteria: maximizing profit while minimizing customer response time and stock-outs or lost sales. The other criteria from the previous models (e.g., power, credit performance, and distributors' reputation) were not included since they were related to the decision of moving customers to be served by independent distributors – and in this model those decisions have already been made.

The tactical-operational (T-O) model takes as input some decisions from the strategic-tactical (S-T) model and then makes the distribution decisions. Figure 5.1 summarizes all the decisions made from both models. The S-T model makes two types of decisions: final and planning decisions. The final decisions are those that are implemented and used as input to the T-O model. These include the locations and sizes of the DC's to be opened and the final list of customers. The final list of customers eliminates the customers that are moved to an independent distributor and considers the independent distributors as customers. The planning decisions are those that help the S-T model in making the final decisions (e.g., distribution from the DC's or using direct shipments from the plant). These are needed to give the S-T model an idea of how the distribution network should look like according to the forecasts, in order to generate the optimal results for DC locations and sizes. The T-O model then uses the DC locations and sizes and the final list of customers as input to make the day-to-day distribution decisions with actual customer orders (e.g., the quantity of each product delivered directly from the plants or from a DC to each customer and the time period it should be sent, and the DC replenishment orders for each product and DC and the time period these should be placed). Figure 5.2 illustrates the integration of the two models. The flowchart shows the data needed for each model, the decisions made by each, and how the decisions from one model are needed as input data for the other.

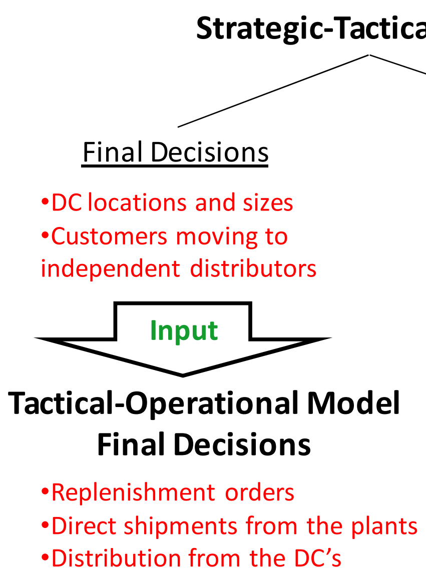

Figure 5.7. Integration of the decisions of the strategic-tactical model and the tactical-operational model

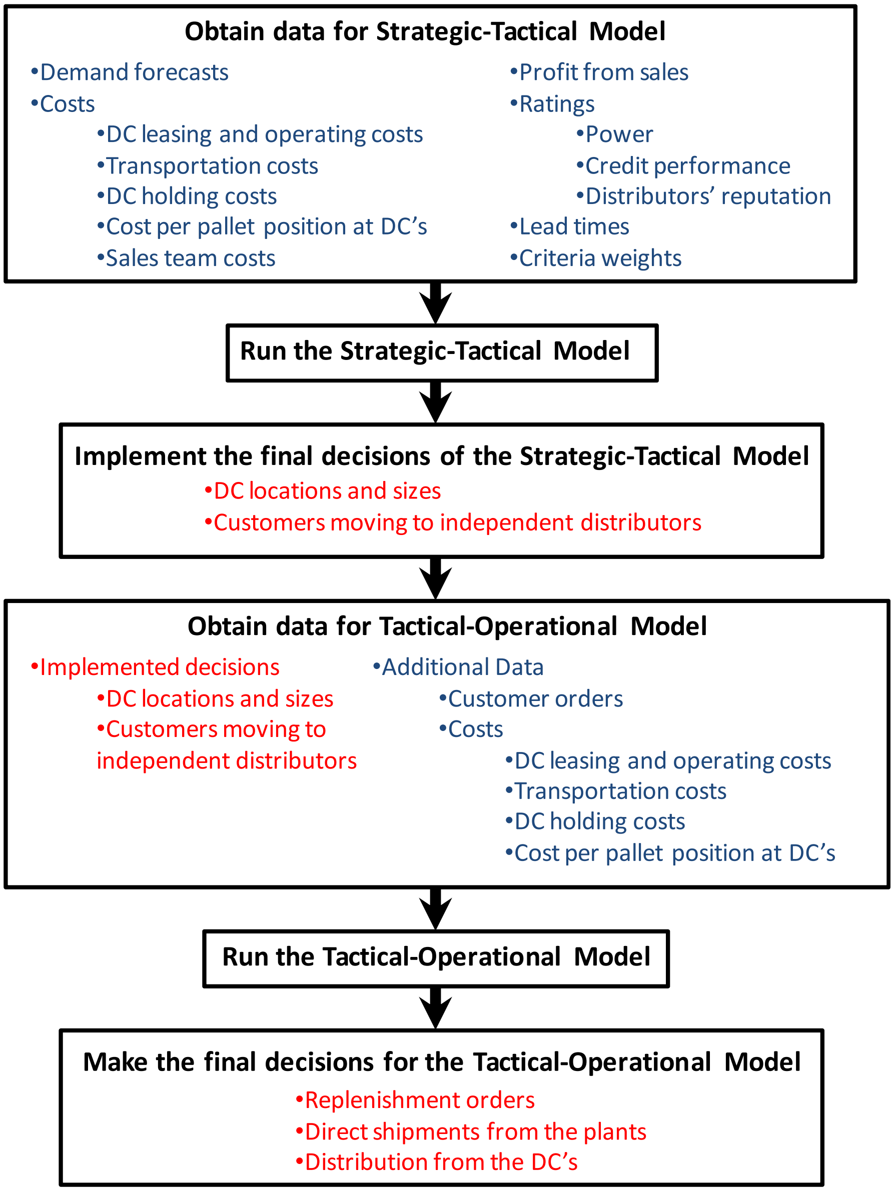

Figure 5.8. Integration of the Strategic-Tactical and Tactical-Operational models

In summary, the multi-criteria tactical-operational integrated model is a multi-period MIP that supports the decision making process of supplying orders to the customers and placing replenishment orders. The model shows when a replenishment order should be placed, when an order to a customer should be sent, and the location it should be sent from (e.g., from a DC or directly from the plant). The demand data in this model are actual orders from the customers, so uncertainty in demand does not need to be considered. In general, this model can be very useful for the companies when making the everyday decisions of meeting the customer orders.

5.2 Mathematical Model

This chapter presents a multiple criteria dynamic optimization model that makes straight distribution decisions (e.g., distribution plans for supplying the customer demands and replenishment orders' planning). This model is meant to be used more frequently than the model from the previous chapter. As an operational model it makes decisions for day to day operations. On the other hand, as a tactical model, decisions at the later periods in the time horizon are used for planning and are not meant to be implemented as they may change (due to customer or replenishment orders' alterations, adjustments in DC capacities, or possible bounds in the number of vehicles).

This model uses as input some of the results from the strategic-tactical model, such as DC locations and capacities and the final list of customers (i.e., the independent distributors and the customers from the previous models except those moved to an independent distributor). Since the independent distributors are treated as customers in this model and the decision of moving customers to a distributor is not being considered in this model, only two of the distribution options from Figure 3.1 are considered: options 1 and 2 (Figure 5.3). Hence, this model provides the optimal distribution strategy for the orders placed by the customers – the source that will supply the order (e.g., manufacturing plant *s* directly or DC *r*), the time period it should be sent to the customer, the vehicles to be used to deliver the orders from the DC's, and the time period and quantity for replenishments orders.

