A Combined Inventory-Location Model for Distribution Network Design

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Abstract

Two important areas of decision-making in distribution system design involve facility location and inventory policy determination. Facility location analyzes questions such as how many facilities should be opened, where they should be located, and which customers should be assigned to which DCs. Inventory policy determination involves more tactical decisions such as the order quantities and frequencies at each level or echelon in the network. It is believed that these two decisions can influence each other significantly. Including a multi-echelon inventory policy decision in a location analysis allows a user to capitalize on the strengths that each DC has to offer (e.g., lower labor rates, land costs, etc.). Likewise, when the locations of two facilities are known, a multi-echelon inventory policy can be designed better to incorporate the exact lead times and fixed costs between the facilities at each level of the system. Despite this, the two problems are typically solved independently. This research addresses these problems together and investigates different heuristic methods for solving a combined inventory-location model. We begin by presenting the background and formulation for each problem. These formulations are then combined to show how the two problems can be mathematically formulated together. Rather than solve the problem exactly, two heuristic methods using different philosophies are tested. We apply these heuristic methods to the combined inventory-location problem to determine how much we can improve distribution network design solutions and what type of heuristic methodology is most effective in gaining these improvements. Our results show that the combined inventory-location model is capable of improving on the solutions obtained by a location model with a fixed inventory policy. The improvement based on the data sets tested in this research was approximately $60,000. However, in cases where the inventory costs are a larger portion of the total cost, the improvement made by the inventory-location model increased to over $1,000,000. We also found that our second heuristic method tested provided statistically significant improved results over our first heuristic method. Moreover, the second heuristic method typically ran 67% faster. The improved results, although small in a relative sense (the average improvement was 0.18%), would still represent a large absolute improvement in supply chain costs. As much as $174,000 was saved in the data sets tested for this research.

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Chapter 1

Introduction

Having a well-designed distribution system network can contribute significantly to the effectiveness of a supply chain. The design components of a distribution system include the number of distribution centers (DCs), the location of each DC, what customers are assigned to each DC, how much a manufacturer supplies to each DC, and the amount of inventory that will be held at each stage of the distribution network. In other words, distribution system design deals with designing the flow and size of shipments from manufacturers to DCs to customers.

This research examines the relationship between the inventory optimization problem and the facility location-allocation problem. These problems are solved together to realize the maximum benefit for the distribution network design. The motivation for this project is further explained in Section 1.1. In Sections 1.2 and 1.3, we give an introduction to the general inventory and multi-echelon inventory problems. Next, we explore the facility location-allocation problem in depth in Section 1.4. In Section 1.5, we then discuss the interdependencies between these two problems. Finally, we present an outline for the rest of the thesis in Section 1.6.

1.1 Motivation

This research is motivated by a company with an after-market spare parts distribution network. This company seeks to analyze the efficiency of their current distribution system design. The Thermo King Corporation, a division of Ingersoll-Rand, currently has one DC located in Minneapolis, MN that distributes production from over 250 manufacturers to over 200 customers across the country.

This research began as an analysis to determine the best location and number of DCs for the Thermo King spare parts distribution network. This thesis suggests the development of an inventory allocation system to complement the potential locations considered in the distribution network design phase. This added portion of the tool will be especially useful to other divisions of Ingersoll-Rand adding an aftermarket operation, and as a result, do not currently have a defined inventory policy in place.

This problem is modelled mathematically as a nonlinear mixed integer problem and we propose to solve it using heuristic methods. The algorithms developed will be implemented in an Excel-based tool to aid in the design of distribution networks.

1.2 The Inventory Control Problem

The classical inventory control problem is centered around the question "How much on-hand stock should we have?" There are trade-offs in using different inventory policies and determining the best policy for any one facility can be difficult. On the one hand, carrying a large amount of inventory provides protection against uncertainty in demand and allows companies to take advantage of economies of scale when ordering material. This type of system is relatively easy to manage; however, the inventory holding costs can be very expensive. On the other hand, a distribution center may choose to carry very little inventory (similar to a Just-In-Time system). In this case, inventory holding costs are typically much lower, but managing the system to ensure parts are available when and where they are needed can be challenging.

So which is the right approach? The answer to this is dependant on the relevant inventory costs. These typically include the inventory holding costs, the order costs (which include fixed and variable components), and the penalty costs. Inventory holding costs include expenses such as storage costs, rent/depreciation, labor, obsolescence, overhead, and opportunity costs. Ordering costs include expenses such as the labor cost of processing orders, and costs associated with quality assurance (inspections). Finally, penalty costs represent the cost of not having sufficient stock on hand to satisfy demand when it occurs. The optimal inventory policy for a company is determined by balancing these costs. Figure 1.1 below shows the general relationship between these costs, and the resulting total cost curve. As can be seen, the primary tradeoff exists between the inventory holding costs and the ordering costs.

The Economic Order Quantity (EOQ) model is a popular inventory model that focuses on this tradeoff between fixed order costs and holding costs. This model has many forms — in this paper we will focus on the continuous review, (Q, R), EOQ model, also known as a "Lot Size-Reorder Point" system. This model considers demand as it occurs and focuses on determining the optimal material order quantity (Q) and reorder level (R). When implemented, an order of Q units will be placed when the on-hand inventory decreases to R units. A notable feature of this model is its consideration of order lead times and fixed setup costs for orders. The inclusion of these costs makes this type of model more realistic and applicable to real systems.

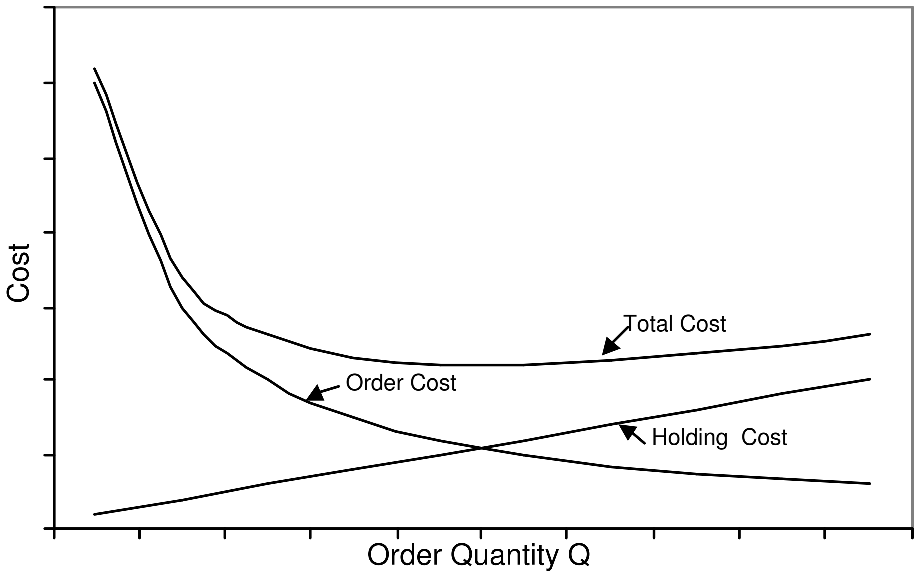


Figure 1.1: Total Inventory Costs.

The EOQ inventory model can be formulated assuming deterministic or stochastic demand. The deterministic case assumes the demand is fixed and known. Thus, an average demand rate parameter is included, while the variance in demand is considered to be 0. The stochastic case incorporates uncertainty in demand by considering the actual variance in demand for the customer(s). Due to the uncertainty present in the stochastic model, safety stock is usually held to prevent stockouts from occurring.

An example of each case is shown in Figures 1.2 and 1.3. Figure 1.2 represents a deterministic EOQ model. The absence of uncertainty is evident in the steady pattern of the decrease in demand and placement of orders. Note that because uncertainty is not present, each order arrives just as the inventory level drops to zero. Figure 1.3 represents a stochastic EOQ model. The rate of decrease in demand in this case is different from one order cycle to the next. Due to the uncertainty in demand, the inventory level sometimes drops below the safety stock level before an order arrives.

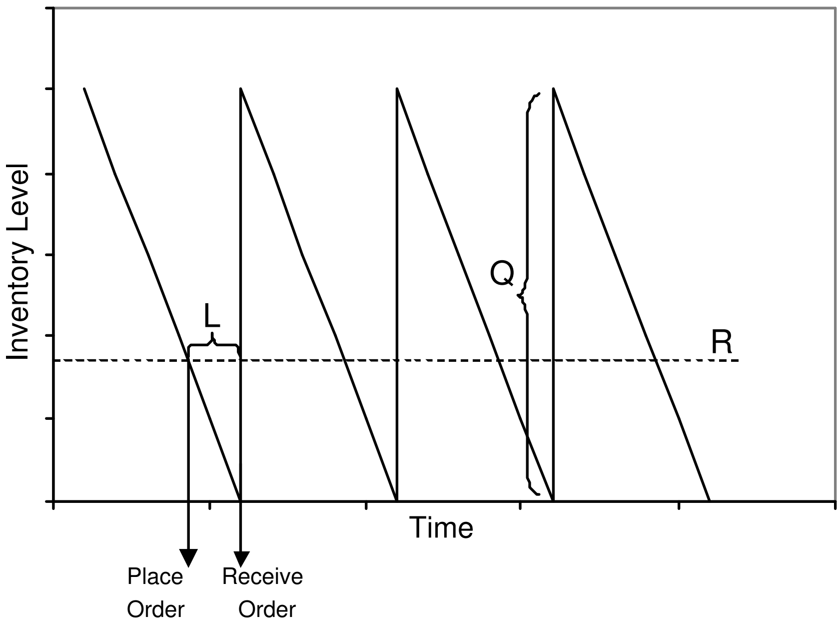


Figure 1.2: Deterministic (Q, R) EOQ Model.

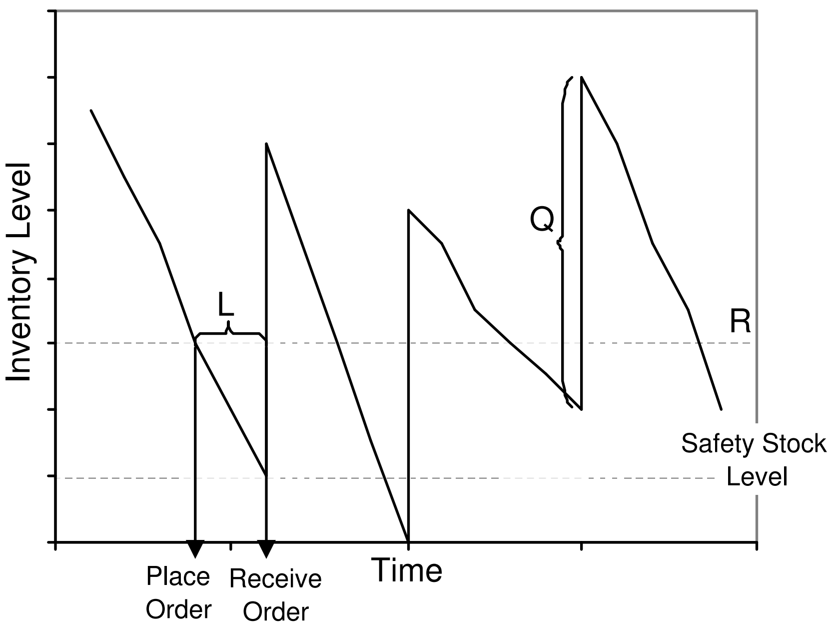


Figure 1.3: Stochastic (Q, R) EOQ Model.

