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Location-Allocation Optimization of Supply Chain Distribution Networks: A Case Study

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ABSTRACT

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Chain Distribution Networks:
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The location of distribution centers is an important strategic decision in supply chain design, particularly as it relates to service quality, productivity, and profitability of the firm. There has been extensive research performed on distribution location models which require the use of complex algorithms and assumptions that make use of these models difficult in practice for small and medium enterprises (SMEs) that have limited capital and resources. Studies have also failed to capture and quantify potential business results of using more sophisticated methods.

In this study, a deterministic and static location-allocation model is designed using a prototype software tool. The tool is a collection of Excel/VBA programs formulated as a mixed integer programming (MIP) model. Research was done in conjunction with a personal care products company that provided a unique opportunity to evaluate the manual methods typically used in SMEs with the results of the software tool and the potential business impact. Both quantitative data, including customer locations and order information, as well as qualitative data were collected from the company.

A total of five models were simulated using the prototype software tool, including one model of the current supply chain for use as a base comparison, and four future-state models of potential distribution center (DC) location scenarios. The objective in each of these models was to minimize transportation costs while maintaining the desired service fulfillment levels.

The use of the prototype software tool resulted in a more optimal supply chain solution. The optimized DC location resulted in a network design with a 6.5% reduction in transportation costs from the base model, and a 0.8% reduction in transportation costs from a location previously chosen by the company. The results also provided insight into considering weighted shipping volume in location analysis as it can serve as a magnifier of business impact and rapid diminishing returns when shipping product below an average of 10 pounds. The use of an optimization tool was shown to mitigate many issues SMEs encounter in attempting to synthesize multiple variables in the DC location problem.

Keywords: Mark Helberg, location-allocation, network design, optimization model

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1 INTRODUCTION

1.1 Statement of the Problem

Supply chain design is a very important strategic issue for many companies, whether it is in the manufactured goods or services industries. Particularly important is the locating of distribution centers in relation to a plant or supplier and the customer. The quality of services provided to the customer is directly related to the location of the distribution center in relation to other facilities such as a manufacturing plant or supplier and the respective downstream customers. In addition to service quality, the location of distribution centers also directly impacts the productivity and profitability of the supply chain.

There are three primary sub-problems identified in literature involving the design of a distribution network: location-allocation problems, vehicle routing problems, and inventory control problems. Location-allocation decisions address how many distribution centers to locate, where to locate the opened distribution centers, what capacity level to consider for each of them, and how to allocate customers to them. Vehicle routing decisions address how to build the vehicles' routes starting from an opened distribution center to serve its allocated customers. Lastly, inventory decisions address how much and how often to reorder at a distribution center and what level of safety stock to maintain.

Much of the current research integrates two of the above problems, and only recently has research begun to focus on the integration of all three sub-problems. Current research models,

however, also require the use of complex algorithms and assumptions that make use of these models difficult in practice, particularly for small and medium enterprises (SMEs) that have limited human resources and capital. Studies have also failed to capture and quantify the potential business results of using such a sophisticated method in comparison to current SME business approaches more manual in nature.

1.2 Purpose of the Study

The purpose of this study is two-fold:

1. One purpose of the study is to evaluate the effectiveness of a prototype software tool (hereafter referred to as DC Optimizer) designed to optimize distribution center location in a supply chain. The optimizer will allow for the input of various parameters on historical sales, transportation distances and shipping rates, etc. in order to capture appropriate supply chain costs. The output of the optimizer should be customizable to meet the specific objective of the company and the optimization, for example, minimizing total supply chain cost or maximizing the service fulfillment rates. The intent of the DC Optimizer is to serve SMEs by simplifying the amount and type of data to be collected in order to make a well-founded decision in designing a supply chain.
2. A second purpose of the study is to compare more manual methods of making strategic supply chain design decisions in SMEs against the usage of the DC Optimizer previously described and used in this study. This will be done by closely working with a personal care products company. In order to protect any information or data sensitive in nature, this company will be referred to as Fresh throughout the rest of this thesis. Fresh is actually not considered an SME by definition due to their

number of employees and size of revenue, however, their approach and experience in facility location was similar to that of an SME. Fresh was in an interesting position to provide a unique case study at the time of this research. They currently have one large distribution center established in the western region of the United States which served all of their customers; however, they had just recently entered into discussions with another company that would fulfill orders for the entire eastern region of the United States. The timing was critical in order to allow for the comparison of what decision criteria were used and how the location of that distribution center compared with what the DC Optimizer previously discussed had identified. Perhaps more important than comparing the methods and factors in the making of the decision, is comparing where the second distribution center was actually located with where the DC optimizer would have located a second distribution center. This could prove extremely useful in quantifying the benefits of using such an optimizer in cost savings throughout the supply chain or other customer metrics such as order fulfillment rates.

1.3 Hypothesis

As previously described, the purpose of this work is to research the development and use of a software tool designed to target SMEs in order to provide a more optimal distribution center location analysis when compared to more manual SME DC location methods (outlined in section 2.6). In order to effectively evaluate and compare the two methods, the following hypothesis will be tested:

1. The use of an iterative software tool in the distribution center location-allocation decision results in a more optimal supply chain solution when compared to manual

decision methods. The criteria for comparison will include transportation costs and service levels.

1.4 Delimitations and Assumptions

This thesis is largely delimited due to limitations in the DC Optimizer software. General delimitations and assumptions relevant to the overall research are listed here. Further delimitations and assumptions more specific to Fresh and this case study will be discussed in section 3.1.1:

1. The DC Optimizer is deterministic. The model uses historical data on sales volume, shipping rates, customer locations, etc. The uncertainty of product demand and price, raw material supply costs, production costs, etc. are assumed to be constant. In other words, the DC Optimizer uses historical data and assumes similar future business performance in order to optimize the supply chain. There is, however, a provision to scale the data by location or product if future growth is expected.
2. The DC Optimizer assumes that demand is inelastic.
3. The DC Optimizer uses a single planning period, known as a static problem, and attempts to optimize system performance for one representative period.
4. The DC Optimizer assumes a finite and predetermined potential solution space. Specifically, potential DC locations are generated using a database of cities that meet the criteria of having populations greater than 50,000 and located near a major highway.
5. The DC Optimizer considers supply chain costs as those beginning with the inbound shipment from the first-tier supplier to the distribution center, and then the outbound shipment to the fulfillment of the customer order. Total supply chain cost therefore

does not take into consideration internal manufacturing costs or any costs prior to the outbound costs of purchases made from the first-tier supplier. Costs also do not take into account inventory carrying costs and DC operation costs. This is not expected to affect the results of the optimization with the stated objective.

6. The DC Optimizer is restrictive to the 48 contiguous United States. All facility and customer locations are required to be within the United States. External global factors are therefore also ignored and assumed to be constant.

1.5 Definitions and Terms

The following section includes a list of terms and their respective definitions that appear frequently throughout the literature discussion of facility location problems:

ABC Analysis – A method of classifying customers or products into A, B, or C segmentations by order of importance according to volume or profitability in order to apply customized techniques according to the segment

AHP - Analytical Hierarchy Process

Anticenter Problem – Obnoxious facility location problem which attempts to locate a facility to maximize the minimum distance between the facility and demand points

Antimedian Problem – Obnoxious facility location problem which attempts to locate a facility wherein average distance between the facility and demand points is maximized

CVRP – Capacitated Vehicle Routing Problem

Coverage – Most commonly used measure of demand oriented objectives. A source of demand is said to be covered if it is capable of being served within a certain distance or time period.

DC – Distribution Center

DC Optimizer – A prototype software tool designed to optimize the location and sizing of distribution centers in a supply chain

DCVRP – Distance-Constrained Capacitated Vehicle Routing Problem

DVRP – Distance-Constrained Vehicle Routing Problem

Deterministic – Refers to a model in which no randomness is present in the future state of the system

EOQ – Economic Order Quantity

GIS – Geographic Information System

Inventory Control Problem – Addresses how much and how often to order inventory to maintain appropriate levels in a distribution center

Location-Allocation Problem – Addresses where to locate distribution centers and how to allocate customers to them

LRP – Location-Routing Problem

Location Set Covering Problem – Facility location problem whose objective is to minimize the cost of facility location while maintaining a specified level of coverage

Maximal Covering Problem – Facility location problem that seeks to maximize the amount of demand covered within the acceptable service distance by locating a fixed number of facilities

MIP – Mixed Integer Programming

Minimax Problem – See P-center problem

MVRPTW – Vehicle routing problem with time windows and multiple routes

P-center Problem – Location centering problem in which coverage of all demand is required but facilities are located to minimize coverage distance, in other words, minimize the maximum distance between any demand and its nearest facility

P-dispersion Problem – Obnoxious facility location problem that attempts to locate facilities to maximize the minimum distance between any pair of facilities

P-median Problem – Model used to locate *P* facilities so as to minimize the total demand-weighted travel distance between demands and facilities

SCM – Supply Chain Management

Stochastic – Refers to a model in which randomness is present and usually modeled with probability distributions in the future state of the system

UFLP – Uncapacitated facility location problem

VNS – Variable Neighborhood Search; heuristic method used to address location-allocation problems

VRP –Vehicle routing problem; Addresses how to route vehicles to best fulfill customer orders

VRPTW – Vehicle Routing Problem with Time Windows

2 LITERATURE REVIEW

2.1 Introduction to Literature

The study of location theory formally began in 1909 when Alfred Weber investigated how to minimize the distance between a warehouse and customers (McKenzie 1930). Facility location decisions have since been studied from researchers of many different academic disciplines. These include economics, engineering, geography, mathematics, and operations research to name a few. The importance of optimally locating a facility is becoming more and more understood. It has a far reaching impact on the potential profitability and service quality of a company, with inherent strategic implications. These implications stem from the underlying objective in making the respective facility location decision. Although facility location is somewhat of a focused topic, due to the surge of research in this area as of late, this literature review was limited to primarily journal articles and a few key book chapters, and therefore omitted working papers and conference publications.