Figure 5.9. Distributions options considered in the tactical-operational model

This model introduces some additional sets, but some notations have changed. Hence, all the sets and notations will be described here. Let $S = \{1, 2, \ldots, n_S\}$ be the set of manufacturing sites, $M = \{1, 2, \ldots, n_M\}$ be the set of all products, $R = \{1, 2, \ldots, n_R\}$ be the set of all opened DC's, $K = \{1, 2, \ldots, n_K\}$ be the set of vehicle types to be used to supply from a DC to the customers, $J = \{1, 2, \ldots, n_J\}$ be the set of all customers, and $P = \{1, 2, \ldots, n_P\}$ be the set of time periods. It is assumed that a product can only be made in one plant. However, a plant can make multiple products. Sets I_s are introduced to represent the products produced at each manufacturing plant *s*. The following sub-sections describe in detail the notation, constraints, and objective functions utilized in the operational-tactical model.

5.2.1 Notation

This sub-section describes the parameters and variables used in the integrated tactical-operational model. The notations in this chapter are independent of the ones used in the previous chapters and hence, no comparisons should be made with the previous models' notation. Some of the parameters and variables may be similar but are not necessarily the same.

Model Parameters

CAP_{rp}	capacity at DC r in period p (in pallets) – from the results of the S-T model, where capacity expansions may have occurred from one period to another
cd_{mjp}	demand of customer j for product m in period p (in cases)
$cspl_m$	cases per pallet for product m
MSO_j	fraction of maximum stock-outs allowed for customer j
vc_k	capacity of vehicle type k (in pallets)
CC	capacity of a container vehicle used to ship products from a plant's warehouse (in pallets)
MD	minimum demand necessary for direct shipments (in pallets)
M	a very large number
$DCLT_{rj}$	lead time to deliver a product from DC r to customer j (in time periods)
$SCLT_{mj}$	lead time from the plant for product m to customer j (direct shipment lead time) (in time periods)
$SDLT_{mr}$	lead time from the plant for product m to DC r (replenishment lead time) (in time periods)
OHI_{mr0}	initial on-hand inventory of product m at DC r (in cases)
x^0_{mrp}	replenishment order of product m for DC r arriving in period $p = 1,\ldots, SDLT_{mr}$ (in cases)
$VCM1_m$	variable contribution margin of product m when distributed from a DC (in dollars)
$VCM2_m$	variable contribution margin of product m when distributed directly from a plant (in dollars)
$\mathrm{LTCC}_{\mathrm{krj}}$	transportation cost per trip when vehicle k delivers products from DC r to customer j (in dollars)
TCC_{sj}	transportation cost when a container vehicle delivers products from plant s directly to customer j (in dollars)

$TCDC_{sr}$	transportation cost when a container vehicle delivers a replenishment order from plant s to DC r (in dollars)
PV_m	value or cost of product m that the DC's "pay" to the plants (in dollars)
HC_m	inventory holding cost per case and period for product m (in dollars/unit cost/period)
$ITIC_m$	in-transit inventory holding cost per case per period for product m (in dollars /unit cost/period)
SC	replenishment order setup cost (in dollars)
CPP	cost per pallet position at the DC's (in dollars)
MP	maximum profit – ideal target value for the profit criterion
MRT	minimum response time – ideal target value for the customer response time criterion
MLS	minimum lost sales – ideal target value for the stock-out criterion

<u>Model Variables</u>

OHI_{mrp}	on-hand inventory of product m in DC r at the end of period p (in cases)
x_{mrp}	quantity of product m received at DC r in period $p = SDLT_{mr}, \ldots, n_p$ (in cases)
$y_{mrjp,}$	quantity of product m received by customer j in period $p = DCLT_{mj}, \ldots, n_p$ from DC r (in cases)
t_{mjp}	quantity of product m delivered directly from the plant to customer j in period $p = SCLT_{mj}, \ldots, n_p$ (in cases)
SO_{mjp}	stock-out of product m for customer j in period p (all the stock-outs are lost sales) (in cases)
γ_{krjp}	number of vehicles type k (or number of trips) needed to supply the demand (order) of customer j from DC r in period p
α_{sjp}	1 if t_{mjp} divided by its respective cases per pallet is greater than MD, and 0 otherwise
β_{srp}	1 if x_{mrp} divided by its respective cases per pallet is greater than MD, and 0 otherwise
IC_{sjp}	number of containers to be sent directly from plant s to customer j in period p
$DCIC_{srp}$	number of containers to be sent from plant s to DC r in period p
$CODC_{mrjp}$	amount of product m to be sent to customer j from DC r in period p (in cases)
$CODS_{mjp}$	amount of product m to be sent directly to customer j in period p (in cases)
DCO_{smrp}	DC replenishment order from plant s of product m for DC r to be placed in period p (in cases)

5.2.2 Model Constraints

The tactical-operational model presented in this chapter was developed to obtain the optimal distribution plan considering the customers' demands and the locations and capacities of the opened DC's. That is, the model selects the location that will supply each product's demand for each customer at each period (e.g., customer receive from the plants through direct shipments or one or more DC's), and the period when the DC's replenishment orders should be placed to each plant, while considering DC capacity constraints and product availability constraints.

Inventory Balance at DC's

The first sets of constraints considered in the model were the inventory balance equations. Equations (5.1), (5.2), and (5.3) calculate, for each DC, each product's on-hand inventory for a period, using the previous period's on-hand inventory plus the replenishment orders arriving at that period minus the customer orders being delivered in that period. Equations (5.1) and (5.2) were introduced in order to include the initial data for periods 1 through $SDLT_{mr}$. That is, the initialization of the model must include values for the initial on-hand inventory (OHI_{mr0}) and for any incoming DC replenishment orders (x_{mrp}^{0}). Hence, for each m and r, for periods $p = 1,\ldots, SDLT_{mr}$, x_{mrp}^{0} are known constants representing the replenishment orders already in transit, and for periods $p = SDLT_{mr}+1,\ldots,n_P$, x_{mrp} are decision variables.

$$OHI_{mr0} + x_{mr1}^{0} - \sum_{j \in J} CODC_{mrj1} = OHI_{mr1}, \quad m \in M, r \in R, \tag{5.1}$$

$$OHI_{mr,p-1} + x_{mrp}^{0} - \sum_{j \in J} CODC_{mrjp} = OHI_{mrp}, \quad m \in M, r \in R, p \in \{2, \ldots, SDLT_{mr}\}, \tag{5.2}$$

$$OHI_{mr,p-1} + x_{mrp} - \sum_{j \in J} CODC_{mrjp} = OHI_{mrp}, \quad m \in M, r \in R, p \in \{SDLT_{mr} + 1, \ldots, n_P\}. \tag{5.3}$$