1.2.1 Deterministic EOQ Model

The deterministic case of the continuous review, (Q, R), inventory model is solved by minimizing the total cost function. In Section 1.2, we explain that the total inventory cost consists of inventory holding costs, fixed and variable ordering costs, and penalty costs. However, only inventory holding costs and the fixed ordering costs are considered when solving the deterministic EOQ model. Variable order costs are not considered because this cost is a constant value and does not effect the decision for Q or R. Penalty costs due to material being unavailable are not included because the deterministic case does not consider any uncertainty in demand so we can be assured that an order will always arrive before the inventory level drops below zero.

The parameters, decision variables and total cost function for the deterministic EOQ model are described below:

Parameters:

h = holding cost per unit per unit time

λ = expected demand (units per unit time)

L = order lead time

K = fixed order cost

Decision Variables:

Q = order quantity

R = reorder point, in units of inventory

Total Cost Function:

$$\text{Total Cost:} \quad h\left(\frac{Q}{2}\right) + K\left(\frac{\lambda}{Q}\right) \tag{1.1}$$

This cost function represents the average inventory holding costs and fixed order costs, respectively. The value of Q that will minimize the total cost function is obtained by taking the derivative of the total cost function with respect to Q, setting it equal to zero and solving for Q. The reorder point, R, is chosen so that the inventory level will not decrease below zero before the order lead time is over. The resulting formulation for Q and R is:

$$Q = \sqrt{\frac{2\lambda K}{h}}\ , \tag{1.2}$$

$$R = \lambda L\ . \tag{1.3}$$

This formulation will result in a deterministic (Q, R) inventory policy to minimize the total inventory cost for a system by balancing the inventory holding costs and the fixed ordering costs. After solving for Q and R, these values can be substituted in (1.1) to find the total inventory cost for this policy.

1.2.2 Stochastic EOQ Model

The stochastic case of the continuous review, (Q, R), inventory model is more complex than the deterministic form of the problem. With the addition of uncertainty in the model, there will be occasions when the available stock is not enough to fill all the orders as they arrive. When this occurs, there are two possible outcomes: 1) the unavailable material is backordered, and the order is filled late, or 2) the order is lost. Because this research concerns an after-market spare parts distribution network, we will assume this situation results in backorders. Spare parts are typically required items with one (or only a few) suppliers so the order is not likely to be lost.

A common way of representing the total backorder costs for a system is by declaring a unit penalty cost, p, that is applied to the units that are backordered. This cost is added to the total cost function and incorporated into the equations for Q and R. Several equations are solved using an iterative procedure to find the minimum cost solution. More details on this method can be found in Nahmias [14]. The problem with this method is that it is often difficult for managers to determine the exact value of p for their system. This value consists of direct costs as well as intangible factors such as loss of goodwill and potential delays to other parts of the system, which are difficult to calculate.

Service Level

A good substitute to defining p as a parameter in the model is to define a desired customer service level, α. This service level may represent two types of service — Type 1 or Type 2 service. The chosen type of service can have a large impact on the way the inventory problem is modelled so this decision should be made carefully. Type 1 service refers to the probability of a backorder not occurring in an order. In other words, a 90% Type 1 service level requires that no backorders occur in 9 out of 10 orders. If a backorder does occur, the magnitude of the backorder is not taken into account. Type 2 service refers to the proportion of demand that is filled without backorders. A Type 2 service level of 90% dictates that 90 units out of every 100 units must be available when needed, rather than being backordered. If 1 unit is backordered for 10 orders, this would still result in a 90% Type 2 service level. If each order has only one item, then the two service levels are equivalent. However, when orders consist of more than one item, the Type 1 service level is generally more conservative (i. e., less than) the Type 2 service level.

In an after-market spare parts facility, the orders are typically very small. Order sizes with one or only a few items are common. In addition, spare part orders have a tendency to be more urgent and the items are sometimes needed together (i. e., a gasket and a water pump). Thus, measuring service with a Type 1 service level seems more appropriate. Also, as we discuss later, this allows us to represent the service level with a linear (non-iterative) model that is easier to incorporate into our overall modeling framework.

Stochastic Model Formulation

The stochastic EOQ model is formulated below. This formulation is based on a Type 1 service level. Details for the formulation assuming Type 2 service can be found in Nahmias [14].

The parameters given for the deterministic EOQ model formulation will be used in this section as well. In addition, the following parameters must be added for the stochastic model:

μ = mean demand during lead time

σ = standard deviation of demand during lead time

α = Type 1 service level; probability of not stocking out during the lead time

z = z-value from a normal distribution corresponding to the fill rate probability α

p = direct backorder cost estimation

The decision variables for the stochastic model remain the same:

Q = order quantity

R = reorder point, in units of inventory

The total cost function for the stochastic EOQ model is slightly changed from that of the deterministic model. Due to uncertainty, it is usually necessary to carry safety stock to meet the service level defined. The level of safety stock can be represented as $(R - \lambda L)$. In addition, the penalty costs due to backorders must be accounted for somehow. Section 1.2.2 discusses the difficulty in calculating the correct value of the penalty cost, p. However, this model requires an estimation of this parameter so that these costs do not go unnoticed. The direct backorder costs will also be included in the combined inventory-location model. Given these additions, the total cost function is as follows:

$$\text{Total Cost:} \quad h\left(\frac{Q}{2} + R - \lambda L\right) + K\left(\frac{\lambda}{Q}\right) + \lambda p(1-\alpha) \tag{1.4}$$

The calculation of Q and R assuming Type 1 service constraints is very straightforward. The value of Q can be calculated with the same equation from the deterministic EOQ model. Next, the z-value is chosen to satisfy the equation $F(R) = \alpha$, where $F(R)$ represents the cumulative Normal distribution function of demand. The z-value is then used to calculate R, as shown in (1.6).

$$Q = \sqrt{\frac{2\lambda K}{h}} \,, \tag{1.5}$$

$$R = \mu + z\sigma \,. \tag{1.6}$$

The resulting values of Q and R can be substituted into (1.4) along with the other parameters to obtain the total cost of the inventory policy. This formulation will be the basis for the inventory formulation used in the combined inventory-location model, which will be discussed in Chapter 3.

1.3 The Multi-Echelon Inventory Problem

One heavily researched area of distribution system design and inventory optimization is multi-echelon inventory models. These models consider several levels of the supply chain (suppliers, distribution centers, customers, etc.) at once to obtain a global inventory control policy that benefits the entire system. In this kind of integrated inventory system, an order placed at a customer or retailer would generate an order to a DC, which would then generate an order from the DC to a manufacturer, and so on. A graphical description of the multi-echelon inventory system can be found in Figure 1.4.

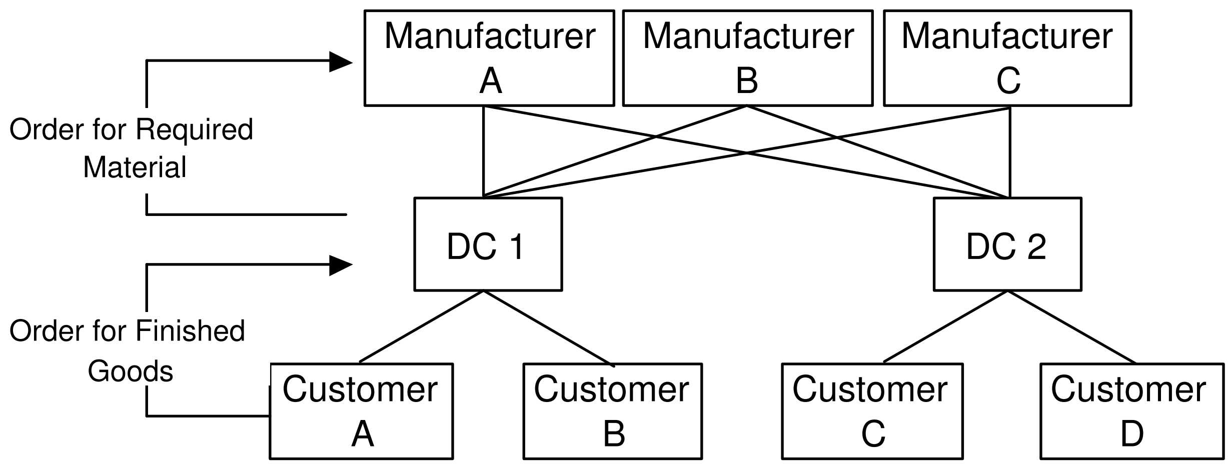


Figure 1.4: Multi-Echelon Inventory System.

Creating a multi-echelon inventory policy is more complicated than the single-echelon case. The single-echelon case, as described in the previous section, only accounts for uncertainty from one customer. In the multi-echelon case, this uncertainty is increased at the lower levels of the supply chain (DCs, manufacturers, etc.). Thus, it is more difficult at the manufacturer level to verify that parts are available at the various levels of the supply chain when they are ordered.

1.3.1 Multi-Echelon Inventory Model Formulation

Suppose a continuous review (Q, R) inventory policy for a distribution center is expanded to include retailers as well. Now, instead of determining the values of Q and R for only the DC, additional Q and R decision variables must be added to determine the inventory policy for the retailers as well. An example of this scenario is shown graphically in Figure 1.5.

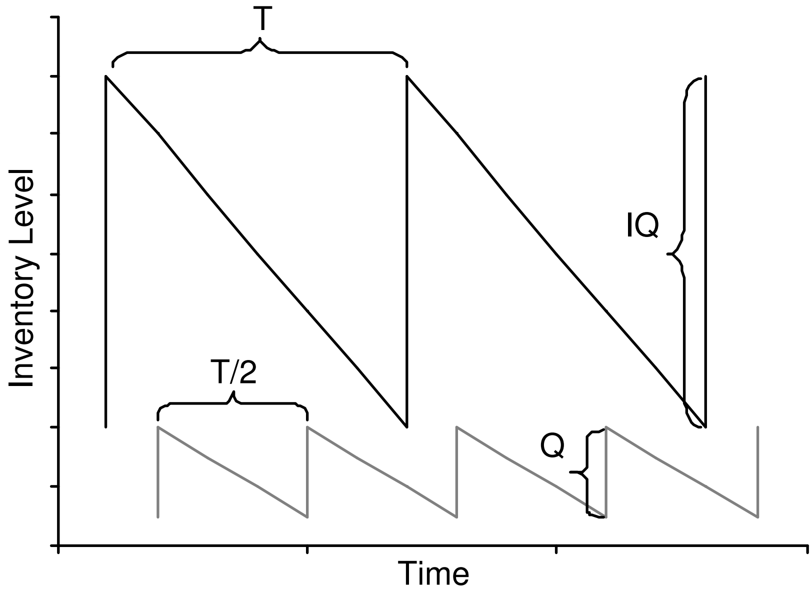


Figure 1.5: Multi-Echelon (Q, R) Model.

The calculation of Q and R for the retailers is generally the same as the method described in Section 1.2.2, using parameters specific for the customers, DCs and manufacturers. However, the multi-echelon model does require an additional constraint to maintain the appropriate relationship between the Q and R values for the DC and the Q and R values for the customers. Assuming there is one DC and $i = 1, \ldots, M$ customers in the system, this constraint can be written as follows:

$$Q^{DC} = I \sum_{i=1}^{M} Q_i^{CUST} \tag{1.7}$$

The parameter I in the constraint above represents an integer value greater or equal to 1. It is good practice in inventory policies for the DC order quantity to be the same as or an integer multiple of the customer order quantity (although this is not necessarily the optimal policy in every case). By having similar order quantities, the practice of stocking unnecessary inventory to account for differences in capacity and/or ordering systems can be avoided. This relationship is represented in (1.7) and is commonly known as the integer-ratio constraint.