The review of literature will begin by first discussing the four potential major objectives of locating a facility. Those objectives have been classified into the following four general categories (Current 1990): cost minimization, demand orientation, profit maximization, and environmental concern. After discussing the potential objectives of locating a facility, the literature review will shift focus towards the three major decisions revolving around the design of a distribution network. These three sub-problems in designing a distribution network include:

location-allocation problems, vehicle routing problems, and inventory control problems (Ahmadi Javid and Azad 2010). An extensive number of models have been developed to address solutions for each sub-problem and even combination of sub-problems. Each of the models for the aforementioned sub-problems range in complexity from linear and deterministic models to non-linear and stochastic models. The majority of research up to this point has dealt primarily with linear and deterministic models. Since the focus of this research is on deterministic modeling the review will therefore omit focusing on non-linear and stochastic literature. Furthermore, although the DC Optimizer focuses primarily on the location-allocation problem, it was seen relevant to discuss each aspect of facility location in order to obtain a holistic perspective of the problem and provide a foundation for further research and development of the tool. Following this discussion, the review will shift towards conducting a survey of the commercially available supply chain design software in order to capture current tools and their capabilities. A baseline of comparison will then be given on a common manual method used by SMEs in facility location. Lastly, the review will cover the implications of making such facility location decisions and the potential impact it can have on a company and its respective supply network.

2.2 Objectives of Facility Location

In the most general terms, the objective of facility location involves a set of spatially distributed customers and a set of facilities to serve those customer demands (Melo, Nickel et al. 2009). As previously mentioned, according to work done by Current, there are four general categories of objectives throughout facility location decisions. Each of these objectives overlap to some extent, but were shown to contain enough differences to be considered unique objectives. As with any far reaching decision, it is only possible to make the best decision

relative to the end objective in mind. Each objective will be discussed in further detail in the sections to follow.

It is also worth noting other objectives mentioned in the literature which will not be discussed in detail here. A few of these objectives include resource accessibility as well as social and political risks (Farahani, SteadieSeifi et al. 2010).

2.2.1 **Cost Objectives**

Cost minimization is the most common objective found throughout the literature, comprising nearly 75% of current literature (Melo, Nickel et al. 2009). The minimization of cost can be achieved through various means. For example, minimizing transportation costs, minimizing the total number of facilities located, or minimizing the total distance traveled between facilities and customers, would all capture a form of cost. Distance is typically the most common metric used to evaluate the degree of cost (Current 1990). Travel time and travel distance are most often used interchangeably to represent the cost of traveling from one facility to another. As the average travel time or travel distance increases the location of the facility is less effective, creating an inverse relationship in most cases.

There are several methods of using distance as a cost objective. This includes minimizing a sum of distances, primarily the distances between demand locations and the nearest facility in the supply network. On the contrary, minimizing the maximum distance between a demand location and the nearest facility is also a potential objective. An equivalent method of measuring location effectiveness weighs the distances between demand nodes and facilities by associated demand quantity. This method is known as the P-median problem (Owen and Daskin 1998; Melo, Nickel et al. 2009; Contreras, Fernández et al. 2012). Inherent in the P-median problem is the assumption that all potential sites are equivalent in terms of the setup cost for

locating a new facility. An improvement upon that shortcoming of the P-median problem is known as the uncapacitated facility location problem (UFLP), in which the function is extended to include fixed facility location costs (Klose and Drexl 2005; Melo, Nickel et al. 2009).

Many of the articles also included actual cost objectives. These cost functions primarily included fixed and variable costs. Fixed costs could include installation and start-up costs, along with investment. Variable costs could include transportation, operations, production, services, distribution, logistics, waste disposal, maintenance, and environment costs, among others (Farahani, SteadieSeifi et al. 2010). Transportation has been shown to be the highest cost, with installation cost as the second highest. A recent study on supply chain design also considers the effect of both linear and non-linear storage and transportation costs (Baumgartner, Fuetterer et al. 2012). Capturing total cost has also been addressed by containing all costs under one objective.

2.2.2 Demand-Oriented Objectives

Another objective of locating a facility is to optimize the demand served. Although distance can also be a proxy for accessibility to a facility as in a cost minimization objective, this objective is grouped into three categories: coverage, demand assignment, and other demand measurements.

Coverage is the most commonly used measure of the aforementioned categories in demand-oriented objectives. A source of demand is said to be covered if it is capable of being served within a certain distance or time period. The two major types of covering problems include that in which coverage is required and that in which it is optimized (Owen and Daskin 1998). These two types of problems can be illustrated by the location set covering problem and the maximal covering problem (Contreras, Fernández et al. 2012).

The objective of the location set covering problem is to minimize the cost of locating a facility while requiring a minimal degree of coverage, specified by a specific distance, to still be ensured. In other terms, find the least number of facilities to cover all customers. This, however, can lead to an impractical solution that suggests locating an infeasible amount of facilities. For example, locating a facility within a certain distance of an outlying small portion of demand would result in a very high cost to serve that customer with minimal benefit.

The maximal covering problem on the other hand, seeks to maximize the amount of demand covered while constraining the number of facilities to be located, this is particularly important when resources are limited. It can also be described as finding the maximum number of customers to cover within a prescribed distance.

Another common problem class that avoids the drawbacks of the location set covering problem are P-center problems, also known as the minimax problem (Owen and Daskin 1998; Contreras, Fernández et al. 2012). The p-center problem locates a given number (p) of facilities while minimizing the maximum distance between demands and facilities (Şahin and Süral 2007).

2.2.3 **Profit Objectives**

Surprisingly, the amount of research focusing on a clear objective related to profit is minimal (Melo, Nickel et al. 2009). As Current points out, this could clearly be due to the fact that demand satisfaction and cost minimization objectives may be viewed as strategies to identify profit maximizing locations (Current 1990). Melo states that two categories of profit maximization most commonly found in literature are the maximization of revenues minus costs, and after-tax profit maximization. Other profit objectives found in literature include measures for maximizing the rate of return, the real rate of return on selected facilities, total expected

dollar market share, and production level or output (Hansen, Peeters et al. 1995; Alonso-Ayuso, Escudero et al. 2003; Kozanidis 2009).

One foundational study in this area considers a bi-objective uncapacitated facility location problem in which the problem is to select a location that maximizes profit and also maximizes the profitability of the total investment (Myung, Kim et al. 1997). The authors argue that profit maximization may not always be the best objective, and consideration should also be taken into the profitability of each investment alternative.

In certain cases it may not be profitable to satisfy all potential customer demands as most cost minimization models assume. This is particularly the case when the cost to serve an additional customer is higher than the additional revenue serving that additional customer will bring, or the marginal profit is negative. More recently, a study has been done that proposes a profit maximizing supply chain design model in which a company can choose whether to satisfy a customer's demand (Shen 2006). A similar approach was taken by Zhang by assigning a reservation price to each customer for the product, with the reservation price decreasing as a function of distance to the warehouse (Zhang 2001). If the price of the product exceeded the customer's reservation price, then the customer turned to some other supplier. The objective then became to find the best location for a firm's warehouse and the best price for its product in order to maximize profit.

2.2.4 **Environmental Objectives**

As can be noted throughout all of the previous objectives, most models focus on locating facilities in a way that maximizes the access to either another facility or to customers. On the contrary, some applications exist that require locating facilities which are undesirable to large populations and therefore require a potential objective of maximizing access distances, otherwise

known as “obnoxious” or “semi-obnoxious” facility location problems. This could be the case with waste disposal, power plants, and airports. Current specifically highlights objectives in which environmental issues addressed included air quality, risk to the surrounding population, quality of life, and low-flow stream augmentation (Current 1990). Recently, environment and social objectives based on energy cost, land use and construction cost, congestion, noise, quality of life, pollution, fossil fuel crisis and tourism are becoming more customary (Farahani, SteadieSeifi et al. 2010). With the growing environmental awareness and increasing number of obnoxious and/or semi-desirable facilities, the necessity of addressing such facility location objectives has become more important.

There are a few different classical problems that have typically addressed the situations previously mentioned. These include the antimedian problem, which locates a facility to maximize average distance between the facility and demand points; the anticenter problem, which maximizes the minimum distance between the facility and demand points; and the p-dispersion problem, which locates facilities to maximize the minimum distance between any pair of facilities (Owen and Daskin 1998).

More recently, bi-objective models including environmental and facility location objectives have garnered more focus and have been addressed in various ways throughout the literature. Bhattacharya uses a vertex converging obnoxious facility location model with weighted demand points based on the degree of undesirability or desirability to keep locations further or closer to central populations, respectively (Bhattacharya 2011). Similarly, Yapicioglu composes a weighted minisum function to represent the transportation costs and a distance-based piecewise function to represent the obnoxious effects of the facility (Yapicioglu, Smith et al. 2007). Melachrinoudis and Xanthopulos apply the use of Euclidean distance metrics in the

objective of minimizing the unpleasant effects introduced by a new facility, which they reason is the path that most pollution agents from power plants and radiation from nuclear plants (Melachrinoudis and Xanthopulos 2003).