Next, it is important to assure that the total on-hand inventory does not exceed the capacity of the DC. Equation (5.4) forces the total inventory for each DC at each period to be lower than the DC capacity. Since the on-hand inventory for each product is in cases, it is divided by the cases per pallet for each product ($cspl_m$), to compare it to the DC capacity, which is in pallets.

$$\sum_{m\in M} {OHI_{mrp}}\Big/{cspl_m} \leq CAP_{rp}, \quad r \in R, p \in P. \tag{5.4}$$

<u>Demand Distribution Constraints</u>

Equation (5.5) shows the set of constraints that represent the distribution plan to meet the customer demand. In this equation, the sum of the shipments from the DC's and the amount supplied directly from the plant to a customer at a specific period must be lower than or equal to that period's customer demand for a given product. That is, customers do not receive more than what they ordered. Product stock-outs are allowed and are considered as lost sales. Later, stock-outs will be minimized as another objective to maintain good customer service. Also, in this model, it is assumed that a customer can receive a product from both sources, directly from the plant or from one or more DC's, independent of the results obtained from the S-T model. Similar to equations (5.1) – (5.3), equation (5.5) contains some terms that will be constants for some periods. That is, y_{mrjp} are known constants for periods $p = 1,\ldots,DCLT_{mj}$ and decision variables for periods $p = DCLT_{mj},\ldots,n_p$, and t_{mjp} are known constants for periods $p = 1,\ldots,SCLT_{mj}$ and decision variables for periods $p = SCLT_{mj},\ldots,n_p$.

$$\sum_{r\in R} y_{mrjp} + t_{mjp} + SO_{mjp} = cd_{mjp}, \quad m \in M, j \in J, p \in P. \tag{5.5}$$

It is assumed that the company has a policy that, even though stock-outs are allowed, a certain percentage of the demand must be met. Equation (5.6) limits the stock-outs of each product for each customer at each period by an MSO_j fraction of the demand. This fraction is determined by the decision makers for each customer, according to their importance; the more important the customer is, the lower the MSO_j value, and vice versa. This number is normally set between 0% and 25% of the demand, where 0% represents a no-stock-outs policy.

$$SO_{mjp} \leq MSO_j cd_{mjp}, \quad m \in M, j \in J, p \in P. \tag{5.6}$$

Equation (5.7) selects the best vehicle types for each customer order delivered from a DC, similar to the transportation constraints used in the previous models. Different vehicles with different capacities are available, and the most profitable ones, subject to capacities, are selected for each customer order delivered from each DC in a specific period. The model assumes that there are an infinite number of vehicles, meaning that all necessary vehicles are always available.

$$\sum_{m\in M} {y_{mrjp}}/{cspl_m} \leq \sum_{k\in K} \gamma_{krjp} vc_k\,, \quad r \in R, j \in J, p \in P. \tag{5.7}$$

On the other hand, the orders to the plants require a minimum of *MD* pallets. Hence, the sum of a specific customer's demands of all the products for a specific plant and period must be greater than or equal to *MD*. Likewise, a DC replenishment order must exceed *MD* pallets when adding the quantities of all the products from the specific plant. Equations (5.8) and (5.10) represent the orders to the plant for the customers and for the DC's, respectively. Equations (5.9) and (5.11) were introduced to assign a value of zero to t_{mjp} and x_{mrp} if the plant order requirements are not met. Binary variables α_{sjp} and β_{srp} were introduced in these sets of equations to force the t_{mjp} and x_{mrp} variables divided by their corresponding cases per pallet ($cspl_m$) to be greater than *MD* or to be exactly 0. When the binary variables are equal to 1, t_{mjp} and x_{mrp} divided by $cspl_m$ may obtain a value greater than *MD* and less than a very large number *M*. However, when these binary variables are equal to 0, t_{mjp} and x_{mrp} are forced to be 0 as well.

$$\sum_{m\in I_s} {t_{mjp}}/{cspl_m} \geq MD\alpha_{sjp}, \quad s \in S, j \in J, p \in P, \tag{5.8}$$

$$\sum_{m\in I_s} t_{mjp} \leq M\alpha_{sjp}, \quad s \in S, j \in J, p \in P, \tag{5.9}$$

$$\sum_{m\in I_s} {x_{mrp}}/{cspl_m} \geq MD\beta_{srp}, \quad s \in S, r \in R, p \in P, \tag{5.10}$$

$$\sum_{m\in I_s} x_{mrp} \leq M\beta_{srp}, \quad s \in S, r \in R, p \in P. \tag{5.11}$$

Also, for the orders to the plants, the number of containers needed is calculated in order to determine the transportation cost later on. Equations (5.12) and (5.13) compute the number of containers to be sent from a specific plant to a customer in a specific period, given that the container capacity is *CC*. Likewise, for DC replenishment orders, equations (5.14) and (5.15) use the same container capacity (*CC*) to calculate the number of containers to be sent from a plant to a specific DC to arrive at a given period.

Equations (5.13) and (5.14) would not be needed if the model only considered maximizing profit, but since other objectives are included, these constraints are necessary.

$$\frac{\sum_{m\in I_s} {t_{mjp}}/{cspl_m}}{CC} \leq IC_{sjp}, \quad s \in S, j \in J, p \in P, \tag{5.12}$$

$$\frac{\sum_{m\in I_s} {t_{mjp}}/{cspl_m}}{CC} + 1 \geq IC_{sjp}, \quad s \in S, j \in J, p \in P, \tag{5.13}$$

$$\frac{\sum_{m\in I_s} {x_{mrp}}/{cspl_m}}{CC} \leq DCIC_{srp}, \quad s \in S, r \in R, p \in P, \tag{5.14}$$

$$\frac{\sum_{m\in I_s} {x_{mrp}}/{cspl_m}}{CC} + 1 \geq DCIC_{srp}, \quad s \in S, r \in R, p \in P. \tag{5.15}$$

Finally, some equations are introduced to get the period when orders should be placed or sent. That is, equation (5.16) shows the period when a specific product should be sent to a specific customer, equation (5.17) represents the moment in which a customer order should be placed at a plant for it to arrive at the customer at their desired period, and equation (5.18) gives the period in which a DC replenishment order should be placed at the plant for it to arrive when needed. These equations are to be used with the results obtained from the model and are introduced to help the decision makers view the periods when the orders should be placed or sent.

$$CODC_{mrjp} = y_{mrj,p+DCLT_{rj}}, \quad m \in M, r \in R, j \in J, p \in P, \tag{5.16}$$

$$CODS_{mjp} = t_{mj,p+SCLT_{mj}}, \quad m \in M, j \in J, p \in P, \tag{5.17}$$

$$DCO_{mrp} = x_{mr,p+SDLT_{mr}}, \quad m \in M, r \in R, p \in P, \tag{5.18}$$

5.2.3 Objective Functions

This model considers three different objectives: maximize profit, minimize customer response time for filled orders, and minimize the number of stock-outs. Equations (5.19) – (5.21) present these three objectives. The profit goal includes the variable contribution margins or profit per product sold for each distribution option and the following costs: transportation costs for each distribution option and for replenishment orders, warehouse holding costs, cost per pallet position at the DC's, and replenishment order costs (in-transit holding cost, order set up cost, and the amount paid per product ordered to the manufacturing plant). In this model, the stock-outs are not being penalized in the profit function since their cost is difficult to calculate, and hence they are being handled in another objective (and it is assumed in the constraints that the company has a maximum stock-outs policy).