1.4 The Facility Location Problem

Choosing the right location for a distribution center is one of the most important decisions in supply chain design. For this reason, the facility location problem has been an area of extensive research. Whether a company is new or old, determining its initial network or expanding on a current one, the facility location decision is critical.

Common questions when dealing with the facility location problem include: How many facilities should be opened? Where should the open facilities be located? The facility location problem seeks to answer these questions by finding a balance between the fixed and variable costs of a distribution system. In doing this, constraints such as capacity, customer service levels, and demand (sometimes for multiple product families) are considered. The facility location problem in this research is modelled as a discrete case, where several known locations are considered as possible facility locations. This problem is modelled using (0,1) binary variables to represent the opening or closing of a distribution center in a given location.The objective is to minimize the total distribution system costs.

An extension to the facility location problem is the facility location-allocation problem. This problem is very applicable to distribution systems because in addition to deciding where to locate facilities (DCs), the location-allocation problem also determines what DC each of the existing customers will be assigned to. An example of this allocation decision is shown in Figure 1.6, where the large black squares represent DCs and the + signs represent customers. The modeling of this problem is similar to that of the discrete facility location problem. In addition to the binary open/close decision variables for the DCs, more decision variables are added to represent the assignment of customers to open DCs.

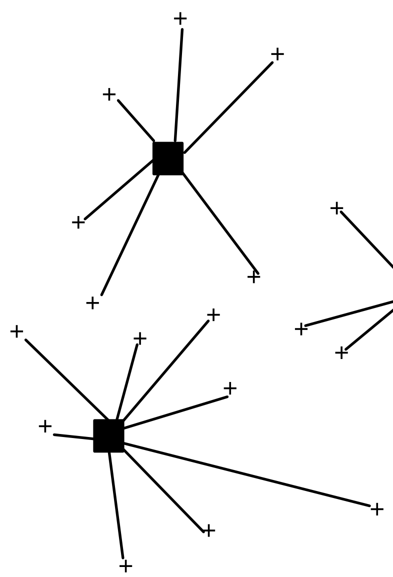


Figure 1.6: The Location-Allocation Decision.

1.4.1 Location-Allocation Model Formulation

The objective of the facility location-allocation problem is to minimize the total cost of a distribution system. Constraints are also required to ensure that each customer is allocated to only one DC (i.e. no partial allocations are permitted). Although many costs could be included in the cost objective, this problem typically seeks to balance the transportation costs and operating costs of the resulting network. Given a discrete set of location possibilities, the formulation of this problem using binary (0,1) decision variables is shown below.

Parameters:

i = index for customers ($i = 1, \ldots, M$)

j = index for DC locations ($j = 1, \ldots, N$)

λ_i = expected demand for customer i

w_{ij} = unit transportation cost from DC j to customer i

d_{ij} = distance units from DC j to customer i

f_j = fixed operating cost of operating DC j

v_j = variable operating costs of operating DC j (\$/unit)

Decision Variables:

$$x_j = \begin{cases} 1 & \text{if DC } j \text{ is opened,} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if DC } j \text{ is assigned to customer } i, \\ 0 & \text{otherwise} \end{cases}$$

Objective Function (Total Distribution System Cost):

$$\text{Minimize} \quad \sum_{j=1}^{N} f_j x_j + \sum_{j=1}^{N} \sum_{i=1}^{M} y_{ij} \lambda_i \left(v_j + w_{ij} d_{ij} \right) \tag{1.8}$$

$$\text{Subject to:} \quad \sum_{j=1}^{N} y_{ij} = 1 \quad \forall i, \tag{1.9}$$

$$y_{ij} \leq x_j \quad \forall i, j. \tag{1.10}$$

This problem can be quite difficult to solve, due to the potentially large number of (0,1) decision variables. Therefore, heuristic methods are very popular for solving this problem. One characteristic of the facility location problem is that there are typically a number of "good" locations in addition to the optimal solution. This is very helpful because there are often a number of qualitative issues that must also be considered when making a location decision. These may include factors like the quality of labor, business climate, local suppliers, and environmental regulations. Other factors like infrastructure, communication and ease of trading are some additional factors that are considered when dealing with international locations. Therefore, facility location models are typically used to generate several near-optimal solutions. A user can then decide on the best solution by incorporating these other qualitative factors into the decision.

One thing to note about the formulation above is the parameter for distance. Typically, it is not efficient to determine and enter exact distances for every transportation link. A common alternative is to estimate distances using Rectilinear or Euclidean calculation methods. For example, if Rectilinear distances are used, the calculation for distances would be $d_{ij} = [|c_j - a_i| + |d_j - b_i|]$ where (c_j, d_j) represents the DC location coordinates and (a_i, b_i) represents the customer location coordinates.

1.4.2 Inclusion of Nonlinear Inventory Costs

Many facility location problems are solved independent of inventory cost considerations. However, there is a very distinct relationship between the inventory cost and the number of open DCs, otherwise known as the "square-root growth" relationship. This relationship shows that as the number of DCs increases, the amount of inventory necessary in the system increases in a nonlinear fashion. This relationship is shown graphically in Figure 1.7.

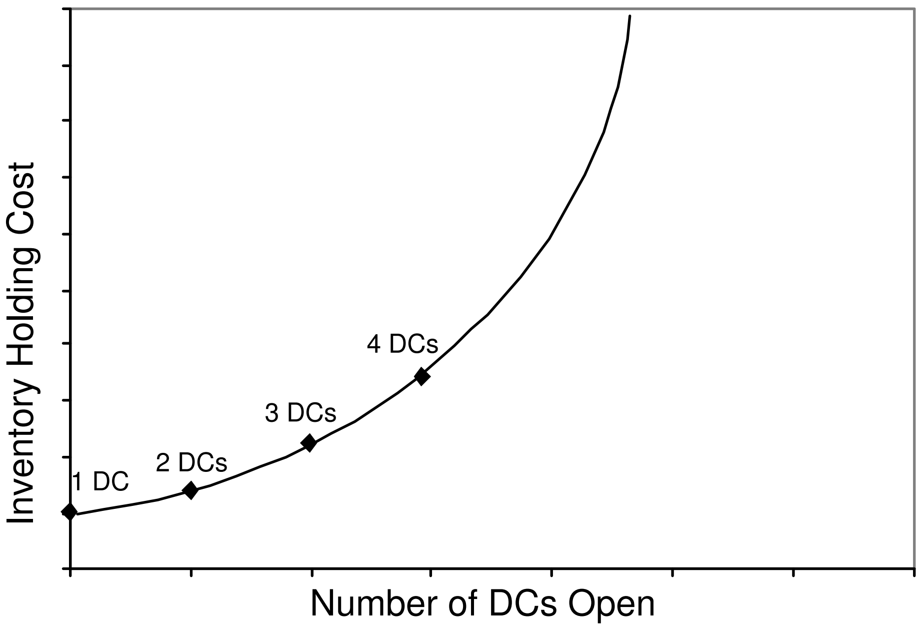


Figure 1.7: Square-Root Growth.

The square-root growth relationship is strongly effected by the centralization of inventory across the DCs. Inventory holding costs become lower as demand is more centralized. When equal demand is satisfied by each DC, inventory holding costs are maximized. Eppen [8] discusses the effects of demand centralization in a multi-location newsboy problem, showing the benefits of pooling inventory. Similarly, Schwarz [20] shows the benefit of pooling inventory in a multi-location EOQ framework. This research shows that inventory costs should be included in facility location analysis.

Knowing that an added DC will increase inventory holding costs, why would one want to consider this? There are some situations that do justify the need for additional DCs. Meller [12] describes some of these situations and looks at the problem from an economic standpoint. He then determines the increase in profit necessary to justify the increased cost of having more facilities open.

Expanding the facility location model to include the nonlinear inventory costs is not difficult. One way of doing this for a fixed inventory policy is to include inventory holding costs for one DC, along with the factor for the square-root growth. The total cost objective will then be:

$$\text{Minimize} \quad \sum_{j=1}^{N} f_j x_j + \sum_{j=1}^{N} \sum_{i=1}^{M} y_{ij} \lambda_i \left(v_j + w_{ij} d_{ij} \right)$$
$$+ h \sum_{j=1}^{N} \left[(INV) \left(\sqrt{\frac{\sum_{i=1}^{M} y_{ij} \lambda_i}{\sum_{i=1}^{M} \lambda_i}} \right) \right] \tag{1.11}$$

The parameter INV in the formulation above represents the inventory level necessary for a one-DC distribution network. The inventory costs are then calculated by scaling this value according to the square-root growth rule. This formulation of the facility location-allocation problem is very difficult to solve because the inventory costs are based on the square root of the demand at a DC, which is based on the assignment decision variables for the customers to DCs.

Note that the inclusion of these inventory costs in the facility location-allocation formulation is not optimizing the inventory policy in any way. This addition only allows the facility location-allocation problem to consider inventory costs and to alter demand assignments to the DCs (and thus, alter the demand centralization) to balance the inventory cost component with the other cost components.

1.4.3 The Thermo King Facility Location-Allocation Model

As stated in Section 1.1, the motivation for this research stems from a previous project with Thermo King. This project resulted in a facility location-allocation tool for analysis of their distribution network. This tool is based on a model that includes the costs discussed in the facility location-allocation model formulation in Section 1.4.1 as well as some additional costs. The costs included are nonlinear inventory costs, nonlinear land costs, labor costs, transportation costs (to and from the DC) and overhead costs.

The Thermo King Location Tool operates in two phases. The first phase solves several iterations of the location problem in a continuous fashion using a mini-sum heuristic procedure. The results of this phase are then used to recommend "good" candidate locations for the second phase. This phase solves the facility location problem discretely, considering a number of specific locations to place the open DCs. The user must specify how many DCs will be open in both stages of the tool.

This tool is unique in that it is linked to a database that holds labor and land costs for 330 different locations across the United States. With this data, the tool is able to calculate accurate land and labor costs, accounting for regional cost of living differences. The tool is also capable of scaling the land and inventory costs accurately as the number of DCs increase.

In order to do this, we include Thermo King's exact cost structure and current inventory policy as a fixed component of the model. When a new distribution network is obtained, this same inventory policy is applied to the system to calculate the accurate land and inventory costs. These capabilities allow the tool to accurately calculate the total distribution system cost for any network configuration.

1.5 The Combined Inventory-Location Problem

In this section we discuss the relationship between the inventory and location problems. Table 1.1 begins by giving a detailed comparison of the two problems. From a modeling and output standpoint, the focus of each problem is different. Despite their differences, these two problems address complementary supply chain issues. Because of the complementary and interdependent nature of the factors driving these issues, the facility location problem and the inventory control problem should be analyzed together to obtain the maximum benefit.

An explanation of the nonlinear relationship between inventory costs and the number of DCs is given in Section 1.4.2. Yet, there are several other links between these two problems. Facility location decisions typically balance fixed operating costs (overhead, equipment, etc.) and variable costs (transportation, direct labor, etc.). Many of these variable costs are affected by the outcome of the inventory problem. For example, the multi-echelon inventory control problem defines the order/shipment quantities for each level of the supply chain. These quantities have a direct impact on the unit transportation costs, which is a significant factor in the facility location problem. The inventory optimization problem also defines the average level of inventory carried at each DC. This has an impact on the land and equipment necessary to handle the proposed quantities. Both of these costs are considered in the facility location problem as well. Thus, if the inventory values are chosen to optimize both the inventory policy and the costs linked to the facility location problem, the outcome will be better for the overall system.