2.3 Distribution Network Design Sub-Problems

Designing a distribution network consists of three sub-problems: the location-allocation problem, the vehicle routing problem, and the inventory control problem (Ahmadi Javid and Azad 2010). In the following sections each of these problems will be addressed individually in more detail.

2.3.1 Location-Allocation Problems

The classical location-allocation problem forms the basis of many of the location models that have been built upon throughout the supply chain design literature. The location-allocation problem has been defined as follows in literature: a set of customer locations with known demands and a set of candidate facility locations are given. When a facility is located at one of the candidate sites a known fixed cost is incurred. There is also a known unit shipment cost between each candidate site and each customer location. The problem then becomes to find the locations of the facilities and the shipment pattern between the facilities and the customers to achieve the desired objective (Brimberg, Hansen et al. 2000; Daskin, Snyder et al. 2005).

It should be noted that the location-allocation problem in its simplest form decomposes into two basic components (Scott 1970). If, for example, the locations of the facilities are given in advance, and the assignment of the flows between the facilities and the demand points are unknown (i.e. allocation), then the problem becomes a vehicle routing problem as will be discussed in section 2.3.2. On the contrary, if the assignment of flows is known, but the location

of facilities is unknown, then the problem is a pure locational problem and can be treated as the original Weber problem. The Weber problem aims to find the point which minimizes the sum of weighted Euclidean distances from itself to *n* fixed points, with weights of some unit measure being associated with each fixed point (Drezner and Hamacher 2001).

There has been a lot of research devoted to the original Weber problem and even more-so recently to extensions of the facility location-allocation problem. As a result, there has been a plethora of different approaches and solution attempts using both heuristic and exact solutions. One common approach is using a sequential procedure that rotates between optimizing the location and allocation phase until the end criteria or negligible improvements are met. Brimberg et. al. provide a great review in comparing various heuristics including alternative location-allocation, projection, Tabu search, p-Median plus Weber, Genetic search and several versions of variable neighborhood search (VNS) (Brimberg, Hansen et al. 2000). The authors were able to show that most traditional, along with some recent heuristics, give poor results when the number of facilities to locate is large and that VNS consistently gives the best results in computing time. VNS combines the elements of random search with a systematic way of exploring different regions of solution space. Exact methods, only until recently, have been limited to solving problems with fewer than 100 customers and also require the use of a solution from a heuristics method to provide a good starting point.

2.3.2 **Vehicle Routing Problem**

The classical vehicle routing problem (VRP) can be defined as follows according to most recent literature (Salhi and Nagy 2009; Macedo, Alves et al. 2011; Liu and Jiang 2012). A facility and a set of customers have a known and specified demand for goods. A vehicle fleet is located at the facility. Every vehicle has a specified capacity and operating cost. The travelling

cost between the depot and the customers, as well as between any pair of customers is known. Each customer must be served by a single vehicle and no vehicle can serve a customer whose demand exceeds its capacity. As such, the VRP takes both the location of the facility and customer locations as a given. It is therefore much more of a tactical problem, considering the short-term view and relative ease of change in routes when compared to the long-term planning of a facility location.

The most common objective of VRP is to find the number of routes and their respective configurations which minimize total transportation costs. Other objectives which can also be considered are the minimization of the number of vehicles required to serve all customers, the balancing of routes when considering travel time and vehicle load, and the minimization of the penalties associated with partial service of the customers (Toth and Vigo 2002). Any of these objectives can also be combined and weighted for a multi-objective analysis.

The most basic version of the VRP is known as the Capacitated Vehicle Routing Problem (CVRP). In this problem all of the customers correspond to deliveries, the demands are deterministic and may not be split, the vehicle fleet is homogenous and based at out of one central facility, only the capacity restrictions are imposed and the objective is to minimize cost (Toth and Vigo 2002; Toth and Vigo 2002). Exact algorithms solving the CVRP, such as branch and bound methods, can currently only be consistently solved in problems containing up to 50 customers. The best available exact approach for the CVRP are constituted by branch-and-cut algorithms which have been shown to solve problems with over 100 customers (Cordeau, Laporte et al. 2007).

In practical applications customers are typically much more numerous than is currently capable of being solved with exact methods, requiring the use of heuristic methods to find good,

but not necessarily optimal solutions (Cordeau, Laporte et al. 2007). Classical VRP heuristics include route construction methods, two-phase methods, and route improvement methods. Route construction methods typically start from an empty solution and iteratively build routes by inserting one or more customers until all customers are routed. Two-phase methods involve decomposing the VRP first, into clusters of customers and second, determining the sequence of each customers on each route. Route improvement methods involve starting from a given solution, and then individual changes are made to customer movements, for example, to obtain a solution with lower cost.

One interesting recent development of using heuristics to solve the CVRP involves using the artificial bee colony algorithm (ABC) (Szeto, Wu et al. 2011). The ABC algorithm is an iterative approach that is based on the foraging behavior of honey bees and has been shown to produce good solutions when applied to the CVRP. Another variation of the CVRP includes the Distance-Constrained VRP (DVRP), where for each route the capacity constraint is replaced by a maximum length or time constraint. Additionally, if both capacity and distance constraints are imposed it is referred to as a Distance-Constrained CVRP (DCVRP).

An important extension of CVRP, in which capacity constraints are imposed and service to customers must be completed within a given time interval, is known as VRP with Time Windows (VRPTW). Exact algorithms for solving the VRPTW include lagrangian relaxation, column generation, and brand-and-cut approaches (Cordeau, Laporte et al. 2007). The same difficulties that exact algorithms face in classical VRP are also faced in VRPTW; heuristics are again useful to provide quality solutions in short computing times. A variant of this problem is addressed in the research by Macedo and Alves et al. (Macedo, Alves et al. 2011). The authors address the VRP with time windows and multiple routes (MVRPTW), in which each vehicle can

perform several routes during a workday. Their exact solution approach is shown to outperform the column-generation based algorithm in many cases.

2.3.3 Inventory Control Problem

The literature on inventory control focuses on developing and evaluating policies for supplying distribution centers and fulfilling customer orders. Different factors that are taken into consideration include service levels (percentage of retailer orders that are filled within the acceptable waiting period), shipping costs, inventory costs, and shortage costs (costs incurred when an order cannot be filled within the acceptable waiting period) (Shen, Coullard et al. 2003). The objective of the inventory problem is to find the optimal method that minimizes these inventory holding costs while still meeting appropriate service levels (Gülpınar, Pachamanova et al. 2013).

Inventory is essential in order to provide flexibility throughout the supply chain. This flexibility is derived from the different stages of inventory: raw materials, work in process, and finished goods. Each classification of inventory removes dependencies from supplier to plant, between machines on a production line, and from plant to customers, respectively. Inventory can serve multiple purposes such as smoothing out irregularities in supply or demand, minimizing the production cost, and allowing corporation to cope with perishable goods. Panneerselvam states that there are two basic inventory decisions: when to replenish the inventory of an item, and how much of that item to order when it is to be replenished (Panneerselvam 2006).

Economies of scale come into play with inventory orders: as order size increases, the average order cost decreases, and vice versa. However, as order sizes increase there is also an increase in inventory holding costs. A basic inventory model which explains this relationship between costs and order quantity as explained by Porteus is known as the Economic Order

Quantity (EOQ) (Porteus 2002). This model reflects the total cost curve as the sum of ordering cost and carrying cost for each order size, with the order size at which the total cost is minimized referred to as the EOQ.

In practice it is difficult to implement an effective operation of an inventory management system, this is as a consequence of what is known as the newsvendor model (Porteus 2002). In this model, an unknown quantity will be demanded, and while the probability distribution of that demand is known, the actual demand will not be known until after the order has been placed. In this situation, the tradeoff is between making too many and having a surplus of inventory, or making too few and not meeting demand. It is due to this difficulty in forecasting that safety stock is necessary. In this case, it is necessary to calculate the cost associated with holding inventory versus the cost of stocking out.

2.3.4 Multi-Objective Problems

The location-allocation, vehicle routing, and inventory control problems described in detail above all represent sub-problems to the overall objective of locating a facility. Some of the literature has analyzed two of the sub-problems jointly, and a few have even analyzed solutions for considering all three sub-problems simultaneously. In the sections that follow, multi-objective problems that will be discussed include: location-routing problems and location-inventory problems, as well as location-routing-inventory problems.

2.3.4.1 Location-Routing Problem

It has been discussed that facility location and vehicle routing are interrelated areas. Location-routing aims to solve locational problems while taking into account vehicle routing considerations (Salhi and Nagy 2009). One common criticism of the location-routing problem

(LRP) as explained by Nagy and Salhi, is that location is a strategic planning issue while routing is a tactical problem (Nagy and Salhi 2007). They highlight that routes can be re-calculated and re-drawn, even daily, while the location of a facility is considered over a much longer time horizon. The authors however found that the use of location-routing could decrease costs over a long planning horizon, within which routes are allowed to change. Furthermore, it is pointed out that both the location problem and vehicle routing problem can be viewed as special cases of the LRP. If all customers are required to be directly linked to a depot, the LRP becomes a standard location problem, while if facility locations are fixed the LRP becomes a VRP.