- <u>Maximize Profit</u>

$$\sum_{m\in M}\sum_{j\in J}\sum_{p\in P} VCM1_{mjp}\sum_{r\in R} y_{mrjp} + \sum_{m\in M}\sum_{j\in J}\sum_{p\in P} VCM2_{mjp}t_{mjp} - \sum_{k\in K}\sum_{r\in R}\sum_{j\in J} LTCC_{krj}\sum_{p\in P}\gamma_{krjp} - \sum_{s\in S}\sum_{j\in J} TCC_{sj}\sum_{p\in P} IC_{sjp}$$
$$- \sum_{s\in S}\sum_{r\in R} TCDC_{sr}\sum_{p\in P} DCIC_{srp} - \sum_{m\in M} HC_m\sum_{r\in R}\sum_{p\in P} OHI_{mrp} - \sum_{m\in M} ITIC_m\sum_{r\in R}\sum_{p\in P} SDLT_{mr}x_{mrp}$$
$$-SC\sum_{s\in S}\sum_{r\in R}\sum_{p\in P}\beta_{srp} - \sum_{m\in M} PV_m\sum_{r\in R}\sum_{p\in P} x_{mrp} - CPP\sum_{m\in M}\sum_{r\in R}\sum_{p\in P} {OHI_{mrp}}/{cspl_m}, \tag{5.19}$$

- <u>Minimize Weighted Response Time for Filled Orders</u>

$$\sum_{r\in R}\sum_{j\in J} DCLT_{rj}\sum_{m\in M}\sum_{p\in P} y_{mrjp} + \sum_{m\in M}\sum_{j\in J} SCLT_{mj}\sum_{p\in P} t_{mjp}, \tag{5.20}$$

- <u>Minimize Stock-Outs</u>

$$\sum_{m\in M}\sum_{j\in J}\sum_{p\in P} SO_{mjp}. \tag{5.21}$$

5.2.3.1 Non-Preemptive Goal Programming

Similar to the S-T model, weighted non-preemptive goal programming is used to solve the multiple objective model. As it was mentioned before, non-preemptive goal programming allows for tradeoffs between objectives and allows the decision makers to reconsider their preferences easily (i.e., the decision makers' preferences can be easily changed by just changing the criteria weights). The objective functions presented above are modeled as goals and ideal values are used as the targets. The ideal values are obtained by solving each criterion as a single objective model, ignoring the other criteria. The respective ideal values are represented by MP, MRT, and MLS. Equations (5.22) – (5.24) show the goal constraints of the tactical-operational model. The goal constraints are scaled using their ideal values.

- Profit goal

$$\Bigg(\sum_{m\in M}\sum_{j\in J}\sum_{p\in P} VCM1_{mjp}\sum_{r\in R} y_{mrjp} + \sum_{m\in M}\sum_{j\in J}\sum_{p\in P} VCM2_{mjp} t_{mjp} - \sum_{k\in K}\sum_{r\in R}\sum_{j\in J} LTCC_{krj}\sum_{p\in P}\gamma_{krjp} - \sum_{s\in S}\sum_{j\in J} TCC_{sj}\sum_{p\in P} IC_{sjp}$$
$$-\sum_{s\in S}\sum_{r\in R} TCDC_{sr}\sum_{p\in P} DCIC_{srp} - \sum_{m\in M} HC_m \sum_{r\in R}\sum_{p\in P} OHI_{mrp} - \sum_{m\in M} ITIC_m \sum_{r\in R}\sum_{p\in P} SDLT_{mr} x_{mrp}$$
$$-SC\sum_{s\in S}\sum_{r\in R}\sum_{p\in P}\beta_{srp} - \sum_{m\in M} PV_m \sum_{r\in R}\sum_{p\in P} x_{mrp} - CPP\sum_{m\in M}\sum_{r\in R}\sum_{p\in P} {OHI_{mrp}}/{cspl_m}\Bigg)/MP + d_1^- - d_1^+ = 1, \quad (5.22)$$

- Response time goal

$$\left(\sum_{r\in R}\sum_{j\in J} DCLT_{rj}\sum_{m\in M}\sum_{p\in P} y_{mrjp} + \sum_{m\in M}\sum_{j\in J} SCLT_{mj}\sum_{p\in P} t_{mjp}\right)/MRT + d_2^- - d_2^+ = 1, \quad (5.23)$$

- Lost sales or stock-outs goal

$$\left(\sum_{m\in M}\sum_{j\in J}\sum_{p\in P} SO_{mjp}\right)/MLS + d_3^- - d_3^+ = 1. \quad (5.24)$$

Finally, objective function (5.25) is minimized, which is a weighted sum of the deviations from the goals. w_1, w_2, w_3 in this equation represent the weights for each criterion.

$$z = w_1 d_1^- + w_2 d_2^+ + w_3 d_3^+. \quad (5.25)$$

In the case where the minimum stock-outs (*MLS*) is 0 (e.g., not enough product in the DC's at the beginning of the time horizon), a value of 1 can be used, and adjustments should be made to the objective function to scale the lost sales deviation term. For example, a simple scaling method could be used, where d_3^+ is divided by a number that will make any value of d_3^+ between 0 and 1.

In summary, the tactical-operational non-preemptive goal programming model minimizes equation (5.25) subject to equations (5.1) – (5.15) and (5.22) – (5.24).

5.3 Case Study

The functionality of the tactical-operational model was illustrated with the case study described in the previous chapters. In this case, the data for the actual customer orders and the location and size of each DC with their respective costs were used. Also, the model included data on profit from sales, transportation costs, warehouse costs (e.g., leasing and operational costs, holding costs, and cost per pallet position), replenishment order costs (e.g., order costs and in-transit inventory holding costs), initial inventory, in-transit replenishment orders, in-transit direct shipments, in-transit customer orders from the DC, and lead times. With this input, the model generated the optimal distribution plan to meet the customer demands. The strategy used to set the data for the initial conditions was to not let the model become infeasible. That is, the data for the initial inventory, in-transit replenishment orders, in-transit direct shipments, and in-transit customer orders from the DC's were set to meet the full demand for those periods prior to the products' respective lead times. Hence, the generated solutions would be sensitive to initial values.

The tactical-operational model was run for 15 time periods, each time period representing 2 working days. Since the demand and lead times were obtained for working days (week days), 15 time periods represent about one month and a half. This allowed planning for direct shipments and replenishment orders from the plants that had longer lead times. The lead times from plants 1, 2, 3, and 4 to all customers and DC's were 8, 8, 12, and 5 time periods, respectively, whereas the lead times from the DC's were 1 or 2 time periods. To convert the lead times from days into periods, the working days given were divided by 2 days. In the cases were the lead times in days were odd numbers, the resulting value in periods was rounded up.