The following example demonstrates a specific case where the consideration of inventory and facility location together influences the outcome of the optimal solution in a location analysis.

Suppose a different division of Ingersoll-Rand decides to add an aftermarket parts distribution operation. This company decides to use the Facility Location Tool developed for Thermo King to find the best location for a single DC to serve the new aftermarket parts distribution network.

Recall that the Thermo King Facility Location Tool does not have the functionality to determine the details of the inventory policy. Rather, it is based on the current inventory policy used at Thermo King. The inventory costs for any location are estimated by applying this same inventory policy to the new facility. Thus, if a new company were to use this tool, it would have to assume that it would use the exact same cost structure and inventory policy

Table 1.1: Facility Location Model vs. Inventory Model.

	Facility Location Model	**Inventory Model**
Optimized Outputs	Facility Locations Customer to DC Assignments	Order Quantities Reorder Points
Customer Service Criteria	Lead Times	% Backorders (Type 1 Service)
Cost Perspective	Total Distribution Cost	Total Inventory Policy Cost
Planning Perspective	Strategic	Tactical
Level of Aggregation	Major Product Categories/Families	Product Line/SKU
Treatment of Uncertainty	Deterministic	Stochastic

as Thermo King. It is not likely a company would make this assumption but for the purpose of this example we will assume the new company does this.

The new company uses the Thermo King Facility Location Tool to obtain several good solutions for potential DC locations. For this example we will look only at the trade-off between transportation costs, labor costs and land costs. The costs for two hypothetical locations are shown below:

Location 1: $**2.5M**

Transportation Cost = $1.0 M

Labor Cost = $1.0 M

Land Cost = $0.5 M

Location 2: $**2.7M**

Transportation Cost = $1.6 M

Labor Cost = $0.8 M

Land Cost = $0.3 M

According to this location analysis, Location 1 seems to be the better option. However, it is clear that the labor and land costs for Location 2 are less expensive than those for Location 1. Recall that these costs are based on a fixed inventory policy. Now suppose the capability of the tool is expanded to allow for a flexible inventory policy that is capable of considering the cost impact of a different inventory policy and lower land costs. This may result in changes to the order quantity and reorder point, which will have an impact on the total unit holding cost and the inventory level. This type of analysis allows us to explore the real potential of each location. The solutions shown above are run again, using the new tool. The costs now change to:

Location 1: $**2.5M**

Transportation Cost = $1.0 M

Labor Cost = $1.0 M

Land Cost = $0.5 M

Location 2: $**2.3M**

Transportation Cost = $1.0 M

Labor Cost = $0.8 M

Land Cost = $0.5 M

By allowing the inventory policy to be flexible, the inventory policy at Location 2 is calculated more accurately based on the exact cost data for the new company's supply chain. In this case, the result is an inventory policy with larger shipments with less frequency. This policy requires a larger facility to hold the extra inventory, causing the land costs to increase. However, the decrease in transportation costs due to less shipments is more than enough to justify the change. Furthermore, this allows the company to take advantage of the less expensive land and labor rate at Location 2. Note that the labor costs do not change due to the change in inventory level since labor costs are based on the throughput assigned to the DC.

It is certainly possible to re-define the inventory policy after moving to a new location. However, if this is not considered in the beginning stages of a location analysis, we may never see the true potential of many locations and discard them as inferior solutions. Furthermore, we can estimate the distribution system costs much more accurately by knowing the details of the inventory policy. This example illustrates the impact the inventory and location problems can have on each other and justifies the need for a tool that can consider the two decisions in one analysis.

1.6 Thesis Outline

This document discusses the research for the combined inventory-location problems. In Chapter 2, we will begin by reviewing the current literature on the facility location problem, multi-echelon inventory models, and other models that consider both inventory and location issues. We will then present the problem statement and the mathematical formulation of the proposed inventory-location model in Chapter 3. Next, we discuss the research goals in Chapter 4 followed by the results of the research and data analysis in Chapter 5. Finally, the conclusions are presented in Chapter 6.

Chapter 2

Literature Review

This chapter reviews the research literature, first for the inventory aspect of our problem, then for the facility location problem aspect. The literature for the inventory problem is restricted to multi-echelon models and is discussed in Section 2.1. Facility location literature is reviewed in Section 2.2, and similar attempts to study the combined inventory-location problem are discussed in Section 2.3. Finally, Section 2.4 shows how the proposed research relates to the reviewed literature.

2.1 Multi-Echelon Inventory Models

The classical (Q, R) inventory control problem consists of determining how much should be ordered and at what point the order should be placed. The multi-echelon inventory control model is more complex in that this problem must be solved for each facility at each echelon. Rather than solving the problem independently for each facility, there are relationship constraints between the different echelons that should be followed to ensure the best inventory policy for the overall system.

Several examples of both exact and heuristic models for the multi-echelon inventory problem can be easily found. Schwarz [19] provides a sample of approximately 250 references of various adaptations of this problem. Some common methods of simplifying the model are to assume the transportation decision is independent, assume all retailers are identical, reduce the number of echelons considered, and/or view each location as an independent entity. The exact methods reviewed in Section 2.1.1 focus primarily on representing different types of demand using different distributions. Several heuristic methods are presented in Section 2.1.2 that are capable of considering unique aspects of the multi-echelon inventory policy that are not considered in the exact models.

2.1.1 Exact Methods

Numerous authors have researched exact methods for solving the multi-echelon inventory model. The methods discussed in this section focus heavily on the nature of demand and the type of inventory policy used. These models cover the very basic form of the multi-echelon inventory model. Models that incorporate more detail such as transportation constraints and dynamic ordering policies will be discussed in Section 2.1.2.

Axsätar [2] develops an exact model for a multi-echelon continuous review inventory system with one central DC and N retailers. Lead times are constant and retailers experience Poisson demand. This model is unique in that all facilities (DCs and retailers) use batch-ordering policies. Axsätar begins by developing a model for a simple case (batch size = 1) and expanding the model to include batch quantities. This expanded model also incorporates backorders, which are filled using a first-come-first-serve policy. The resulting model keeps track of each unit as it moves through the supply chain and provides exact evaluation of holding and backorder costs. The aim of the model is to calculate the steady-state inventory holding costs and backorder costs for each retailer and the DC. The model is effective in doing this for a small number of retailers; however, the computational time increases exponentially as the number of retailers increase.

Axsäter [3] expands on his exact multi-echelon inventory model by allowing for an approximation of demand. The exact model provides a good methodology to the multi-echelon inventory problem, but it is not very efficient for inventory systems with a large number of retailers. Thus, Axsäter provides an approximation technique to simplify the problem. This technique is based on normal approximations for both the retailer demand and the demand at the DC due to orders from the retailers. This approximation performs well in optimizing very large systems efficiently. The cost outcome for the approximate policy is only 0.6% higher than the costs for the exact solution.

Kalchschmidt, Zotteri and Verganti [11] create a model that is capable on handling high uncertainty in demand. This is a significant problem because uncertainty in demand often leads to higher inventory levels and lower customer service levels. Their approach combines research that focuses on forecasting for lumpy demand and development of stock-policies for supply chains. The resulting model splits demand data into two categories: stable and irregular demand items. Separate forecasting and inventory systems are designed for each category. The stable demand category uses a simple order-up-to inventory policy while the irregular series uses an inventory system similar to a (Q, R) policy that balances backorder and inventory holding costs. The analysis shows that this method can result in good solutions. However, the analysis is performed using a complex simulation model, which is somewhat expensive and time-consuming.

Nahmias and Smith [15] consider a retailer inventory system with N retailers and one central DC. In this case, a fixed-interval order-up-to policy is considered for both echelons, rather than a (Q, R) policy. The integer ratio constraint is included in this model, where the order frequency of the retailers must be an integer multiple of the order frequency of the DC. A unique aspect of the model developed in this research is that the demand is considered to follow a negative binomial distribution, while most DC/retailer models assume Poisson or Normal distributed demand. The negative binomial distribution is chosen because it can accurately model both high and low demand rates — a capability that is important in many retail industries. The resulting formulas from the model provide the total expected cost per cycle at both echelons.

Other exact models of interest include Graves [10] and Svoronos and Zipkin [22]. Graves presents a model that uses a "virtual allocation" system to assign unallocated stock across each echelon as demand occurs at the customer. Svoronos and Zipkin make a unique contribution by including uncertainty of transportation costs in a multi-echelon inventory model. Their analysis focuses on the interplay between transit times and delays due to stockouts.

2.1.2 Heuristic Methods

Heuristic methods for the multi-echelon inventory model are very popular when incorporating additional aspects of the problem into the multi-echelon inventory models. These additional considerations range from capacity limitations, different transportation methods and dynamic analysis of the ordering policy. Some of these additions can complicate the model, making it very difficult to solve with an exact model. The heuristic methods presented below show good examples of how heuristic methods make it possible to incorporate unique components of an inventory system, resulting in a more specialized inventory model.

Bregman *et al.* [5] develop and test a heuristic procedure for a multi-echelon inventory model with transportation costs and capacity limitations on storage and transportation resources. The heuristic procedure begins by calculating the demand requirements for each item at each DC (Echelon 1) and each regional warehouse (Echelon 2). Next, an initial solution is generated assuming only variable transportation costs for each transportation link. The variable transportation costs do not allow for quantity discounts and therefore are generally more expensive. This represents the lowest inventory holding cost and highest transportation cost solution. Next, a subroutine uses a search procedure that analyzes the effect of replacing variable cost transportation with a fixed cost transportation option. The fixed transportation option is less expensive, but requires a minimum number of units. Finally, a second subroutine calculates potential improvements by eliminating/replacing a fixed cost transportation option in future periods with one in the current period. Based on several randomly generated sample problems, this heuristic method is very effective in solving problems close to optimality.

Watson and Polito [23] present a unique method for solving a multi-product, multi-echelon inventory problem. Their research compares the financial performance of a heuristic-based theory-of-constraints (TOC) method and a traditional distribution resources planning (DRP) system. TOC is based on logic that minimizes the total cost of a system by identifying the bottleneck and ensuring it is never idle. TOC has been quite successful in manufacturing and production applications. This research attempts to apply the same logic in distribution planning with the expected results of lowered inventory investment, lead-times and transportation costs. The results for the TOC heuristic method and the DRP method are obtained by simulation. The TOC method performed better with respect to the inventory carrying costs, retail-level shipments, and obsolescence cost.

Yoo *et al.* [24] propose an improved DRP method for scheduling multi-echelon inventory orders. This method calculates the order-quantities and reorder points dynamically to meet the demand and minimize the out-of-stock probability. This research proposes an order-planning heuristic method based on inventory level changes and orders schedules where the objective is to minimize total costs while reducing the number of backorders. The model deals with situations when a DC is unable to completely fill an order from a customer. Heuristic methods are constructed to determine whether to order the available quantity, even though it is less than Q, or wait until the full order quantity is available to place the order. The heuristic methods are tested using a simulation model and result in lower total costs.

2.2 Facility Location Models

Facility location has been another popular area of research. A number of facility location models have been developed, ranging from exact solution approaches to heuristic approaches to simulation approaches. However, many of these approaches do not include any inventory costs in the optimization procedure. Although the nonlinear inventory cost component complicates the determination of the number of DCs, it has an important role in the facility location model and should not be excluded. Therefore, the facility location literature reviewed in this section only considers models that include inventory costs by considering a fixed inventory allocation system.