There are certain classification criteria which most LRP problems abide by. Most of the LRP literature deals with a discrete location, multiple depots, an unfixed number of vehicles and a homogenous fleet; along with a route structure that involves starting from a depot, progressing through different customer nodes to deliver products and then returning to the original depot. The LRP literature is also predominantly devoted to heuristic solutions. Nagy and Salhi classified these solutions by how they approached the relationship between location and routing problems. Due to the relevance in considering that interaction to this review, the same approach will be followed. The solution methods identified include sequential methods, clustering-based methods, and iterative methods.

Sequential methods first solve the locational problem by minimizing the sum of distances from the facility to the customers and then solving the routing problem based on the locations previously determined. The sequential method does not allow for feedback between the stage of locating a facility and determining the routing and as a result can lead to a solution that is suboptimal.

The clustering-based method is similar in nature to the sequential method in that there is no feedback that occurs between the location and routing stages. However, clustering improves upon the sequential method by partitioning the customer set into clusters by common characteristics, usually by a potential facility location or vehicle route (Barreto, Ferreira et al. 2007). Those clusters may then be used to first locate a facility and then solve a VRP or vice versa, and solve a TSP for each cluster to solve the facility location problem (Nagy and Salhi 2007). Barreto and Ferreira et al. use a quantitative measure (maximum vehicle capacity limit) in their problem in order to form clusters. Following the assigning of clusters they then determine the distribution route in each customer group, and locate the DCs to those routes. The authors compared various grouping techniques and proximity measures in order to measure their relative performance on minimizing cost. The one-phase hierarchical method was shown to produce the best results along with the group average measure.

The iterative method iterates between optimizing locational and routing phases. A traditional location problem method is used to minimize the sum of distances between the facility and the "end-points" of routes found in the routing phase. The iteration is completed when the cost improvement in either phase is found to be zero or negligible (Nagy and Salhi 2007). Salhi and Nagy in their work using end-points attempt to solve an LRP by transforming it into a pure location problem (Salhi and Nagy 2009). The authors do this by considering the first and last customers of each route for a facility and assign them as a set of nodes. For each facility the Weiszfeld procedure is used on the set to find the newly optimized location of a facility. The Weiszfeld procedure finds the point (facility) that minimizes the sum of weighted distances to a given number of fixed points (customers). The authors were able to improve on average by 1.6%

from the original facility location, with very high improvements of 9% and 14% in certain scenarios, showing that it is beneficial to consider routing when locating a facility.

2.3.4.2 **Location-Inventory Problem**

As has been previously discussed in the sub-problem sections, companies have considered the strategic decision of facility location and network design separate from the tactical decisions of stocking and distribution (Daskin, Coullard et al. 2002; Mak and Shen 2009). In fact, these decisions are usually made sequentially. However, due to an increased focus on time-based service level requirements, the interaction between strategic facility location and tactical inventory decisions is becoming critical for optimization (Candas and Kutanoglu 2007). This problem has been further heightened by e-commerce, raising expectations of high service levels and speedy deliveries (Daskin, Coullard et al. 2002).

In recent literature, models studying the interaction between facility location and inventory management (i.e. inventory-location problems) have garnered more attention. Daskin and Coullard considered a three-tiered system (supplier, DC, retailer) and modeled the problem of determining the number and location of distribution centers along with the optimal ordering policy (Daskin, Coullard et al. 2002). The authors presented it as a set portioning problem and then solved the model using column generation. Using a 150 node dataset, they obtained results that showed that as the transport costs increased, the number of DCs also increased, while conversely, as inventory costs increase, the number of DCs goes down. Furthermore, when inventory considerations dominate, it can be optimal to assign one or more retailers to a DC that is not the least cost DC. With the rise of e-commerce it was also shown that it can be optimal to locate more DCs when compared to the base case.

Another study considered an inventory-location problem involving a single supplier and multiple retailers, however they also allowed for variable demand and modeled the use of safety stock at the retailers (Shen, Coullard et al. 2003). Retailers were allowed to serve as a distribution center in order to achieve risk-pooling benefits. The model was motivated by work being done for a local blood bank and the distribution of platelets, the most perishable and expensive of all blood products. The authors build a location-allocation model and include nonlinear terms in the objective function in order to reflect the shipment, inventory and penalty costs. Results showed that as the nonlinear safety stock increases (or as the desired service level increases), optimal solutions become more difficult to identify. By taking into account risk-pooling, as these costs increase, the number of DCs located decreases, in contrast to Daskin and Coullard's findings on the effect of e-commerce.

Recent studies have also begun to take into account facility location and inventory consideration models while sourcing from multiple locations (Ozsen, Daskin et al. 2009; Yao, Lee et al. 2010). In Yao and Lee's model, customers can be replenished by either a warehouse or direct from the plant, as can be the case with companies who lease warehouses from third-party logistics. The authors compared the results of their model by comparing the solution against a normal two-stage procedure (first locating the facilities while ignoring inventory costs and second computing inventory costs based on the previously determined locations). As the inventory holding cost rate increased from $1/unit to $5/unit, the gap between the two models also increased from 1% to 7%, respectively. Candas and Kutanoglu were also able to show significant cost savings when the fixed facility and transportation costs are relatively low and/or the holding costs are relatively high (Candas and Kutanoglu 2007). These results therefore show that simultaneously considering both inventory holding cost and transportation cost can achieve

better solutions. Additionally, Ozsen and Daskin were able to conclude that multi-sourcing becomes a more valuable option as transportation costs increase as a percentage of total logistics cost (Ozsen, Daskin et al. 2009). However, in the reverse scenario, when facility and transportation costs are high and holding costs are low, sequential facility location and inventory planning produce accurate results.

2.3.4.3 **Location-Routing-Inventory Problem**

Due to the complexity of incorporating location-allocation, routing and inventory problems in a single model, only recently have studies begun to address all three of these problems simultaneously. One such study was performed by Ahmadi and Azad in which their goal was to choose, locate and allocate a set of distribution centers, to determine the inventory policy and to schedule vehicles' routes to meet demands such that the total cost is minimized (Ahmadi Javid and Azad 2010). They approached the problem by decomposing a heuristic method into a constructive stage and an improvement stage. In the constructive stage an initial solution is built at random. There are also two stages within the improvement stage: the location phase and the routing phase. A hybrid algorithm is used to improve the initial solution in each phase. The authors were able to show a range of improvements from approximately 10-28% for different problem sizes when compared against a base model developed by Shen and Qi (Max Shen and Qi 2007).

2.4 **Other Factors to Consider**

It is important to note that there are also other factors to consider when locating a facility beyond the three primary sub-problems (location-allocation, routing, and inventory) discussed here. Melo and Nickel et al. for example provide a list of other important factors to consider

when designing a supply chain network. Some of these factors include financial aspects and risk management, along with other considerations such as network redesign to locate into a region with more favorable economic conditions and the importance of considering the bill of materials when locating (Melo, Nickel et al. 2009).

The authors divide each of the major categories into different sub-sections. The financial factors are divided into three categories: international factors, incentives, and budget constraints. International factors include taxes, duties, tariffs, exchange rates, transfer prices, and local content rules. Incentives included either financing or taxation incentives which a government might offer to attract facility investment in certain regions. Lastly, budget constraints refer to investment expenditures which are usually limited by total available budget.

Risk management factors are also further divided into three categories: robustness, reliability, and risk pooling. Robust models have been discussed in literature to attempt to find a solution that performs well under any possible realization of the random parameters (Snyder 2006). Reliability refers to the risk of disruption that may occur due to political uncertainties, strikes, trade barriers, and natural catastrophes. One recent study suggests that it is important to examine the tradeoff between the objective of accounting for these types of failures and classical location objectives in order to determine how significant of a cost increase it requires to add reliability to the system by building in excess capacity, purchasing insurance policies, etc. (Snyder and Daskin 2007).

2.5 Survey of the State of the Art Supply Chain Design Software

Supply chain design software has played a major role in supporting decision makers to analyze the strategic design of their supply chain network by allowing for the analysis of a large number of parameters and their respective trade-offs. Supply chain design software must attempt

to address in its functionality each of the previously discussed facility location issues in this review. It was therefore viewed as important to capture the current status of commercially available software tools for supply chain design in order to examine their respective features.

Using a recent survey on the state of the art commercial software for supply chain design conducted by Funaki as a basis of inclusion, a list of 14 software tools and their respective vendors was compiled and listed alphabetically by name in Table 2-1 (Funaki 2009). The software tools listed are limited to the major tools available for use in the United States and also made known to this author through a study of recent research and online resources. Furthermore, software tools that solely focused on the optimization of supply chain aspects such as inventory and production control without considering location decisions as a specific functionality were not included. These included the elimination of optimization tools provided by well-known vendors such as Logility, ToolsGroup, and SmartOps.

Table 2-1: Commercial Software Tools for Supply Chain Design

Name	Vendor
4flow vista	4flow
CAST	Barloworld Supply Chain Software
ISCO	INSIGHT
LogicNet Plus XE	IBM ILOG
LOPTIS	Ketron Optimization
NETWORK	Supply Chain Associates
Network Design	Infor

Table 2-1 Continued

Network Design & Optimization	JDA
Opti-Net	Technologix Decision Sciences
planLM Network Optimization Solution	Solvoyo
PRODISI SCO	PROLOGOS
Profit Network	Profit Point
Supply Chain Design	Quintiq
Supply Chain Guru	LLamasoft

Due to the proprietary nature of the software tools commercially available it was difficult to gain any deep insight into specific algorithms and models specific to each tool. However, this author attempted to extract major trends and offerings common to most tools which will be presented in the sections to follow.