For illustration, the results from the strategic-tactical model for Scenario 6 of Chapter 4 were used. With these results, the tactical-operational model ended up with a list of 69 customers, which included the 5 independent distributors and excluded the two customers that were suggested to be moved to an independent distributor in the strategic-tactical model (assuming that this was implemented). Also, according to the results from the S-T model, the plan was to have a large size DC opened at location 1 and small size DC's opened at locations 2 and 3 for two years. Hence, the T-O model used a DC with capacity of 2,000 pallets at location 1 and DC's with capacity of 500 pallets at locations 2 and 3 in all its periods.

As in the previous chapters, this case study was run with GAMS optimization software. The model had nearly 1.5 million variables and more than 1 million constraints (see Table 5.1). The case study included 169 products, 69 customers, 3 DC's, and 15 time periods, which can be considered as a large problem. The MIP problem took from 15 minutes to 4 hours to run the model with an Intel Pentium Dual

Core, 2 GHz processor with 4 GB memory, depending on the weights used for the different criteria. The three criteria included were: maximizing profit, minimizing the weighted response time for filled orders, and minimizing the number of stock-outs or lost sales.

Table 5.4. Problem size

Model Statistics	
Equations	**1,000,606**
Objective Function	1
Goal Constraints	3
Hard Constraints	1,000,602
Variables	**1,438,702**
Continuous	707,272
Discrete	731,430
Binary	*4,320*
Integer	*727,110*

A rolling horizon approach should be used to implement the results. That is, the model should be run at least every three periods with the planning horizon of 15 periods (i.e., 15 – 12 = 3 time periods, where the largest lead time is 12 periods) or when new customer orders are received, and only the results from these first three periods should be implemented at the moment. This is to allow last minute changes to customer orders and replenishment orders to be included in the analysis. The next sub-section shows the results obtained from this model. These results include the optimal distributions and a sensitivity analysis of the weights.

5.3.1 Results

The tactical-operational model generates a distribution plan to supply the customer demands, given the actual customer orders and the location and size of the opened DC's. When running this model, several weight scenarios should be evaluated to observe which results represent the decision makers' preferences the best. Table 5.2 presents the results for the single objective models.

Table 5.5. Single objective models' results

	Weights (Profit, Response Time, Lost Sales)		
	Scenario 1	Scenario 2	Scenario 3
	(1,0,0)	(0,1,0)	(0,0,1)
Profit Goal	$1,934,267	$484,003	$1,131,807
Response Time Goal	743,700	138,346	598,570
Lost Sales Goal	1,214	6,188	0
Stock-outs %	0.9%	4.3%	0.0%
Direct shipments %	57.4%	0.0%	43.8%
Cross-docking %	9.2%	21.5%	23.7%
Avg. Response Time	5.263	1.015	4.200

In this table, the values for the first three rows were obtained directly from the GAMS model results – these were the values resulting from equations 5.22, 5.23, and 5.24. The profit goal value included the variable revenues and distribution costs. The response time goal (in periods) values represent the sum of the lead times per case for all the cases delivered. The lost sales goal number shows the amount of cases that were not delivered (i.e., stock-out cases). The percentages results in the table were obtained from a total demand of 142,521 cases. For example, in Scenario 1, the stock-outs % of 0.9 % was obtained by dividing 1,214 by 142,521 cases. Likewise, the direct shipments % and cross-docking % of 57.4% and 9.2%, respectively, were calculated using the model results of 81,807 and 13,112 cases and the total demand in cases. The 81,807 cases represent the demand sent directly from the plants to the customers in all periods (i.e., the sum of the model results for t_{mjp}). The 13,112 cross-docked cases were obtained from the model results for the y_{mrjp} cases (i.e., demand sent from the DC's to the customers) that were delivered at the same period that x_{mrp} cases (i.e., replenishment orders for the DC's) were received. Finally, the average response time represents the mean time (in periods) it takes to deliver one case to the customers. In Scenario 1, this number (5.263) was calculated by dividing 743,700 (the response time goal value) by the filled orders, the difference between 142,521 and 1,214 (total demand minus the lost sales or stock-outs).

Scenarios 1, 2, and 3 represent the single objective models. In Scenario 1, where profit is the only objective considered, the profit is at its highest or ideal value, but the response time and lost sales goals are affected significantly (437% deviation from the ideal response time and 1,214 cases in lost sales). Scenario 2 shows the results from the single objective model that minimizes response time. In this case, the response time is at its lowest, but the profit and lost sales goals are impacted radically (75% away from the profit ideal value and 6,188 cases of lost sales). Scenario 3 represents the single objective model where lost sales are minimized, in which no stock-outs occur, but the profit and response time goals are significantly affected (41% and 333% difference between the ideal and achieved values, respectively).

Table 5.3 shows the results obtained from different weight scenarios generated from the multi-criteria models. The weights used in Scenarios 4, 5, 6, 7, 8, and 9 were selected to show the interactions of the different criteria. In all these scenarios, the profit objective always had a higher weight. The weights of the response time and lost sales objectives were varied from having equal importance in one scenario, to each being more important than the other in other scenarios. The values in this table were calculated the in same way the numbers in Table 5.2 were obtained.

Table 5.6. Multi-criteria model scenarios

	Weights (Profit, Response Time, Lost Sales)					
	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9
	(0.4,0.3,0.3)	(0.7,0.2,0.1)	(0.7,0.1,0.2)	(0.7,0.3,0)	(0.8,0.2,0)	(0.6,0.4,0)
Profit Goal	$523,870	$1,523,256	$1,862,679	$533,374	$1,725,676	$527,326
Response Time Goal	153,841	573,444	711,652	234,220	646,629	148,307
Lost Sales Goal	0	102	6	5,262	3,716	5,734
Stock-outs %	0.0%	0.1%	0.0%	3.7%	2.6%	4.0%
Direct shipments %	0.6%	42.4%	56.1%	9.1%	50.2%	0.6%
Cross-docking %	66.7%	24.1%	10.6%	55.0%	13.5%	62.9%
Avg. Response Time	1.079	4.026	4.994	1.706	4.659	1.084

Scenario 4 shows all the goals almost equally important (profit is slightly more important than the others). In this case, the profit decreases significantly from the ideal value, while the other two goals are close to being achieved completely. Scenarios 5, 6, and 7 have a constant profit weight of 0.7, but the weights of the other two criteria are varied. Scenario 5 gives slightly more importance to the response time goal than the lost sales goal, Scenario 6 gives a little more importance to the lost sales goal than the response time goal, and Scenario 7 only considers the profit and response time goals, having the profit weight much higher than that for the response time. As the different scenarios were being run, it seemed like the response time was affecting the profit significantly. Hence, Scenarios 8 and 9 were added, where the lost sales weight was kept constant at zero (like in Scenario 7), to observe the actual behavior of the profit due to changes in response time.

Some interesting results were observed from these scenarios. First, in Scenarios 4, 7, and 9, where the response time goal weight was higher than 0.2, the profit was affected significantly (approximately 73% deviation from the ideal profit). This is because none or very few direct shipments occur, and hence, many replenishment orders have to be made in order to distribute the demands from the DC's, which increases the overall cost. Also, it can be observed from Scenarios 5, 6, and 7 that the response time and lost sales goals are negatively correlated (i.e., have an inverse relationship). This is because, as the response time goal weight is raised (and the profit goal weight stays the same) the number of stock-outs increases while the response time decreases, and vice versa when the lost sales goal weight is raised.