As with the multi-echelon inventory problem, the facility location problem has been approached using both exact and heuristic methods. Both methods include cost components such as transportation costs, inventory costs and various operating costs. Some of these methods also consider customer service levels. Two exact methods are presented in Section 2.2.1; however, only a general overview of the exact models is discussed due to the proprietary nature of the tools. Next, three examples of heuristic methods are presented in Section 2.2.2.

2.2.1 Exact Methods

We have discussed how the inclusion of inventory costs can complicate the facility location problem because of the nonlinear relationship between inventory costs and the number of open DCs. Solving this problem exactly is very difficult due to this nonlinear component of the problem. Only a few authors have published descriptions of models that are capable of doing this. These articles discuss the model capabilities and give a general overview of the tools; however, the details concerning some calculations and methods used are not always available due to proprietary restrictions.

Arntzen *et al.* [1] describe the Global Supply Chain Model (GSCM) — a global supply chain tool developed by Digital Equipment Corporation. The GSCM is a mixed-integer programming model with several supply chain modeling capabilities. It is able to analyze multi-product, multi-facility, multi-echelons and different transportation modes to recommend a production, distribution and vendor network. The objective function minimizes the total costs. This consists of fixed production costs, variable production costs, inventory costs, facility material handling costs, taxes, overhead costs, transportation costs, and duty drawback. The problem is mathematically modeled and given to a solver embedded in the tool. The optimization may be assisted by the user specifying how much each constraint can be violated at a given penalty cost. The model uses a branch and bound method to solve for the decision variable values including the number distribution centers to open, the locations for the open distribution centers, the customer-DC assignments, the number of echelons, and the product to manufacturing plant assignments.

Breitman and Lewis [6] discuss a tool they created for General Motors called PLANETS (Production Location Analysis NETwork System). PLANETS is not a model itself; rather it is a model-building system that generates unique mathematical models to support many business scenarios, including market analysis, resource deployment and facility location. Before the tool is able to build any models, the user must provide information for up to 11 different building blocks. These building blocks require information such as the current facilities, materials, processes and suppliers for the current network. Given the right information, PLANETS is able to build mathematical models for location problems and answer questions such as: How many facilities are needed? What size facility is needed? What is the best sourcing and distribution strategy for my system? These questions are addressed by referring to information given by the user concerning the products produced, the processes used, freight costs, operating costs and capacity information. PLANETS then delivers a number of basic and financial reports to summarize the solution results.

2.2.2 Heuristic Methods

Several heuristic methods exist for the facility location problem. In many cases, these heuristic methods are used as a way of simplifying the nonlinear inventory costs. This allows the inventory costs to be included without the complexity caused by a nonlinear formulation. This is evident in the following examples.

Ballou [4] presents a facility location model, DISPLAN, that is unique in its method of including exact nonlinear costs for fixed and inventory holding costs. This model determines the number, size, and location of plants, DCs, and other similar facilities. DISPLAN uses a heuristic procedure that starts by opening a DC at each customer site. Each of these DCs satisfy equal portions of the total demand to create the highest possible inventory cost solution. The per-unit inventory and fixed costs are calculated for this scenario. The problem is then solved using a transportation linear programming algorithm to minimize the total cost, estimating inventory and fixed costs based on the per-unit costs from the previous step. When a new solution is reached, the inventory and fixed costs are re-calculated. The new per-unit costs are then used in the next iteration. When an iteration fails to improve the best solution by more than a defined percentage, the heuristic procedure ends and the best solution is kept. This method has proven to run efficiently and provide accurate estimates of the cost savings.

Nozick and Turnquist [16] have conducted extensive research on the facility location problem, focusing on emphasizing inventory costs more in location models. Demand in other models is typically assumed to be known with certainty and inventory costs are either neglected or considered unrelated to the location problem. This research attempts to include the inventory costs, focusing particularly on the safety stock required due to the uncertainty in demand. Safety stock follows the square-root growth rule as the number of open DCs increases. Yet, the nonlinear relationship is quite modest (almost linear) when more than 10 DCs are open. Therefore, the authors estimate the safety stock necessary for a given the number of open DCs using a linear regression model. This allows safety-stock to be included directly in a facility location model where the tradeoff between inventory costs and other operating costs can be better understood. This approximation works best when used in problems where a relatively large (10 or more) number of DCs are to be located.

Nozick and Turnquist [17] build on their previous research by examining the basic conflict between the desire for a low distribution system cost and a high customer service level. The goal of cost reduction drives the centralization of inventory while the goal of customer responsiveness drives the decentralization of inventory so that goods are close to the customers. In order to find a balance between these conflicting goals, careful attention must be paid to the trade-offs among facility costs, transportation costs, and customer responsiveness. This research does so by focusing on the integration of discrete-choice location models, inventory analysis, and multi-objective techniques to model the overall logistics impact of locating DCs. The authors do this by solving a multi-objective (minimize cost, maximize customer coverage) location model using an approximation for inventory costs. The model is then used to show how a user can explore these trade-offs in a DC location problem.

2.3 Combined Inventory and Location Models

Much of the research discussed in the previous two sections is applicable to our proposed research. This review has shown that several good methods exist for both the multi-echelon inventory problem and the facility location problem. Yet, none of the research discussed so far has attempted to incorporate the capability of determining the optimal inventory policy as a part of the facility location problem. Some authors have explored this area of research and a few heuristic methods have been developed for the combined problem. These methods are capable of considering the two problems together; however none of these heuristics address multi-echelon inventory models. Each policy is optimized based only on the local demand. This section will present these recent heuristic approaches for the combined inventory-location model.

2.3.1 Heuristic Methods

Some researchers have attempted different combinations of the inventory and location problem. Rather than simply including inventory costs in facility location analysis, these researchers determine the best inventory policy as a part of the location analysis. Three examples of different heuristics used for this problem are discussed.

Erlebacher and Meller [9] develop an analytical model for distribution system design that determines the number of distribution centers (DCs), their locations, the customers they serve and a (Q, R) inventory policy for each customer. Their approach uses a combination of simplified analytical models and heuristic methods. First, a "good" starting point for N (the number of open DCs) is determined with an analytical model that considers fixed costs, inventory costs and transportation costs. Bounds for N are also calculated to determine a range of values for N that may also be considered in the analysis. The heuristic begins by assigning the N customers with the largest demand to their own DC and determining which plant ships to which DC. The initial DC locations are then solved for, considering the customer and plants assigned to each DC. An allocation heuristic is then used where customers are assigned to DCs in order of largest demand to smallest demand. For each customer, a (Q, R) inventory policy is determined to minimize the inventory costs and transportation costs for each DC. The DC with the minimum estimated assignment cost is chosen. Next, the plant which is the best choice to ship to the DC under consideration is determined using the same method. Once the customer and plant have been assigned to a DC, the optimal location for the DC is determined considering all the customers and plants assigned to it. The results from the heuristic are then subjected to a pairwise exchange of customers across DCs to guarantee at least a 2-opt solution.

Nozick and Turnquist [18] develop a model for optimizing the location of inventory for individual products in a multi-product two-echelon inventory system. The decisions from this model are then integrated into the location analysis for distribution centers. The inventory problem is approached by determining the products that should be stocked at both a central storage location (manufacturing plant) and a distribution center, and the products that should be stored only at the central storage location. This limits inventory at the DCs to only the higher-volume items and reduces overall inventory holding costs. Next, an iterative procedure is used to solve the location and inventory problems together. First, the location problem is solved (given a pre-existing inventory policy), and next the inventory policy is optimized (given the number and locations of DCs). These iterations continue until the number and location of the DCs do not change from one iteration to the next.

Optiant Inc. and Insight Inc. [21] discuss the fundamental similarities between the facility location problem and the inventory control problem. The authors claims that in order to realize maximum benefit, the interdependencies between these problems must be considered together in an integrated approach. An iterative heuristic procedure is developed to show how the facility location and inventory problem can be solved together for a single-echelon problem using a joint process. This process consists of first gathering data, then generating several "good" facility location scenarios of different types (different number of open DCs, different demand levels at each DC, different location combinations, etc.). Next, the inventory optimization problem is solved for each scenario. The solution with the lowest overall supply chain cost is then chosen. No details concerning the performance of this heuristic are discussed. However, more information on this heuristic procedure and its applications may be obtained through the consulting services and proprietary software solutions from Optiant Inc. and Insight Inc.

2.4 Summary

This review shows that both the multi-echelon inventory problem and the facility location problem have been heavily researched. The multi-echelon inventory literature review shows that many inventory models have been developed, using both exact methods and heuristic procedures. These models provide a vast range, able to incorporate many different distributions to represent many types of demand. In addition, these models are able to consider different costs in the analysis, and can be customized for very specific problems. However, this wide array of multi-echelon inventory research has not yet been applied to the facility location problem.

Similarly, the facility location problem has received much attention. The problem has been modeled many different ways, considering different cost combinations, different optimization criteria and many types of constraints. An increasing number of location models are beginning to consider inventory in the total cost function as well as in the optimization criteria. However, the inventory costs in these models are still based on using a fixed inventory system, rather than determining the best inventory system for each location.

Some good progress has been made in exploring the relationship between the inventory and location problem and how they can be solved together. In Section 2.3, we present several good heuristic approaches to the inventory-location problem. However, only a few approaches have been attempted and none address the same problem we consider in this research. The heuristic methods presented are designed for specific problems with different characteristics than the after-market spare parts problem we consider in this research. Furthermore, none of these examples solve a multi-echelon inventory problem, which is more appropriate for a distribution system inventory policy.

Chapter 3

Problem Statement

This project builds on a previous project where a DC Location Tool was developed for Thermo King. This decision support tool was designed to determine the optimal number of DCs and their locations, based on the Thermo King supply chain network of manufacturers and customers. The tool provided the transportation, labor, land, overhead, and inventory holding costs for the resulting distribution system.

Nonlinear inventory costs are considered in this tool; however, these costs are based on a fixed inventory policy defined by Thermo King. This is a limitation to users who have not already defined an inventory policy for their supply chain. Thus, we propose to expand this facility location tool to include the determination of a multi-echelon inventory control policy, in addition to the number and location of DCs for a distribution system. The multi-echelon inventory policy will include the reorder points and order quantities for the DCs and the customers in the system.

In this chapter we further describe the relationship between the inventory and the location problem by showing how the two problems will be modeled together. The cost components included in the inventory-location model formulation are discussed in Section 3.1. Next, we review the assumptions made for the model in Section 3.2. Finally, the problem formulation is presented in Section 3.3 by reviewing the model parameters in Section 3.3.1, the decision variables in Section 3.3.2 and the mathematical formulation in Section 3.3.3.

3.1 Cost Components

This section will provide a description of each cost component considered in the inventory-location model as well as a brief explanation of how they are calculated. Although many of these costs may seem familiar from the models discussed in Chapter 1, their use in this model may be slightly different.

Transportation Costs: LTL transportation costs are considered for the manufacturer-to-DC and the DC-to-customer portions of the distribution network. For each transportation link, the transportation cost consists of both a fixed and variable cost component. The fixed cost represents the price that must be paid for a shipment, regardless of shipment size or weight. The variable cost is an additional cost for each unit shipped.

DC Land Costs: Land costs are included to account for the investment in land to support a facility large enough for the inventory required at each DC. This cost component follows the square-root growth rule as the number of DCs increases.