2.5.1 **Objectives**

At the most basic level, every tool generates a supply chain model with facilities in the supply chain represented as nodes and the transportation of goods between those facilities represented as arcs. The two primary objectives that the tools generate solutions for are cost minimization and profit maximization. Every tool supports cost minimization as a default objective, while half of them support profit maximization by standard setting and the other half only through customization (Funaki 2009).

Demand-oriented objectives, or degree of coverage, are not a standalone objective in any of the tools. Instead, in the cost minimization models, demand is treated as a constraint and

assumed to be satisfied at some predetermined service level. On the other hand, in the profit maximization models, demand to be satisfied is treated as a variable. This is done by using price, or potential revenue, and cost to serve the additional customer as previously mentioned in two studies (Zhang 2001; Shen 2006).

Approximately one quarter of the tools such as CAST, Network Design, planLM, and LogicNet allow for the consideration of environmental objectives. This is most commonly done by allowing the user to optimize the supply chain in order to minimize the amount of carbon emissions and the resulting footprint.

2.5.2 System

The supply chain design optimization problem is formulated as a mixed integer programming (MIP) model which is solved either by a general-purpose solver provided by third parties or developed in-house and is therefore proprietary (Funaki 2009). The most commonly used general-purpose solvers are Fico's Xpress-MP and IBM's CPLEX. Opti-Net, for example, states that its tool is powered by Xpress-MP while ISCO uses a proprietary engine called X-System Solver. LOPTIS similarly uses a proprietary MIP system which they call MIPIII for its facilities location model. MIPIII can arrive at a solution by using multiple stopping criteria such as a maximum number of branch and bound nodes, a forced first solution, incorporating the use of priorities, bound by an optimal value, etc. PRODISI SCO also uses a custom-made algorithm which it claims is uniquely adapted to solve problems particular to supply chain network optimization. PROLOGOS argues that typical MIP systems are less efficient in the optimization of complex supply chain networks, they only use aggregate quantity per region/demand/period, total volume or average order quantity, fixed time intervals throughout the model, and finally

fixed and linear costs based on total or average quantity without considering economies of scale or synergies.

Most tools allow for the input of the following parameters:

- Customer locations and demand by product and time period
- Locations, costs, and capacities for each facility in the supply chain (supplier, plant, distribution center) for both existing and potential sites
- Transportation costs
- Inventory costs
- Tax rates
- Service level requirements
- Capacity limits for applicable sites (warehouse throughput, storage capacity, production capacity, carrier capacity, etc.)

2.5.3 **Interface**

Many of the tools are stand-alone software packages developed using a Microsoft development platform which provide a familiar user-friendly interface. Most tools therefore run on all Windows platforms. CAST, uniquely, is completely java based and developed in a 3 tiered-client server architecture which lends itself to become open to any platform. A few of the tools such as Opti-Net, Supply Chain Guru, and LogicNet are also beginning to automate a linkage to ERP systems such as SAP.

Geographical visualization of the supply network can prove very useful in representing data and solutions in order to allow users to validate the supply chain. Many of the tools such as

CAST, Opti-Net, Supply Chain Guru, and Profit Network support the use of a geographical view and provide advanced GIS (Geographic Information System) mapping capabilities.

The analysis phase is just as important as the optimization phase. It is in the analysis phase where the user can compare various supply chain performance indicators such as costs, throughput and service levels in order to thoroughly reflect the solution. Most of the tools support graphical statistics output and sensitivity analysis, both pre-packaged and customizable (Funaki 2009). This includes the ability to export to into HTML, PDF, XLS, or CSV file formats for use in programs such as MS-EXCEL and MS-ACCESS or SQL Server.

2.6 Manual SME Location Method

Although the use of sophisticated software techniques such as those mentioned in section 2.5 are becoming more prevalent, many SME's have only slowly begun to adopt the use of such methods. Many SME's still make use of a much more basic approach. One common approach is the analytical hierarchy process (AHP) decision model (Yang and Lee 1997; Badri 1999).

The AHP model provides a framework to assist managers in analyzing various location factors, evaluating site location alternatives and eventually making final location selections. Yang et. al. states that firms typically approach the location decision process in two stages. The first stage establishes the site requirements and their relative importance while the second stage applies those criteria to sites under consideration. When applied to the facility location problem, the AHP solution process involves the following steps:

1. Identify pertinent facility location factors
2. Develop priority weights
3. Collect data and rank each potential location
4. Analyze comparative results

5. Identify preferred site(s)
6. Final recommendations

There are several large assumptions which can serve as major obstacles to the effectiveness of this approach. First, it requires that the firm have preferences or insights on the geographical region desired to locate and that the potential sites be chosen beforehand. Second, in assigning scores to the ranking criteria it assumes that the decision makers have a good understanding and knowledge of the operations and location variables.

2.7 Importance of Facility Location

In recent research, facility location models have been gradually proposed within the supply chain context (Melo, Nickel et al. 2009). Daskin et. al. describes supply chain management (SCM) as entailing decisions about (1) where to produce, what to produce, and how much to produce at each site, (2) what quantity of goods to hold to hold in inventory at each stage of the process, (3) how to share information among parties in the process and finally, (4) where to locate plants and distribution centers (Daskin, Snyder et al. 2005). Essentially, supply chain encompasses all of the transportation and transformation of raw materials into finished goods until the customer's order has been successfully fulfilled. The objective of supply chain managers then becomes to plan, implement and control the operations of the supply chain in an efficient way. It is in this planning attempt to identify the best possible supply chain configuration where facility location becomes a very important, and perhaps the most difficult to solve, aspect in the supply chain.

Melo et. al. provide us with great research on the link that exists between SCM and facility location. They explain that there exist three stages of planning in SCM, usually dependent upon the time horizon. These stages are strategic, tactical and operational. Strategic

planning typically occurs very early on in the planning process and the resulting decisions have a long-lasting impact on the firm. These types of decisions include those regarding how many, where, and how large facilities such as manufacturing plants or distribution centers should be. Due to the significant capital investment required in locating a facility, it is important that a facility operate for a long period of time and do so efficiently, despite changing surroundings.

The globalization of the world's economy has also increased the importance of having a well-designed supply chain network. Advances in information technology have shortened the disconnect between the customer and firm. Customer preferences are changing much more rapidly and firms are being forced to deal internally with shortened product lifecycles in order to remain competitive. Raw materials are supplied globally and advancements in transportation have opened more pathways for distribution and tracking. All of these factors contribute to the necessity and importance of a sophisticated facility location model to determine the best supply chain configuration.

3 RESEARCH METHODOLOGY

The approach taken in this research was both quantitative and qualitative. In the sections to follow, this methodology will be described in further detail. It will begin by describing the design of the software tool, including the system, interface, and functionality of the tool. Following the detailed description of the DC Optimizer, the focus will shift to the data collection methods, followed by outlining the methods used to analyze the data.

3.1 DC Optimizer Design

The DC Optimizer was developed by ProModel Corporation and is currently being used to support the consulting group within ProModel. Therefore, the exact engine and specific code used within the DC Optimizer are proprietary in nature and cannot be disclosed in this research, although they will be discussed to the extent possible. The tool is currently not commercially available.

3.1.1 Model Delimitations and Assumptions

In section 1.4, delimitations and assumptions of the DC Optimizer relative to the overall research were discussed. In this section, assumptions specific to the situation of Fresh will be outlined:

1. The DC Optimizer operates under two potential objectives:
    a) Minimize the sum of unit-miles
    b) Minimize the total shipping cost
2. The DC Optimizer does not place any capacity constraints on facility locations and therefore assumes all potential facility locations have the capability to meet demand allocation. This is assumed to be reasonable since many SMEs use third-party logistics that allow for capacity alterations relatively quickly.
3. All inbound products require routing through the primary DC located in the western United States for quality inspection purposes before being shipped to a second DC location. Therefore, when taking into consideration inbound shipping costs for a second DC location it was assumed that products could not be shipped from the manufacturer to the second DC, thus where each SKU was coming from was assumed to be a common factor. Products were to be routed from the primary DC located in the western United States via sixty full truck loads throughout the year to the second DC location.
4. Although not every SKU would be stocked at the second DC that was held in the primary DC, a high percentage of the large volume SKUs were going to be stocked in both locations. It was estimated that the differences were minimal and therefore assumed that all SKUs were stocked at both distribution centers in the United States, regardless of SKU velocity or volume.

3.1.2 System

The DC Optimizer is powered by a collection of Excel/VBA programs. It is formulated as a MIP model similar to other software tools described in section 2.5.2. The tool is capable of

receiving sales by SKU/SKU attributes, shipping costs, labor costs, DC operation costs, and supplier lead times as inputs. It then attempts to optimize the number and location of DCs across the U.S. in order to minimize the sum of shipping costs (inbound and outbound), inventory carrying costs, and DC operational costs while also maintaining a 95% service level to the customer. However, for the purpose of this initial model validation with Fresh, only sales by SKU/SKU attributes and shipping costs were linked to the model. Incorporating data unique to each SKU avoids the drawback of using aggregate data mentioned by PROLOGOS of typical MIP systems. Furthermore, to calculate the transportation costs of each shipment the DC Optimizer is integrated in the background with PC*MILER, a truck-specific routing, mileage, and reporting system used to generate both practical and optimal routes within North America.