The results from Table 5.2 also show the percentage of the demand that was sent directly from the plants to the customers, the percentage that should be planned to cross-dock, the percentage of stock-outs, and the average response time. It could be observed that when the response time goal had a low weight, a large amount of direct shipments occurred and the average response time was higher. However, when it had a weight higher than 0.2, many orders were supplied from the DC's, the model tried to cross-dock as many cases as possible, and the average response time was between 1 and 2 periods. Also, due to the company's policy of restricting the number of stock-outs by customer, the number of stock-outs never surpassed 5%. In the input data, the maximum stock-outs allowed by customers varied from 5% to 25%, where the most important customers (which also had the highest demands) had the lowest allowable stock-out rate of 5%.

The results discussed above can be illustrated graphically in Figure 5.4. It presents a Value Path Graph, which depicts the different goal achievements from Scenarios 4, 5, 6, 7, 8, and 9 and shows a better view of the tradeoff between the different criteria. This graph is a practical illustrative way to present the results to the decision makers. The y-axis represents the fraction of the goal achievements with respect to the ideal values. A value of one represents the best achievement of the goals (e.g., maximum profit, minimum response time, and minimum lost sales). Lower values for the goals on the y-axis represent larger deviations from their ideal values. Since the ideal value for the lost sales goal is zero, a value of one is used to calculate the ratios for this goal.

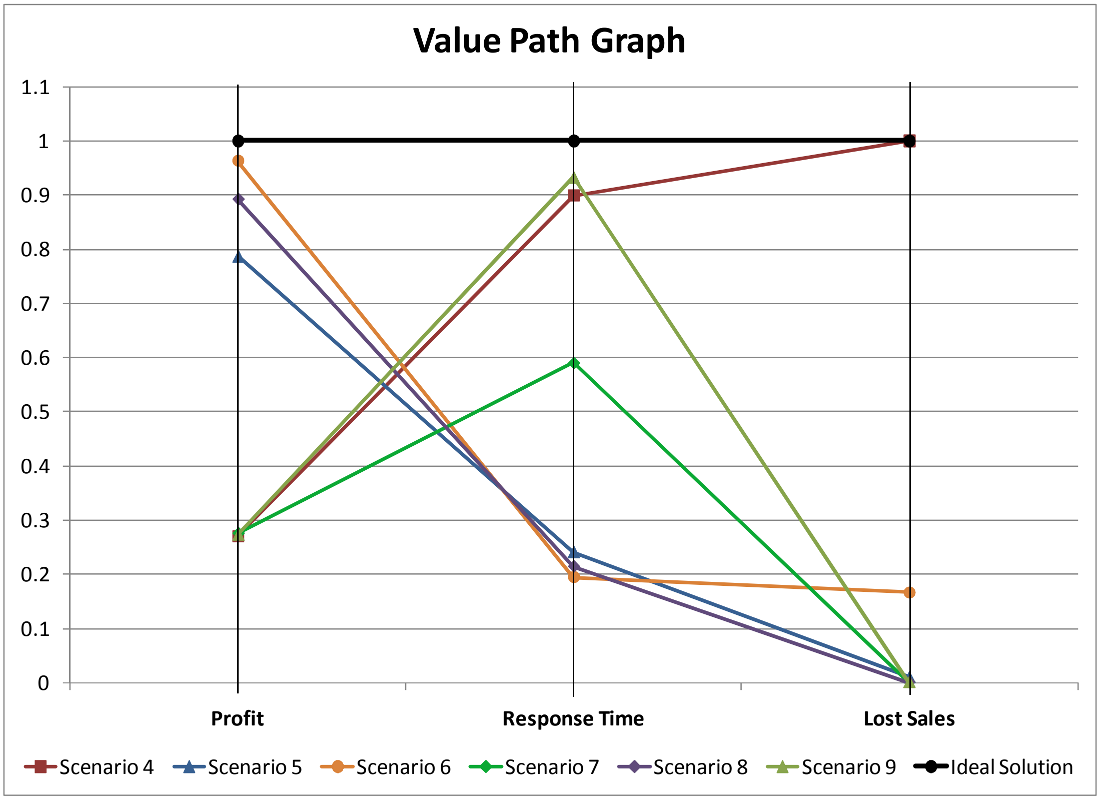

Figure 5.10. Value Path Graph for the T-O model case study

It can be observed that, from these scenarios, only Scenarios 5, 6 and 8 present decent profit values (higher values on the y-axis for profit), which in most cases is the most important objective for companies. Even though Scenario 6 has the worst response time (very low value in the graph) from all other solutions, it seems to have a good solution overall, since the lost sales are low (better than most scenarios) while the profit is close to the ideal. As it was mentioned in the previous chapter, since the lead times are deterministic, it is easy for the company to plan the shipments ahead and deliver the demand on-time at a higher profit. However, if the company is having responsiveness problems, other scenarios should be considered, such as Scenarios 4 and 9. On the other hand, the lost sales goal is far from being achieved in most cases because the ideal solution is zero stock-outs (an ideal value of 1 case was used to allow the calculation of the ideal value divided by the achieved value in the graph). However, this graph allows comparing the achievement results by goal, which shows that, even though the lost sales value for Scenario 6 seems low, it is significantly better than those from Scenarios 5, 7, 8, and 9.

In summary, the graph in Figure 5.4 depicts a visual representation of the results, which helps the decision makers in analyzing the tradeoff between goals and helps them in the selection of the scenario that represents their preferences the best. The results from the first three periods of the selected scenario should be implemented and the model should be run again after these three periods to get updated solutions. This rolling horizon procedure should be followed at least every three periods to get better results for implementation.

Figures 5.5 and 5.6 illustrate the conflicting relationship between the different criteria. Figure 5.5 shows a chart that depicts the changes in profit as the response time goal weight increases (the lost sales weight stays constant). The x-axis of this graph shows the weights of scenarios 1, 8, 7, 9, and 2, respectively, from the one with the lowest response time weight to the highest. The y-axis represents the profit values in dollars. It can be observed that, when the response time weight is between 0 and 0.2, the profit decreases slightly (stays above $1.5 million), but as the weight increases to 0.3 or higher, the profit drops drastically (to almost $0.5 million or less).

Figure 5.11. Profit behavior when increasing the response time goal weight

Finally, Figure 5.6 illustrates the behavior of the three objectives when the response time and lost sales goal weights are varied and the profit weight stays the same. Here, the correlation between the response time and lost sales goals can be observed clearly. In this graph, the y-axis was adjusted to include the values for all three goals. These numbers represent 1 million for the profit and response time values and 10K for the stock-outs number. For example, a value of 1 in the y-axis represents $1 million for the profit goal column, 1million periods for all cases delivered for the response time goal bar, and 10,000 cases for the lost sales goal column. The x-axis shows the weights for scenarios 6, 5, and 7, respectively. In these scenarios the response time goal weight is increased in relation to the lost sales goal weight (the profit weight stays constant). As it can be observed, this makes the number of stock-outs to increase, the response time to decrease, and the profit to shrink. Hence, it illustrates again the dominance of the response time goal when its weight is higher than 0.2 – when the response time goal weight is 0.2 or less, the profit decreases slightly and the stock-outs increase by only a few cases (the bar for the stock-outs is barely seen in the first two scenarios of the graph).