DC Labor Costs: Labor costs are included to account for the human resources necessary to process the throughput at each DC. The labor cost for a DC is calculated based on the sum of the demands for the customers assigned to that DC.

DC Inventory Holding Costs: The inventory holding cost for DCs is a variable cost that follows the square-root growth rule and increases non-linearly as the number of DCs increases (see Figure 1.7). Although some level of inventory will be held at the customer sites, the holding cost in this problem only includes the inventory held at the DCs.

DC Inventory Order Costs: The order costs at the DCs will consist of a fixed cost necessary to place an order, regardless of the order size. The amount of orders placed is based on the order quantity, Q, which is nonlinear due to the square-root growth rule. Therefore, this cost component is also nonlinear.

Pipeline Inventory Holding Costs: Pipeline inventory costs are the inventory holding costs for material while it is in transit. These costs are only considered for inventory in transit from the DCs to the customers. A brief derivation of how these costs are calculated is given in Appendix A.

Overhead Costs: Overhead costs are broken down into three categories. These include: (1) fixed overhead costs, (2) labor-related overhead costs, and (3) land-related overhead costs. The fixed overhead costs represent the basic costs necessary to operate a facility at any location of any size. The labor-related overhead costs are dependant on the amount of labor at a facility and is directly correlated with the labor rates of the area. The land-related overhead costs are dependant on the amount of land required for a DC and is directly related to the size of the facility. The labor and land portions of the overhead cost component are based on a reference point, and adjusted for different locations based on the local labor rates and land costs.

3.2 Assumptions

Several of the assumptions concerning the costs involved in this model are discussed in Section 3.1 above. Other assumptions made for the model are listed below:

1. Demand is random and stationary. In other words, the expected value of demand over a defined time interval is constant.
2. Locations of customers and manufacturers are fixed and known, as well as their respective demand/supply.
3. Each customer is assigned to only one DC, meaning all of the demand (including different product families) for this customer is filled by the DC assigned to it.
4. All demand is shipped directly from a DC to the customer. In other words, no direct shipments from manufacturers to customers are considered.
5. If more than one manufacturer is able to produce a product type, we assume that the price for that product at each manufacturer is the same.
6. The inventory policy is continuous review — demand is processed as it occurs and the inventory level is known at all times. Both customers and the DCs employ an optimal (Q, R) inventory system.
7. Inventory costs for distribution systems with multiple DCs follow the "square-root growth" assumption. Individual companies may control inventory growth better/worse.
8. Lead times for demand are deterministic. The lead time for any delivery consists of a standard lead time parameter, L, and the travel time from the supplier to the customer.
9. Transportation times are deterministic.
10. Although backorder costs are concern in any inventory system, we assume that they represent a fixed percentage of the total demand, and thus, are ignored in our formulation. This assumption will be discussed in greater detail in Chapter 6.

3.3 Problem Formulation

The inventory and location problems are modeled independently in Sections 1.2, 1.3, and 1.4. This section will expand on these models to develop the formulation for the inventory-location model. We do this to illustrate the complexity of the combined problem. The parameters, decision variables, and a non-linear formulation are presented in the following sections.

3.3.1 Parameters

The parameters for the mathematical model are listed in this section. Many of the parameters are identical to the ones presented in Chapter 1; however, several use different notation in this formulation. Note that although several costs are not included in the objective function, the related parameters are still necessary for the calculation of other values. For example, ordering costs for the customer are not included in the objective function. Yet, the fixed order cost for the customer is still needed to calculate the customer order quantity.

Indices:

i = index for customers ($i = 1, \ldots, M$)

j = index for DCs ($j = 1, \ldots, N$)

l = index for manufacturers ($l = 1, \ldots, O$)

k = index for products ($k = 1, \ldots, P$)

Demand/Supply Parameters:

d_{ik} = average annual demand of customer i for product k; Total Demand $(D) = \sum_{i=1}^{M}\sum_{k=1}^{P} d_{ik}$

μ_{ik} = average daily demand at customer i for product k ($\mu_{ik} = \frac{d_{ik}}{ND}$)

σ_{ik} = standard deviation of daily demand at customer i for product k

σ_{jk} = standard deviation of daily demand at DC j for product k

v_{lk} = percentage of annual supply from manufacturer l for product k

$NManf_k$ = Number of manufacturers that produce product k

Transportation Parameters:

S_i = fixed shipment cost for customer i

S_j = fixed shipment cost for DC j

TC_k = variable unit transportation cost for product k (\$/unit/mile)

m_{ji} = mileage from DC j to customer i

m_{lj} = mileage from manufacturer l to DC j

avg = Average mileage travelled in one day (miles/day)

$trav_{ji}$ = Number of days necessary to travel from DC j to customer i $\left(trav_{ji} = \lceil \frac{m_{ji}}{avg} \rceil\right)$

ND = Number of business days in one year

Land and Labor Parameters:

C_j^{lb} = burdened labor wage at DC j (\$/person/year)

r^{lb} = inventory processing rate per person (# units/person/year)

C_j^{ld} = land cost at DC j (\$/acre/year)

r^{ld} = inventory holding capability per acre (# units/acre/year)

Inventory Parameters:

h_k = unit inventory holding cost for product k (\$/unit/year)

A_i = order placement cost at customer i

A_j = order placement cost at DC j

Overhead Parameters:

F = annual fixed cost for an open DC

OH^{lb} = labor-related overhead cost for a reference city with labor-rate lab

lab = burdened labor rate for overhead reference city (\$/person/year)

OH^{ld} = land-related overhead cost for a reference city with land rate $land$ and inv units of inventory

$land$ = burdened labor rate for overhead reference city (\$/acre/year)

inv = # units of inventory for overhead reference city

Service Level Parameter:

α = Type 1 service level; probability of not stocking out during the lead time

z = z-value from a normal distribution corresponding to the Type 1 service level, α

Leadtime Parameters:

L = Fixed lead time parameter (# days)

LT_{ji} = Total lead time from DC j to customer i including the lead time parameter and the transit time ($LT_{ji} = L + m_{ji}/avg$)

LT_{lj} = Total lead time from manufacturer l to DC j including the lead time parameter and the transit time ($LT_{lj} = L + m_{lj}/avg$)

3.3.2 Decision Variables

The following are the decision variables for the mathematical model:

$$x_j = \begin{cases} 1 & \text{if DC } j \text{ is opened,} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1 & \text{if DC } j \text{ is assigned to customer } i, \\ 0 & \text{otherwise} \end{cases}$$

Q_{ik}^{C}= Optimal Order Quantity at customer i for product k

Q_{jk}^{DC}= Optimal Order Quantity at DC j for product k

R_{ik}^{C}= Reorder point for customer i for product k

R_{jk}^{DC}= Reorder point for DC j for product k

3.3.3 Mathematic Formulation

The resulting formulation is as follows:

$$
\begin{aligned}
\text{Minimize} \quad & \sum_{j=1}^{N}\sum_{l=1}^{O}\sum_{k=1}^{P}\left[S_j\left(\frac{\sum_{i=1}^{M} d_{ik}y_{ij}}{Q_{jk}^{DC}}\right)+\left(\sum_{i=1}^{M} d_{ik}y_{ij}\right)(v_{lk})(m_{lj})(TC_k)\right] \\
& + \sum_{j=1}^{N}\sum_{i=1}^{M}\sum_{k=1}^{P}\left[S_i\left(\frac{d_{ik}}{Q_{ik}^{C}}\right)+(d_{ik}y_{ji})(m_{ji})(TC_k)\right] \\
& + \sum_{j=1}^{N}\sum_{k=1}^{P}\left[\left(\frac{C_j^{ld}}{r^{ld}}\right)\left(\frac{Q_{jk}^{DC}}{2}+R_{jk}^{DC}-\sum_{i=1}^{M}(LT_{ji}\mu_{ik}y_{ji})\right)\right]+\sum_{j=1}^{N}\sum_{k=1}^{P}\left[\left(\frac{C_j^{lb}}{r^{lb}}\right)\sum_{i=1}^{M}(d_{ik}y_{ji})\right] \\
& + \sum_{j=1}^{N}\sum_{k=1}^{P}\left[A_j\sum_{k=1}^{P}\left(\frac{\sum_{i=1}^{M} d_{ik}yji}{Q_{jk}^{DC}}\right)+h_k\left(\frac{Q_{jk}^{DC}}{2}+R_{jk}^{DC}-\sum_{i=1}^{M}(LT_{ji}\mu_{ik}y_{ji})\right)\right] \\
& + \sum_{j=1}^{N}\sum_{i=1}^{M}\sum_{k=1}^{P}\left[h_k\left(\frac{d_{ik}y_{ji}}{ND}\right)trav_{ji}\right]+F\sum_{j=1}^{N}x_j+\sum_{j=1}^{N}x_j\left(OH^{lb}\frac{C_j^{lb}}{lab}\right) \\
& + \sum_{j=1}^{N}\sum_{k=1}^{P}x_jOH^{ld}\left[\frac{C_j^{ld}}{land}\right]\left[\frac{\left(\frac{Q_{jk}^{DC}}{2}+R_{jk}^{DC}-\sum_{i=1}^{M}(LT_{ji}\mu_{ik}y_{ji})\right)}{inv}\right]
\end{aligned}
\tag{3.1}
$$

Subject To:

$$Q_{ik}^{C} = \sqrt{\frac{2d_{ik}\left(A_i + S_i\right))}{h_k}} \quad \forall i, k \tag{3.2}$$

$$Q_{jk}^{DC} = \sqrt{\frac{2\sum_{i=1}^{M}[(d_{ik}y_{ji})(A_j + S_j)]}{h_k + \left(\frac{C_j^{ld}}{r^{ld}}\right) + \left(\frac{OH^{ld}}{inv}\right)\left(\frac{C_j^{ld}}{land}\right)}} \quad \forall j, k \tag{3.3}$$

$$Q_{jk}^{DC} = I\sum_{i=1}^{M} Q_{ik}^{C} \quad \forall j, k \tag{3.4}$$

$$\sigma_{jk} = \sqrt{\sum_{i=1}^{M}\left(\sigma_{ik}y_{ji}\right)^2} \quad \forall j, k \tag{3.5}$$

$$R_{ik}^{C} = z\sqrt{\sigma_{ik}^2\sum_{j=1}^{N}(LT_{ji}y_{ji})} + \mu\sum_{j=1}^{N}(LT_{ji}y_{ji}) \quad \forall i, k, \tag{3.6}$$

$$R_{jk}^{DC} = z\sqrt{\sigma_{jk}^2\sum_{l=1}^{O}\lceil\frac{LT_{lj}}{NManf_k}\rceil} + \mu\sum_{l=1}^{O}\lceil\frac{LT_{lj}}{NManf_k}\rceil \quad \forall j, k \tag{3.7}$$

$$\sum_{i=1}^{M} y_{ji} \le Mx_j \quad \forall j \tag{3.8}$$

$$\sum_{j=1}^{N} y_{ji} = 1 \quad \forall i \tag{3.9}$$

$$\sum_{l=1}^{O} v_{lk}\sum_{i=1}^{M} d_{ik}y_{ij} = \sum_{i=1}^{M} d_{ik}y_{ji} \quad \forall j, k \tag{3.10}$$

$$x_j = [0, 1] \quad \forall j \tag{3.11}$$

$$y_{ji} = [0, 1] \quad \forall j, i \tag{3.12}$$

$$v_{lk} \ge 0 \quad \forall l, k \tag{3.13}$$

$$Q_{ik}^{C}, Q_{jk}^{DC} \ge 0 \quad \forall i, j, k \tag{3.14}$$

$$R_{ik}^{C}, R_{jk}^{DC} \ge 0 \quad \forall i, j, k \tag{3.15}$$

The terms in the objective function, (3.1), represent the incoming and outgoing transportation costs, land costs, labor costs, inventory (order and holding) costs, pipeline inventory costs, and overhead costs (fixed, labor-related, and land-related), respectively. The first two constraints, (3.2) and (3.3), show the calculations for the economic order quantities for the customers and DCs. The next constraint, (3.4), represents the integer-ratio constraint for the multi-echelon inventory problem as discussed in Section 1.3. Constraint (3.5) calculates the standard deviation for the DCs based on the customers that are assigned to it. The following two constraints, (3.6) and (3.7), represent the calculations for the reorder points for the customers and DCs. Next, (3.8) and (3.9) limit each customer assignment to one open DC, while (3.10) verifies that each product at each customer is fully supplied by the DC they are assigned to. Finally, (3.11)-(3.15) bound each of the decision variables.