Upon linking all of the appropriate data, the DC Optimizer can be run using the current model of the supply chain and the number of DC's that are desired to be moved or added. Following the completion of the initial pass, and each thereafter, the customers are realigned to the nearest DC. This process repeats until there are no further DC movements and the percent difference from one pass to the next is zero.

3.1.3 **Interface**

The DC Optimizer, being powered by Excel/VBA programs, has the advantage of being run on a very familiar MS Office user interface. As such, it also allows for a high degree of user flexibility. For example, the user can state whether the location of a DC in the current supply chain is moveable or not, how many DCs to add or remove, and even what the priority is of adding or removing those specific DC locations.

The outputs of the DC Optimizer are also primarily Excel based. These outputs include the generation of bar charts displaying items including, but not limited to:

- Optimized service levels
- Optimized supply chain costs broken down into DC costs, inventory carrying costs, inbound transportation costs, and outbound transportation costs
- Percent improvement by pass on DC locations

In addition to Excel generated reports, the DC Optimizer also supports the use of a geographical view and provides some GIS mapping capabilities. This includes the mapping of:

- Current and optimized states of both customer and DC locations
- Density maps of customer shipping
- Demand-allocation maps of customer zones by fulfillment center

3.2 Data Collection

As previously mentioned, the data was collected using both quantitative and qualitative methods. All of the data gathered was done in conjunction with Fresh.

3.2.1 Quantitative Data

There were two major groups of quantitative data that needed to be gathered. As outlined in Section 1.4 of this report, the DC Optimizer is both static and deterministic. In other words, it optimizes results from one representative period and assumes similar future business performance. Therefore, the first major group of quantitative data required was information on all of the customer locations and the products shipped to them along with their respective dimensions, weight, and shipping cost. It is important to note that because Fresh only had one DC in the United States all customer orders were fulfilled from that facility. The second major

group of quantitative data arose from needing the ability to calculate transportation costs from the shipment data. This required the use of zone tables from major carriers to be used in conjunction with the pricing sheets. Both of these data sets will be explained in further detail in the sections to follow.

3.2.1.1 **Shipment Data**

The data collection began by obtaining Fresh's order shipped information from the most recent 12 month period. The data was received in 12 separate .TXT files separated by month beginning in November 2011 and spanning to November 2012, each containing approximately 300,000 lines of individual shipment data. The following data was requested:

- Shipment Date
- Order Number
- From Zip Code
- To Zip Code
- SKU List
- SKU Quantity list
- Size of each box (3 fields: Length, Width, Height)
- Weight of each box
- Shipping cost for each box

Once received, the data was saved as 12 separate .XLS files and formatted according to the following table for uploading into the DC Optimizer:

Table 3-1: Shipping Data Format

Ship Date	Order No.	SKU	Qty.	Customer Zip	DC Zip	Box Length	Box Width	Box Height	Shipping Weight	Shipping Cost
						(in.)	(in.)	(in.)	(lbs.)	($)

Due to the proprietary nature of the shipment data received, no reference to individual data points will be provided in this research. However, the results chapter will include a summary of the data analyzed.

3.2.1.2 **Shipping Zone Charts**

As stated, the objective of the optimizer is to minimize the transportation costs in selecting the location of new facilities. The optimizer accomplishes this by performing an exhaustive analysis of potential sites and their accompanying effects on transportation cost and delivery service levels. Major shipping carriers determine a shipping rate by first choosing a method of shipment (Next Day Air, 2nd Day Air, Ground, etc.) and coupling that with a shipping zone. The zone chart is uniquely generated for each origin zip code, then using a matrix incorporating the destination zip code and mode of shipment, a zone is established. That zone is then used in the appropriate rate table to calculate the rate by shipment weight. Fresh has a table of negotiated rates reflecting a percent discount by zone on standard rates of packages ranging from 1 to 150 pounds. The table was used in conjunction with the zone charts for the aforementioned purpose. An example of the table layout is shown below:

Table 3-2: Percent Discount on Shipping Rates

Lbs.	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8
X	(%)	(%)	(%)	(%)	(%)	(%)	(%)

In order to calculate the respective shipping costs from different origin zip codes it was necessary to obtain each zone chart from each unique origin zip code for the contiguous United States.

Fresh uses primarily three carriers including the United Parcel Service of America (UPS), the United States Postal Service (USPS), and FedEx, with UPS comprising approximately three-quarters of all shipping volume. In the DC optimizer it was assumed that all packages were carried by UPS or a similarly priced 3rd party carrier. It is fairly straightforward to obtain FedEx's zone charts as they provide a ZIP file containing all 708 zone charts for the U.S. UPS, however, does not allow for the capability to download all zone charts simultaneously. Their systems require that each origin zip code be input individually in order to download the respective zone chart. It was impractical to manually enter nearly 40,000 U.S. zip codes and download their respective zone charts. Therefore, an Excel VBA program was written to access UPS' website and automate the retrieval of the zone charts. It was unknown how many UPS zone charts existed, but it was known that the charts were saved using the first 3 digits of the beginning range of the zip code pertaining to that particular zone chart, therefore it could be deduced that the charts would range from 1-1000. The VBA program attempted to download each file and if none existed under that file number it proceeded to the next number until all files had been downloaded in that range. A total of 594 UPS zone charts were downloaded for the contiguous U.S. An example of a UPS zone chart outline is shown below:

Table 3-3: UPS Zone Chart Example

ZONE CHART						
UPS Ground/UPS 3 Day Select/UPS 2nd Day Air/UPS 2nd Day Air A.M./UPS Next Day Air Saver/UPS Next Day Air						
For shipments originating in ZIP Codes XXX-XX to XXX-XX. To determine zone take the first three digits of the receiver's ZIP Code and refer to the chart below:						
ZONES						
Dest. ZIP	**Ground**	**3 Day Select**	**2nd Day Air**	**2nd Day Air A.M.**	**Next Day Air Saver**	**Next Day Air**
XXX						

It should be noted that it was unnecessary to gather information on where individual SKUs were being sourced from to effectively model Fresh's supply chain. As mentioned, due to quality inspection purposes, all products were to be shipped from the original DC located in the western U.S. to the second DC. This was to be done via full truck loads serviced by a contract freight provider on an estimated sixty 53' trailers annually.

3.2.2 Qualitative Data

As previously stated in section 1.2, one of the objectives of this research is to compare manual methods of making strategic supply chain design decisions in SMEs (as outlined in section 2.6) against the usage of a DC Optimizer. Working in collaboration with Fresh proved pivotal in gaining a deeper understanding of this objective, primarily as a result of their current situation in having very recently undergone the process of determining where to locate a second DC. Multiple meetings were held with the vice president of logistics at Fresh, the direct point of

contact for the project on the location of the second DC, to further understand the decision process. The following topics were addressed during these meetings:

- The objective in locating a new DC (cost minimization, demand oriented, profit maximization)
- The importance of timing
- Criterion used to identify/eliminate candidate locations
- Decision between owning versus leasing/third party agreement
- Qualitative factors that influenced the final selection
- Data or financial analysis conducted

3.3 Data Analysis

Upon the successful collection of all the quantitative data it was input into the DC Optimizer. A total of five models were simulated, one current state model and four future state models. The current state model included:

1. Model of Fresh's U.S. supply chain with the original and sole DC location in the western U.S.

The four future state models included:

1. Model of Fresh's U.S. supply chain with the original DC location and the second DC location in the eastern U.S. already chosen prior to this research
2. Optimized model of Fresh's U.S. supply chain with the original DC location and a second location determined by the DC Optimizer

3. Optimized model of Fresh's U.S. supply chain with the original DC location, the previously determined second DC location, and a third DC location determined by the DC optimizer
4. Optimized model of Fresh's U.S. supply chain with the original DC location and two DC locations determined by the DC Optimizer

These models were then used to test the hypothesis that the use of an iterative software tool in the DC location-allocation decision results in a more optimal supply chain solution when compared to more manual SME DC location methods. A more optimal supply chain solution was defined as one that minimized transportation costs while still obtaining the desired service fulfillment levels, in Fresh's case, three days. An analysis was done on each of the solutions to the models in order to effectively compare the current state models against the future state models. The results from the second current state model were also compared with the financial analysis performed during the original decision to compare the decision making methods.