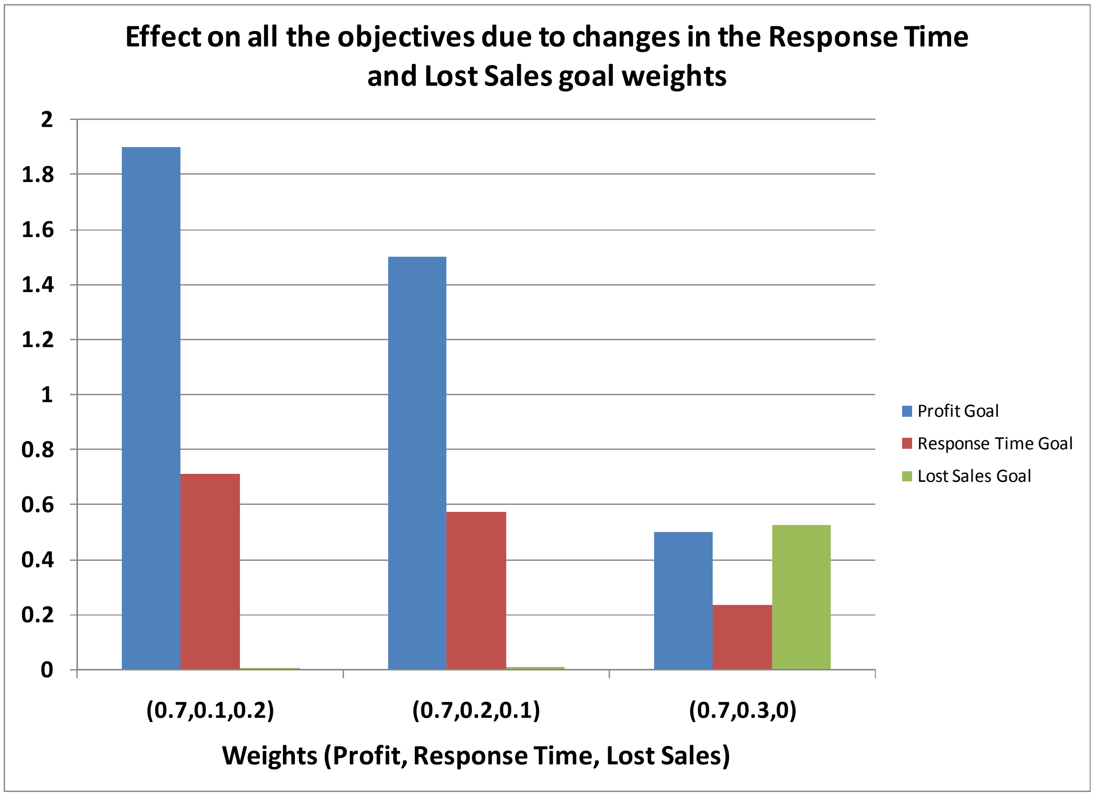

Figure 5.12. Behavior of the three objectives due to changes in the weights for response time and lost sales

5.4 Conclusions

This chapter presented a tactical-operational integrated model. This model makes distribution decisions for filling customer orders, by using as input the results from the strategic-tactical model presented in Chapter 4 and actual customer orders. Being an operational model, this model is meant to be run at least once a week. The model makes operational decisions since it selects the optimal distribution for the daily demand. However, the model is run for a longer time horizon, which makes the decisions for the later periods tactical. That is, the distribution decisions for the later periods may change when the model is run again the next week according to new orders that may arrive and changes to delivery schedules for replenishments. Hence, the resulting decisions for the later periods are simply planning decisions.

This model was run for the consumer goods company case study. Several weight scenarios were run to show how the model results should be presented to the decision makers and to perform a sensitivity analysis of the weights. It took between 15 minutes to 4 hours to run each scenario using an Intel Pentium Dual Core, 2 GHz processor with 4 GB memory. Results showed that the response time goal weight affected the profit significantly. It could be observed that as the response time goal weight increased, the percentage of direct shipments reduced and the profit decreased drastically since many replenishment orders were placed. Also, it was shown that there was an inverse relationship between response time and lost sales, as the response time increased significantly when the lost sales were decreased, and vice versa.

In summary, the tactical-operational model was shown to be a useful tool for companies. This model can be very helpful in the decision making process of the customer orders distribution and planning of replenishment orders. This is because it allows the supply chain team and/or decision makers to view different distribution plans according to the importance of each objective at the moment the model is run.

Chapter 6

CONCLUSIONS, CONTRIBUTIONS, AND FUTURE WORK

6.1 Summary

Multi-criteria supply chain decision-making models were developed in this research. First, a basic model was presented in Chapter 3 that was used as the foundation for the integrated models developed in the later chapters. This model made strategic decisions for distribution, such as supplying the customers via direct shipments from the plants, from a distribution center, or from an independent distributor. Here, it was assumed that there was only one DC with infinite capacity. Also, the basic model was not a multi-period model, but was run several times with the demands of different periods to observe the behavior in the results according to the demand changes. The model included five criteria: maximizing profit, power, credit performance, and distributors' reputation, and minimizing customer response time. Weighted non-preemptive goal programming was discussed and used to solve this model. Using this model as a basis, two integrated models were developed: a strategic-tactical (S-T) model and a tactical-operational (T-O) model.

The S-T model was described in detailed in Chapter 4. This model made similar decisions as the basic model, but included several DC's with different locations and capacities and was modeled as a multi-period model. The model selected the best location for the DC's and the capacities it should have for each period. The model assumed that after a DC was opened it was not allowed to close but it could expand during the planning horizon. Also, this model made decisions about the order fulfillment distribution to the customers (e.g., supply the demand directly from the plants, from a DC, or from an independent distributor). All these decisions were categorized under two types of decisions: final and planning decisions. The final decisions were the ones obtained from the model to be implemented at the moment, whereas the planning ones were included in the model to aid in making the final decisions. The DC locations and sizes and the list of customers being moved to independent distributors were considered as final decisions. The planning decisions were the ones related to the distribution, since these were added only to help the model in selecting the best DC location and capacity. The final decisions should then be implemented and used as input data for the T-O model. The model used the same criteria as the basic model and was also solved using weighted non-preemptive goal programming. This model should be run at the end of every quarter or before a DC was suggested to be opened or expanded to make sure that the demand still behaves the same.

Chapter 4 also discussed the sensitivity and uncertainty in demand. A step-by-step procedure was developed to analyze the results using different demand patterns. This is due to the sensitivity in the results for opening DC's according to when the large demands happen. A similar procedure was suggested to deal with the uncertainty in demand but using discrete economic-scenarios instead of different demand patterns. This is because the S-T model used demand forecasts, which are not always reliable. The procedures were simple and practical to use by companies.