One unique feature of the formulation above is the formulation of the DC order quantity, Q_{jk}^{DC}. This decision variable is formulated somewhat differently than the method discussed in Section 1.2.2. To begin with, the fixed shipping cost component, S_j, is added as a part of the fixed costs. In addition, the holding costs in the denominator of the formulation for Q now consist of more than just the unit inventory holding costs. Rather, the unit land cost and unit land-related overhead costs are also considered here. An increase or decrease in the land cost at a given location will allow for less or more inventory to be held for the same price. Therefore, these costs should have an impact on the decision of how much inventory to carry at a DC, which is determined largely by the DC order quantity, Q_{jk}^{DC}. For this reason, the unit land cost and unit land-related overhead costs are included as part of unit holding costs in the formulation of Q_{jk}^{DC}. Although the impact of these costs will typically be low in comparison to the unit inventory holding costs, it is necessary to include this relationship.

In addition to the unique formulation of Q_{jk}^{DC}, there are several other distinct factors included in this formulation of the inventory-location problem. To begin with, the exact nonlinear costs are calculated for several cost components, including inventory holding costs, land costs, and land-related overhead costs. Furthermore, the formulations for these costs are based on the order quantity and re-order point, which are decision variables themselves. Another unique feature of this formulation is the inclusion of several types of operating costs. Fixed operating costs, transportation costs, and inventory costs are often included in location analysis but cost factors such as land costs and detailed overhead costs (i.e. land-related overhead costs, labor-related overhead costs) are rarely considered. Furthermore, very few models are capable of calculating land and labor costs exactly, considering the cost of living differences at different locations. Several of these capabilities are present in various inventory, location, or combined inventory-location models; however, this is the first time they are all seen together in one mathematical formulation.

3.4 Problem Summary

The formulation for the combined inventory-location problem in Section 3.3.3 is a nonlinear mixed-integer problem. The difficulty in solving this problem lies in the fact that several costs such as land and inventory are based on the square-root of the demand for each DC. However, the demand for each DC is based on many DC-to-customer assignment decision variables, resulting in a quadratic problem that is very difficult to solve. Note that when only one DC is opened, this is a special case of the problem because there is no allocation decision to consider.

It is theoretically possible to develop a program to solve this problem optimally; however, the size of the problems that could be solved using this method would be severely limited. For this reason, an optimal approach will not be pursued for this combined inventory-location problem. We propose to solve this problem using various heuristic methods, which will be compared to determine the method that performs best on this problem. More details on the heuristic methods and approach to this problem can be found in Chapter 4.

Chapter 4

Research Performed

In this chapter we will provide details on our approach to the combined inventory-location problem and give an overview of the research performed. We begin in Section 4.1 by presenting the research questions posed for this project. We will then elaborate on some of the heuristic methods applied to the inventory-location problem in Section 4.2 and how we measure the performance of these heuristic methods in Section 4.3. Next, we discuss our testing methods for the heuristics and the data requirements in Section4.4. Finally, we present the deliverables of an inventory-location decision-support tool in Section 4.5.

4.1 Research Questions

Several research questions have been mentioned briefly in various sections of this document. In this section, we will better define the specific research questions addressed regarding the combined inventory-location problem. These research questions have dictated the necessary steps for this research project.

4.1.1 Research Question #1

In Chapter 1 we gave an extensive background for both the inventory and the facility location problems. We have also investigated how these models influence each other by giving a specific example and by mathematically formulating the two problems in one model. We know with certainty that the inventory-location model can not perform worse than the facility location model. If the fixed inventory policy in the location problem is already optimal, the inventory-location problem will not choose a policy that is worse. However, we do not know how much better the solutions will be using the combined inventory-location problem. Therefore, our first research question is:

Research Question 1: *To what extent will the solutions from the combined inventory-location model improve on the solutions from the location model with a fixed inventory policy?*

In order to answer this question, we have solved sample problems using separate algorithms for the inventory-location model and for the facility location model with a fixed inventory policy. The results from these two algorithms have been compared for a large number of sample problems.

4.1.2 Research Question #2

As we discussed in Chapter 3, we do not attempt to solve the inventory-location problem exactly due to the complexity of the problem formulation. Instead, we approached the problem using heuristic methods. The research in this area is limited and there is little knowledge about what kind of heuristics perform best for this problem. We will contribute to the research by testing different heuristic methods to determine what type of method results in the best solutions for this problem. This brings us to our second research question:

Research Question 2: *What type of heuristic method is the most effective in finding good solutions for the inventory-location problem?*

This question is answered by applying two different heuristic procedures to the inventory-location problem and comparing the results for several sample problems. Details concerning the experimental design of these sample problems are discussed in detail in Section 4.4. Although we test only two heuristics, the philosophies behind the two methods are significantly different. The first heuristic solves the location problem first, followed by the multi-echelon inventory problem and a pair-wise exchange improvement algorithm. The second heuristic first solves for the optimal inventory policy and then uses this information to solve the facility location problem. Comparing the results of these methods provides insight to the inventory-location problem and how it behaves under different optimization criteria.

4.2 Heuristic Approaches

Several heuristic approaches have been designed for the inventory problem, the facility location problem and the combined inventory-location problem. These methods employ a variety of different philosophies and procedures that attempt to solve the given problem at or close to optimality. One common procedure involves solving a simplified version of the problem and improving the solution. Another procedure is to use an iterative process to explore several different solution possibilities. The heuristics presented in this section will use a combination of these methods to jointly solve the multi-echelon inventory problem and the facility location problem. Furthermore, the two heuristics use very different philosophies in their method of solving the inventory-location problem. These are explained in detail in the following sections.

4.2.1 Heuristic Approach #1

The philosophy of the methodology for the first heuristic is to begin with the optimal facility location-allocation solution and to then improve the solution with the addition of an optimized inventory policy. By looking at the facility location problem first, we can identify what regions are best suited for the distribution system network. The solution obtained is then be improved by solving for the optimal multi-echelon inventory policy for each DC and its assigned customers. Two improvement algorithms are applied in the heuristic in order to verify the quality of the resulting solution. The first algorithm tests the value of N, the number of open DCs, to determine if it is truly at the minimum point of the convex function. The second algorithm performs a neighborhood pair-wise exchange for the open DCs as an attempt to decrease the value of the total cost function.

A flow diagram for this heuristic procedure is presented in Figure 4.1. This diagram illustrates a step-by-step process for the heuristic. Several variables are used in this and other diagrams. These are:

N = Number of DCs to open. This value may change throughout the heuristic procedure.

N^* = Initial value of N used at the beginning of the heuristic procedure.

J_i = Number of neighbors for DC i.

i = Index for DCs ($i = 1, \ldots, N$).

j = Index for neighbors ($j = 1, \ldots, J_i$).

TC = Total distribution cost.

N', i', and j' = These variables are used to save the values of N, i, and j when an improved solution is found.

The first step in the heuristic is to calculate the appropriate number of open DCs, N, for the given distribution system. We calculate N using the method presented in Erlebacher and Meller [9]. Details of this formulation are discussed in Appendix B. Note that this is only the starting value for N. We explore other values of N later in the heuristic procedure to verify that the final value of N minimizes the total cost function.

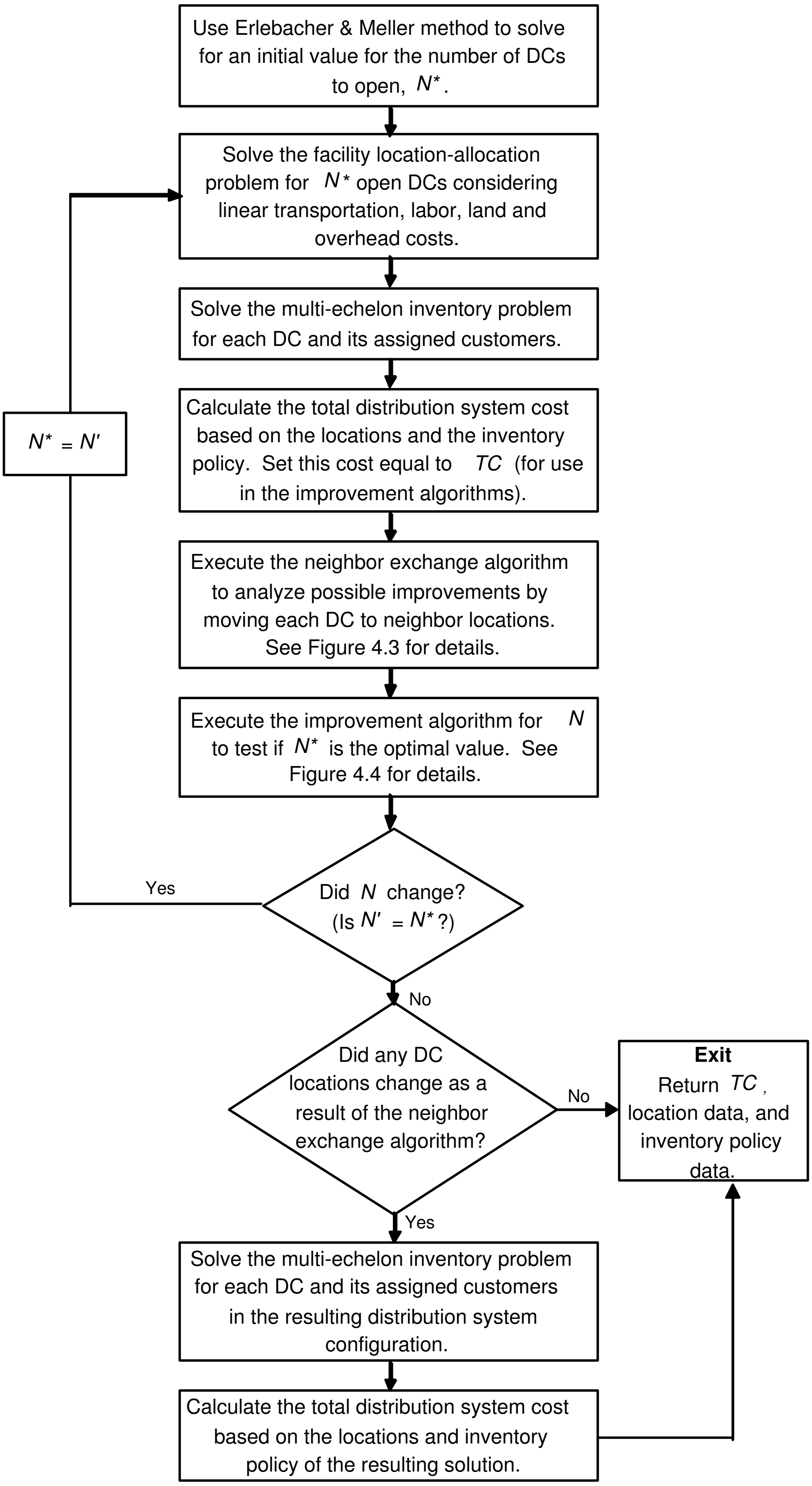


Figure 4.1: Heuristic #1 Flow Diagram.