4 RESULTS

4.1 Data Preparation

A consistency and integrity check was performed on the data in order to ensure the reliability of the model. In total, 3,444,259 records of shipment data were analyzed, reflecting 5,107,392 customer demand locations (filtering out 125,509 records that were shipped outside the 48 contiguous states) in 1,196,326 orders contained in the United States. The data was found to be very consistent and integral. There were 0 orders without a quantity, 247 orders that did not have a corresponding shipment weight (for which the average package weight of 4.04 pounds was assumed), 91,530 orders that did not have a corresponding shipment cost (for which the average shipping cost of $9.30 per package was assumed), and nearly 99% of all the zip codes provided were accurate. The following table summarizes the analysis on the data integrity along with a percent total of erroneous data:

Table 4-1: Data Integrity

Category	Value	Percent of Total
Total Records	3,444,259	
Total Demand	5,232,901	
U.S. 48 States Demand	5,107,392	
Number of Orders	1,196,326	

Table 4-1 Continued

Orders Without a Quantity	0	0%
Orders Without a Weight	247	0.02%
Orders Without a Cost	91,530	7.7%
Erroneous Customer Zip Codes	66,996	1.3%
Total Shipping Cost	$31,271,425	

4.2 Shipping Cost Analysis

As was explained in section 3.2.1.2, shipping cost with major carriers is determined by the package weight and the respective zone chart used in conjunction with a pricing sheet. Due to a high volume of shipping, Fresh has negotiated discounted rates on ground shipping. The relationship between the shipping weight and price to ship was plotted for each zone and is shown below:

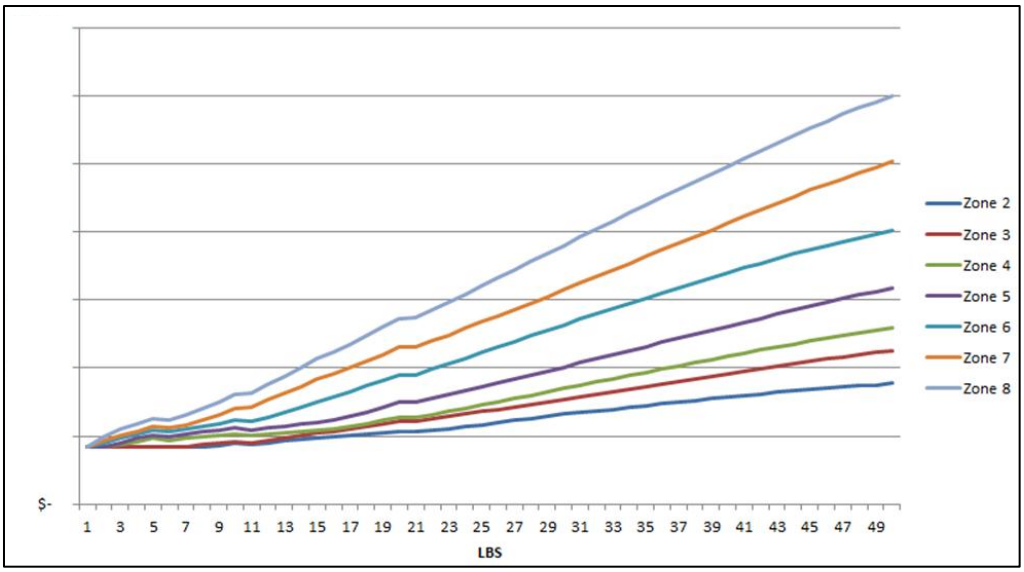

Figure 4-1: Shipping Price by Weight per Zone

As shown above in Figure 4-1, the relationship between package weight and cost was a positive, nearly linear, relationship. As expected, the shipping price increases as the package weight increases, and the slope of that relationship increases more rapidly as the zone (shipping distance) increases. This increasingly diverging linear relationship forced the inquiry into what package weights Fresh typically ships. The table below reflects the relationship between the weight of a package and the accompanying percentage of volume, assuming a sample size of 1,000:

Table 4-2: Percent Shipping Volume by Weight

Package Weight (lbs)	Number of Packages	Percent Shipping Volume
1	197	20%
2	379	58%
3	234	81%
4	31	84%
5	36	88%
6	52	93%

As shown above, approximately 93% of all Fresh's packages are 6 pounds or less. This is significant when considered in conjunction with Figure 4-1. In Figure 4-1, it can be noticed that the price difference to ship a package by increasingly distant zones does not become significant until above approximately 10 pounds. As a result, for nearly all of Fresh's shipments to customers it costs nearly the same to ship within the same zone as it does to ship to the furthest zone. This finding had a significant impact on the conclusions of the study.

It's also important to note here that there existed a discrepancy between the total shipping cost in the data provided ($31 M) and the total shipping cost generated using the zone charts and shipping rates ($26 M). This discrepancy of $5 M could exist for several reasons, including the following:

- The average weight of 4.04 pounds was assumed in cases where a weight was not given.
- The average shipping cost of $9.30 per package was assumed in cases where a shipping cost was not given.
- It was assumed that UPS was the carrier that performed all of the deliveries to customers. UPS is considered to be a low cost carrier which would cause us to expect a lower total shipping cost in comparison to including USPS, FedEx, etc. in their respective shipping volume percentages.
- Fresh pays a $2.55 residential surcharge delivery fee. Discrepancies of when this fee is charged by UPS and the DC Optimizer could contribute to the difference.

Although the discrepancy of $5 M is relatively significant it was not viewed as a concern in the results or the conclusions of this study. The data used in the generation of the UPS rates was used throughout the optimization in each respective model, assuring that the results would be proportional and insignificant in comparison to actual figures.

4.3 Shipping Analysis by Region

Following data validation and the analysis of shipping cost, the study turned toward gaining a better understanding of Fresh's shipping patterns. The cumulative shipping packages were filtered by first digit zip code (0-9) in the contiguous U.S. The volume of packages was

combined with the average weight of each package in that region to obtain weighted shipping quantity and a percent total by first digit zip code. The results of this analysis are shown below in Table 4-3:

Table 4-3: Shipping Weighted by Region

First Digit Zip	Cum Pkgs	Avg Wt	Weighted Qty	% of Total
-	187,949	5	939,745	6%
1	255,127	4	1,020,508	7%
2	182,917	4	731,668	5%
3	335,628	4	1,342,512	9%
4	127,889	4	511,556	3%
5	84,098	4	336,392	2%
6	128,333	4	513,332	3%
7	265,708	4	1,062,832	7%
8	296,279	4	1,185,116	8%
9	1,498,986	5	7,494,930	50%
			15,138,591	100%

As shown above, half of Fresh's weighted quantity shipments are delivered to customers found within the first digit zip code of 9. Zip codes with a first digit of 9 include the states of California, Oregon, and Washington. This validates Fresh's location of its original DC in the western U.S. Also interesting to note is that Fresh's shipments to each of the remaining regions are highly fragmented, with no single region constituting over 10% of the total. Following zip codes beginning with the first digit of 9, zip codes beginning with 3 (Alabama, Florida, Georgia, Mississippi, Tennessee), 8 (Arizona, Colorado, Idaho, New Mexico, Nevada, Utah, Wyoming), 7

(Arkansas, Louisiana, Oklahoma, Texas), and 1 (Delaware, New York, Pennsylvania) comprise the next 30% in weighted quantity shipments. The Midwest (zip codes beginning in 4, 5, and 6) is a region where shipments are particularly light.

4.4 Current State Model

A model was simulated of Fresh's current supply chain configuration of only one DC located in the western United States. As mentioned in section 4.2, the transportation costs totaled approximately $26 M. However, with only that one DC location it is impossible to meet customer service level requirements in the furthest zones using ground transportation. In fact, nearly 50% of the United States would require over three days for delivery, and nearly 20% would require five days.

4.5 Future State Models

As mentioned in section 3.3, four future state models were performed on Fresh's supply chain. The four future state models included: 1) the original DC location and the previously determined DC on the east coast, 2) the original DC location and an optimized DC location determined by the DC Optimizer, 3) the original DC location, the previously determined second DC location and a third DC location determined by the DC Optimizer, and 4) the original DC location and two optimized DC locations determined by the DC Optimizer. It is important to note here that it took approximately four minutes to simulate each of these scenarios using the DC Optimizer. Considering the large amount of records being analyzed (≈3.4 million), the author was pleased with the tool's performance. The results to each of the models will be discussed in further detail in the sections to follow.

4.5.1 Original DC and Previously Determined Second DC

Upon simulating the scenario of the original DC located in the western U.S. and the previously determined second DC in the eastern U.S., the DC Optimizer determined that Fresh's transportation supply chain costs would total approximately $24.5 M. This results in an annual difference of $1.5 M, or a 5.7% reduction in transportation costs from the current supply chain configuration with just the original DC located in the western U.S. Customers would be allocated to each respective DC according to the line dividing the U.S. map shown below in Figure 4-2. In this scenario, 100% of the customers would be capable of being serviced within the three day service level requirement using ground transportation.

Figure 4-2: Original DC and Previously Determined Second DC Customer Allocation

4.5.2 Original DC and Optimized DC Location

Upon simulating the scenario of the original DC located in the western U.S. and allowing the flexibility to locate a second DC in the eastern U.S. to be identified by the DC Optimizer, the DC Optimizer identified an optimal location approximately 500 miles northeast of the previously determined second DC in section 4.5.1. This second DC location would result in total

transportation supply chain costs of approximately $24.3 M for Fresh. This results in an annual improvement of $0.2 M from the previously determined second location and a $1.7 M annual difference from the original DC location, or a 6.5% and 5.7% reduction, respectively, in transportation costs from the current supply chain configuration with just the original DC located in the western U.S. Customers would be allocated to each respective DC according to the line dividing the U.S. map shown below in Figure 4-3. It is noticed that due to the shift of the DC 500 miles northeast, the majority of customers located towards the south, including Texas, Oklahoma and Kansas, would no longer be serviced by the second DC. In this scenario, 100% of the customers would still be capable of being serviced within the three day service level requirement using ground transportation.