The T-O model, described in Chapter 5, is a multi-period distribution program to meet actual customer demands. Given the DC locations and capacities, the daily customer orders, and the lead times of each distribution option, this model selected the optimal plan to supply the products to the customers. That is, for each customer order, the model decided if it should be distributed directly from a plant or from one of the DC's. Also, the model selected the best vehicle arrangement for the orders supplied from each DC. The decisions made in this model were based on three criteria: maximizing profit, minimizing customer response time, and minimizing stock-outs or lost sales. As in the other models, this one was also solved using weighted non-preemptive goal programming. This model was suggested to be run at least once a week to include any new customer orders received. The integration process of the two models was also shown in detail in Chapter 5.

A case study with real data from a consumer goods company was used to demonstrate the applicability of all these models. The solutions from each model using the case study were obtained and compared. The results included the decisions from each model and some sensitivity analyses. Using this case study, the models were shown to be helpful for companies when making supply chain decisions.

Finally, it was observed that the models' run time varied significantly according to the data. The S-T model's run time was as low as 15 minutes and as high as 8 hours. For the T-O model, the run time was between 15 minutes and 4 hours. The run time is affected by the size of the supply chain. Two factors that affect the supply chain's size are the number of periods in the model and the number of products included. In the S-T model, the number of products was reasonable since the demands were aggregated by plant, but the number of time periods was high (24 time periods). The T-O model had a fairly large number of time periods (15 time periods) and a large number of products (169 SKU's). In order to reduce the model size, so that the run time is reasonable, the time period length and the number of SKU's should be selected carefully. A period length can be equal to 2 or 3 days instead of 1 day in operational models in order to reduce the number of time periods. On the other hand, if the number of SKU's is large, it could be reduced by categorizing the products with similar characteristics (e.g., same product, different packaging).

6.2 Conclusions and contributions

This research presented the integration of two models that were used to make supply chain distribution network decisions. The first model made strategic and tactical decisions and the second one made tactical and operational decisions. The first model was used to select the location and sizes of the DC's and to choose which customers, if any, should be moved to independent distributors. This model made its decisions based on five criteria: maximizing profit, power, credit performance, and distributors' reputation, and minimizing customer response time. The second model used the decisions from the first model to make distribution decisions. The decisions made in this model consider three objectives: maximizing profit while minimizing customer response time and lost sales or stock-outs. A case study was used to illustrate the applicability of these models and it was shown that they can be very useful to the company in the distribution decision making process.

Chapter 2 presented some previous research related to the work presented here. Table 2.1 showed the uniqueness of these models, as they consider some aspects that were not included in the previous ones. Also, it was shown with a case study that integrating these two models helped improving the supply chain performance since, at the end, all of these decisions depend on each other. Moreover, these models were developed for the general case so that any company could benefit from them by adjusting it to their own distribution network.

In conclusion, the integration of the two models developed in this research showed to be useful in the research and industry area. These models contribute to the research area by integrating the following aspects that have commonly being studied separately: multiple products, multiple periods, multiple criteria, transportation mode selection, location/allocation decisions, distribution decisions including direct shipments from the plants and independent distributors, and stochastic demand considerations. In addition, the industry sector can be benefited from these models since this integration helps in the supply chain network and distribution decision-making process.

6.3 Future research

The models presented in this research are very useful in supporting companies in the decision making process of their distribution network designs. However, these models can always be improved by adding more aspects and decisions to it. For example, in the S-T model, only one simple method for dealing with stochastic demand was discussed – discrete economic-scenarios. In the future, results from this method should be obtained and other methods should also be discussed and used to solve the model and compare the results. This would show which method would be the most practical and realistic one to use. Other techniques that can be implemented are the two methods discussed by Solo (2009): 1) using discrete-economic scenarios by including all of them in one model (e.g., use the scenarios and their probability of occurrence to get their expected values and include their variability) and 2) chance-constrained goal programming.

For the first approach, Solo (2009) suggests generating the different demand scenarios and their probabilities using the Delphi method, and then using robust optimization to solve the model. The model includes the different demand scenarios with their probability of occurrence and the variability between scenarios, which is attempted to be minimized. The second approach, chance-constrained goal programming, takes care of the demand uncertainty by optimizing decision variables, while the demand related goals and/or constraints are achieved with specified probabilities or confidences levels. That is, this method allows decision makers to state an acceptable probability of a goal or constraint violation. Even though this method is adequate for many models similar to the S-T model, it is very complicated to implement it on our S-T model. This is so because, when adjusting the model into a chance-constrained goal program, it ends up being non-linear. The derivation to linearize the adjusted model gets too complex due to the nature of the equations (e.g., more than one random parameters, such as customer demand and independent distributors' demand, are used in the same equation with different decision variables), and hence, it was not used for this model and case study in particular, but should be investigated in future research.

In many supply chains, in addition to demand uncertainty, stochastic lead times also exists. This may happen due to delays in the system, such as natural disasters (e.g., flooding, earthquakes, hurricanes, etc.), traffic variability, problems at the plants (e.g., machine breakdowns, information system crashing, etc.), vehicle breakdowns, and transportation agencies' variability, among other problems. This lead time uncertainty can be dealt with by using the same stochastic techniques described above for demand uncertainty. That is, the stochastic lead time should also be included as a random parameter in these models that also represent the stochastic demand.

Another extension that can be done to the S-T model is to select the best strategy for the discounts. When delivering direct shipments from the plants to the customers, the model assumes that a constant 2% discount is given to the customer. However, when negotiating with the clients to incentivize them to receive direct shipments, they might find that discount insufficient. A possible approach would be to use game theory to find the best strategy for these discounts that would be best for both, the company and the customer. An option might be to determine the largest discount number that can be given to each potential customer and to give different discounts to different customers.

Finally, the T-O model can also be improved. In this model it is assumed that the vehicles deliver the demand of only one customer. To make this model more efficient and realistic, vehicle routing optimization can be included, where each vehicle may contain the demand for different customers. The model would select which demands to consolidate in one vehicle and will show the optimal route to deliver this demand. This is a highly studied problem in the supply chain area, but is commonly used independent of the other supply chain decisions. These decisions were not integrated in our T-O model in this research due to its complexity, but should be considered for future analysis.

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EDUCATION

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- B. S. in Industrial Engineering, University of Puerto Rico, Mayagüez Campus, 2005

TEACHING EXPERIENCE

- Teaching Assistant, The Pennsylvania State University, 2007 – 2009
    - Courses: Statistical Methods in Industrial Engineering

RESEARCH EXPERIENCE

- Doctoral Dissertation: "Optimizing an Integrated Supply Chain"

PUBLICATIONS

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PRESENTATIONS

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HONORS/AWARDS

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- Harold & Inge Marcus Graduate Fellowship, Penn State University, 2006
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- Magna cum Laude, University of Puerto Rico, Mayagüez, 2005
- The National Dean's List, University of Puerto Rico, Mayagüez, 2004- 2005
- Industrial Engineering Honor Award, University of Puerto Rico, Mayagüez, 2002- 2005
- National Collegiate Minority Leadership Award, University of Puerto Rico, Mayagüez, 2002

PROFESSIONAL ACTIVITIES

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PROFESSIONAL EXPERIENCE

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- Researcher, Institutional Research and Planning Office at UPR, Mayagüez, PR, June 2003 – December 2004