Figure 4-3: Original DC Location and Optimized Second DC Customer Allocation

4.5.3 Original DC, a Second Previously Determined DC, and a Third Optimized DC Location

It was important to attempt to gain an understanding of potential future DC locations should Fresh experience growth in sales or a desire to shorten service times that would require

the location of a third DC. Upon simulating the scenario of the original DC located in the western U.S., the previously determined second DC in the eastern U.S., and a third optimized DC location the DC Optimizer located the third DC in the southern U.S. Fresh's transportation supply chain costs would total approximately $24.3 M. This results in an annual difference of $1.7 M, or a 6.5 % reduction in transportation costs from the current supply chain configuration with just the original DC located in the western U.S. Interestingly, there is no significant difference in transportation costs from this scenario to the optimized two DC scenario discussed in section 4.5.2. However, customer allocation changes dramatically from the two DC scenario to this three DC scenario. As shown in Figure 4-4, the customers allocated to both DC's one and two naturally decrease, and the third DC is allocated customers primarily in the Midwest. In this scenario, 100% of the customers would be capable of being serviced within the three day service level requirement using ground transportation.

Figure 4-4: Original DC, Previously Determined Second DC, and Optimized Third DC Customer Allocation

4.5.4 **Original DC and Two Optimized DC Locations**

Upon simulating the scenario of the original DC located in the western U.S and two optimized DC locations, the DC Optimizer located the second DC in the same eastern location as the optimized result in the 2 DC scenario and the third DC in the same location as 4.5.3. It was interesting that regardless of the second DC's location in the eastern U.S. it had no effect upon the location of the third DC in the southern U.S. Fresh's transportation supply chain costs were shown to total approximately $24.0 M. This results in an annual difference of $2 M, or a 7.7 % reduction in transportation costs from the current supply chain configuration with just the original DC located in the western U.S. Furthermore, it is a $0.3 M reduction, or 1.2%, from both the three DC scenario and optimized two DC scenario discussed in sections 4.5.3 and 4.5.2, respectively. Customer allocation among the DC's changes slightly when compared with the allocation resulting from the previously discussed three DC scenario. In this case, the third DC now services areas further east including Alabama and parts of Kentucky, Georgia, and Florida (see Figure 4-5 below). In this scenario, 100% of the customers would be capable of being serviced within the three day service level requirement using ground transportation.

Figure 4-5: Original DC and Two Optimized DC Locations Customer Allocation

4.5.5 Scenario Results Summary

The results of the current state model (one DC located in the western U.S.) and each future state model and their respective scenario simulations from sections 4.5.1-4.5.4 are summarized in the table below. The table includes the respective transportation costs, a percent improvement upon the baseline, and whether that scenario is capable of meeting the three day delivery service level.

Table 4-4: DC Scenario Results Summary

DC Scenario	Transportation Cost	Percent Improvement	Service Level Capable
Baseline (1 DC)	$26M	-	No
Two DC	$24.5M	5.77%	Yes
Two DC Optimized	$24.3M	6.54%	Yes
Three DC	$24.3M	6.54%	Yes
Three DC Optimized	$24M	7.69%	Yes

4.6 Qualitative Results

As mentioned, an objective of this research was to gain a deeper understanding into how strategic supply decisions are made in an SME, particularly with respect to location-allocation decisions of DCs. Working in collaboration with Fresh proved pivotal in gaining a deeper understanding of this objective, primarily as a result of their current situation in having very recently undergone the process of determining where to locate a second DC. The following sections will highlight the findings from meetings held with the vice president of logistics at Fresh.

4.6.1 **Objective and Timing**

The situation Fresh found itself in contributed greatly to the objective and timing of locating a new DC. As discussed in the analysis of Fresh's shipping patterns, 50% of the weighted shipping volume was done to the western U.S. That had traditionally been where their business had been concentrated and as a result, where their primary DC was located. However, a shift had been occurring recently, business in the eastern U.S. was now growing faster than business in the western U.S. Fresh consistently tracks the cost of freight and materials globally and they had traditionally allocated 1% of revenue to subsidize the cost of freight. Operations in the U.S. had actually been profitable and within one year it was nearly a $1M loss. When Fresh had been operating in the black they had been using a UPS service known as SurePost. The UPS SurePost service is a hybrid service with the majority of the shipping distance performed by UPS and the final mile of each delivery to customer's mailboxes performed by USPS. However, as demand increased and with the desire of meeting a 3-day delivery service goal, Fresh shifted to using air freight, which allowed them to increase service levels but it also dramatically increased costs. As Fresh began considering the potential of locating a new DC, their objective really became two-fold: 1) cost minimization and 2) demand coverage. Timing also became a concern as the growth on the east coast was expected to be a trend that continued.

4.6.2 **Decision Process**

Having identified a need, Fresh first performed an internal analysis to attempt to quantify the benefits and costs of having a second DC on the east coast. Identified benefits included the reduction in transportation costs coupled with the reduction in labor cost at the primary DC. The indirect benefit of business continuity in the U.S. was also identified. Costs identified included annual software maintenance fees, material handling solution hardware, consulting on the use of

ERP systems, additional labor, increase in inventory cost of capital, travel between facilities, and potential bulk transportation costs. Both the NPV and IRR of the identified measures were appealing, and Fresh's payback period would occur in just over a year.

The process then shifted towards identifying a location. Fresh consulted with two parties to run a quantitative analysis: UPS Supply Chain Solutions and an independent consultant. The UPS Supply Chain Solutions group conducted an analysis using Fresh's UPS order history to help design the supply network. The independent consultant performed a similar analysis but focused on specifics such as the potential facility layout, cost of labor, and which SKU's and in what quantity to locate at each facility.

Following the collection of results on potential locations and facility specifics, Fresh began to consider the decision of whether to run their own facility or use a third party logistics provider. Fresh's CFO was hesitant to invest the necessary capital required to purchase and set up a new DC, and combined with the risk of operating in an unfamiliar part of the country, Fresh decided that it was best to contract with a third party logistics (3PL) provider. They initially considered UPS but learned that they didn't have any available assets in the proper location, so they created a request for proposal (RFP) and contacted a few 3PLs in or around the area identified. Fresh narrowed the pool of candidates down to 2 finalists. The final decision of whom to enter into an agreement with between the two came down to qualitative factors. These factors included IT capability and support level, financial stability of the 3PL, any previous history in dealing with larger clients, access to a large pool of labor, FDA certification, clean and high-quality facilities, and professional management.

5 CONCLUSIONS AND FUTURE DIRECTIONS

5.1 Conclusions

The following sections will outline the conclusions from the results of the DC Optimizer followed by the conclusions from the comparison of methods.

5.1.1 DC Optimizer

The use of the DC Optimizer in the distribution center location-allocation decision resulted in a more optimal supply chain solution. The optimized DC location resulted in a network design with a 6.5% reduction in transportation costs from the base model, and a 0.8% reduction in transportation costs from the previously determined network design. The performance of the DC Optimizer in analyzing approximately 3.4 million records within an average of 4 minutes for each scenario created was impressive.

The DC Optimizer also provided insight into the importance of considering weighted shipping volume. The separation in shipping costs by region did not become significant until shipping packages over 10 pounds. Approximately 93% of Fresh's packages averaged 6 pounds or less and as a result, it costs relatively little more to ship longer distances. As a result, adding a second DC did not have as large an impact on the reduction of transportation costs as one might have anticipated. Additionally, adding a third DC and further DCs beyond that would lead to

only drastically diminishing returns in transportation cost reduction, while incurring rapidly increasing DC operation and inventory holding costs.

The insight into the importance of weighted shipping volumes also highlighted the potential impact of service levels. If, in the case of Fresh, a three day service level were not a customer requirement then the additional costs of a second DC, particularly if the decision were made to own and operate a DC, would greatly exceed the reduction in transportation costs. Additionally, in terms of meeting the three day service level for 100% of customer orders, it made very little difference where the second DC was located. However, customer allocation to the respective DCs did experience significant changes when DCs were moved. This finding highlights the importance of classifying customers using methods such as an ABC analysis. It is more important to place a DC in a location that would allow for allocation to A customers with the shortest possible service levels.

5.1.2 **Methods Comparison**

Timing was determined to be the largest influencing factor in locating a new DC within the supply network. As business shifted it was important that the company be able to respond quickly and efficiently in order to make efficient use of resources. In this case, Fresh contracted out the services of analyzing demand and costs to make a recommendation on the location of a second DC. This both slowed down the supply chain design process and forced them to incur additional costs. The only analysis done internal to the company included an NPV analysis using projections that included the benefits of reduced freight costs and the reduction of labor at the original DC location. A tool such as the DC Optimizer is shown to mitigate many of these issues.

5.2 Future Direction

This research served as a validation model for proving the effectiveness of using an optimization tool. Specifically, it validated that the location-allocation decision can be optimized when compared to current manual methods used amongst SMEs. Although effective as a base model, there are several additions which can be made to gain a more holistic view of the supply network design problem. This would include research on allowing for the capability to model the following:

- Inventory carrying costs. Specifically, the relationship between the cost of holding inventory as the number and location of DCs changes.
- The increased supply chain cost of operating an additional DC, both owned and leased.

Currently the DC Optimizer is limited to static, deterministic problems. As discussed in current literature, this brings inherent difficulties in translating the model to future business. An added capability of the model to allow for stochastic, dynamic problems by using sensitivity analysis or scenario planning methods would prove valuable to users. Furthermore, a comparison of similar DC optimization tools and their respective results could provide interesting findings in terms of further model validation.

As mentioned in the previous section, one of the conclusions of this research highlighted the relationship between service level and transportation cost. Further research into this relationship would prove beneficial in understanding the cost of incrementally increasing service levels in comparison to a benefit of increased revenue.

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