After solving for N, we then solve the facility location-allocation problem for N open DCs. The objective function for this step will include transportation costs, labor costs, linear land costs and overhead costs. Because we already know the value of N, it is not necessary to incorporate inventory costs in this step. Once the facility location allocation solution is obtained, we then solve the multi-echelon inventory problem for each DC and it's assigned customers. After the inventory policy for each facility is determined, it is then be necessary to calculate the total costs for the resulting distribution system network and inventory policy.

Once the facility and inventory problems have been solved, we then try to improve on the solution using two different improvement algorithms. The first algorithm will test a pair-wise exchange for each open DC with its neighboring cities. The neighbors for each location are dictated by a map with arcs between adjacent cities. Figure 4.2 shows an map of the locations we consider, including the arcs between their neighbor cities (shown primarily on the eastern half of the country). This figure also shows a closer view of some cities on the western side of the map. In the example shown, the neighbors for Bakersfield, CA would be Los Angeles, San Diego, Barstow, Bishop and San Luis Obispo in California and Las Vegas in Nevada. Cities like Yuma in Arizona and Blythe, San Francisco and Sacramento in California are nearby, but are not direct neighbors and would not be considered in this exchange algorithm.

A flow diagram for this algorithm procedure can be found in Figure 4.3. For each DC, i, this procedure changes the DC location to the location of each neighbor, j, to see if there is an improvement in the value of the total cost function. The variable TC_{ij} represents the total cost when DC i is moved to the location of its neighbor j. These exchanges are made assuming that the current inventory policy for each DC is used at the neighboring city. If an improvement is found, the i and j values are saved as i' and j' and the location for the DC is changed to the neighbor resulting in the most improvement. The algorithm then continues, considering exchanges for the new location and its neighbors. This exchange procedure continues until no improvements can be made with any existing DC neighbors in the system, resulting in a 2-opt solution (within the neighborhood).

The second improvement algorithm conducts a search on other values of N to determine if the initially calculated value correlates with the minimum cost solution. We assume here that the objective function is convex in N, where the optimal value of N lies at the minimum point of the function. This assumption is valid because we know the two extremes of the objective function (N=1 and N=M) result in very high-cost solutions. For example, if only one DC exists, the average distance to customers will be maximized and therefore, the transportation costs are maximized. As more DCs are added, the average distance to customers decreases and thus the transportation costs are lower. However, as the number of DCs increases, more inventory must be held, resulting in higher inventory costs. The optimal solution of this objective function lies at the minimum point of the convex function, resulting in a solution where transportation and inventory costs are balanced.

The N improvement algorithm allows us to explore slightly higher and lower values of N

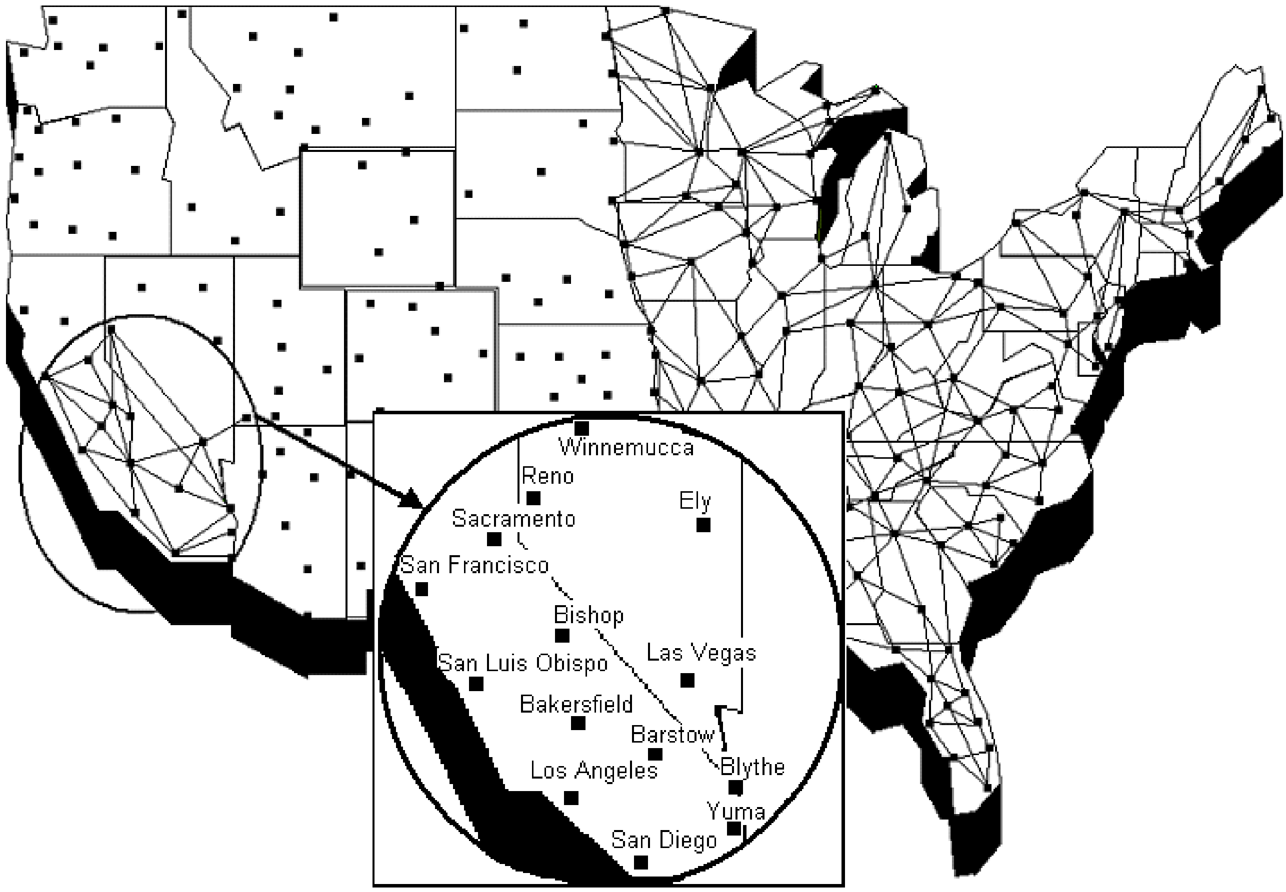


Figure 4.2: Network of Locations.

to determine if the total cost function is decreasing in either direction. If this occurs, we use this algorithm to follow the direction of descent until we find the number of DCs that corresponds with the minimum cost solution. We refer to this optimal value of N as N'. Figure 4.4 presents a flow diagram for this algorithm. This algorithm begins by increasing the value of N. If this results in an improved total cost function, it is not necessary to test any decreasing values of N. If increasing the value of N does not improve the total cost, the algorithm continues by decreasing the value of N. If the total cost is improved by doing this, the procedure is continued until the minimum total cost is reached. We then use the value of N corresponding with the minimum cost solution, N', and begin another iteration of the heuristic, beginning with the facility allocation-location step near the beginning of the heuristic procedure. If neither increasing or decreasing the value of N results in lower total costs, we can assume that we have the optimal value for N and continue with the heuristic.

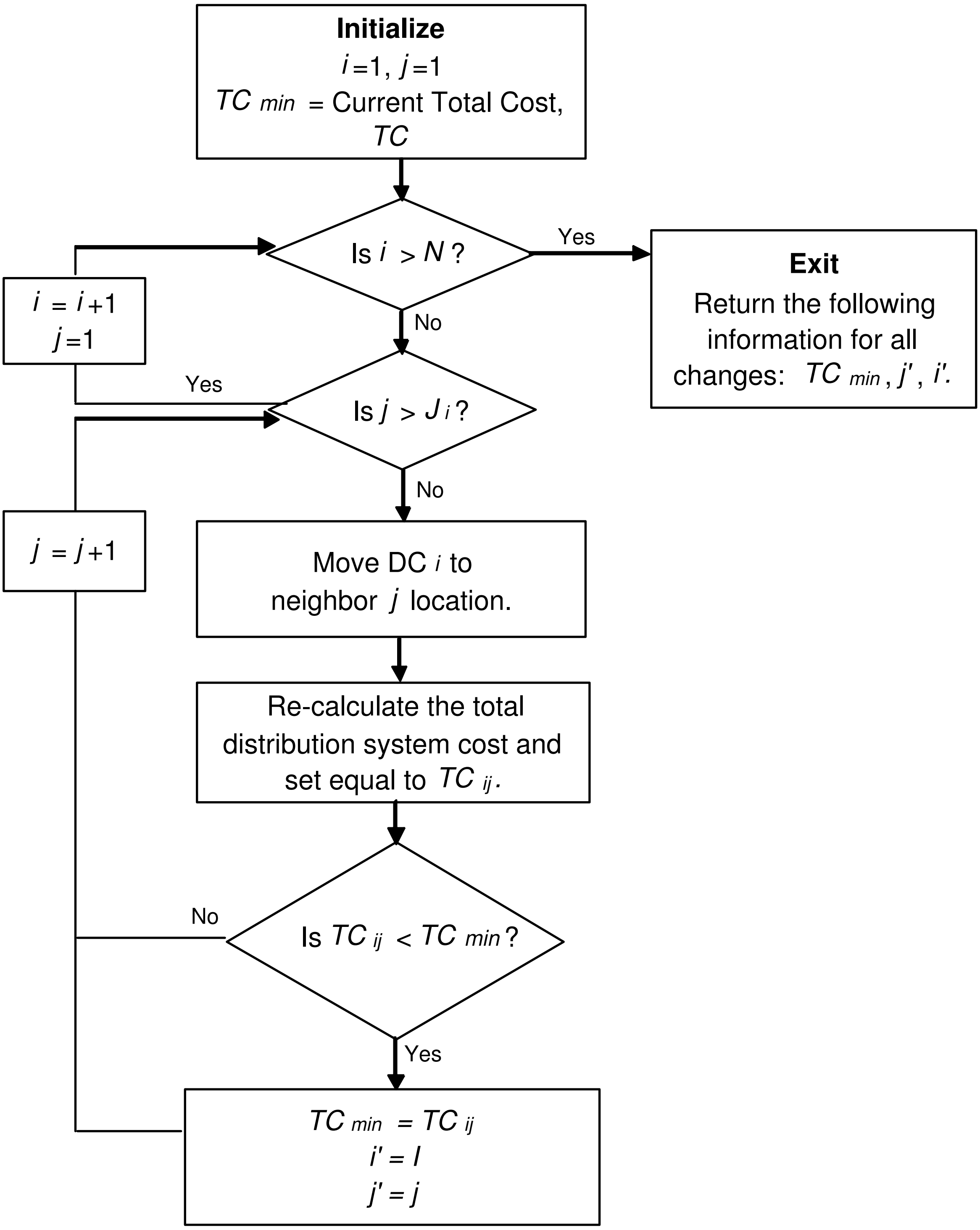


Figure 4.3: Neighbor Exchange Algorithm.

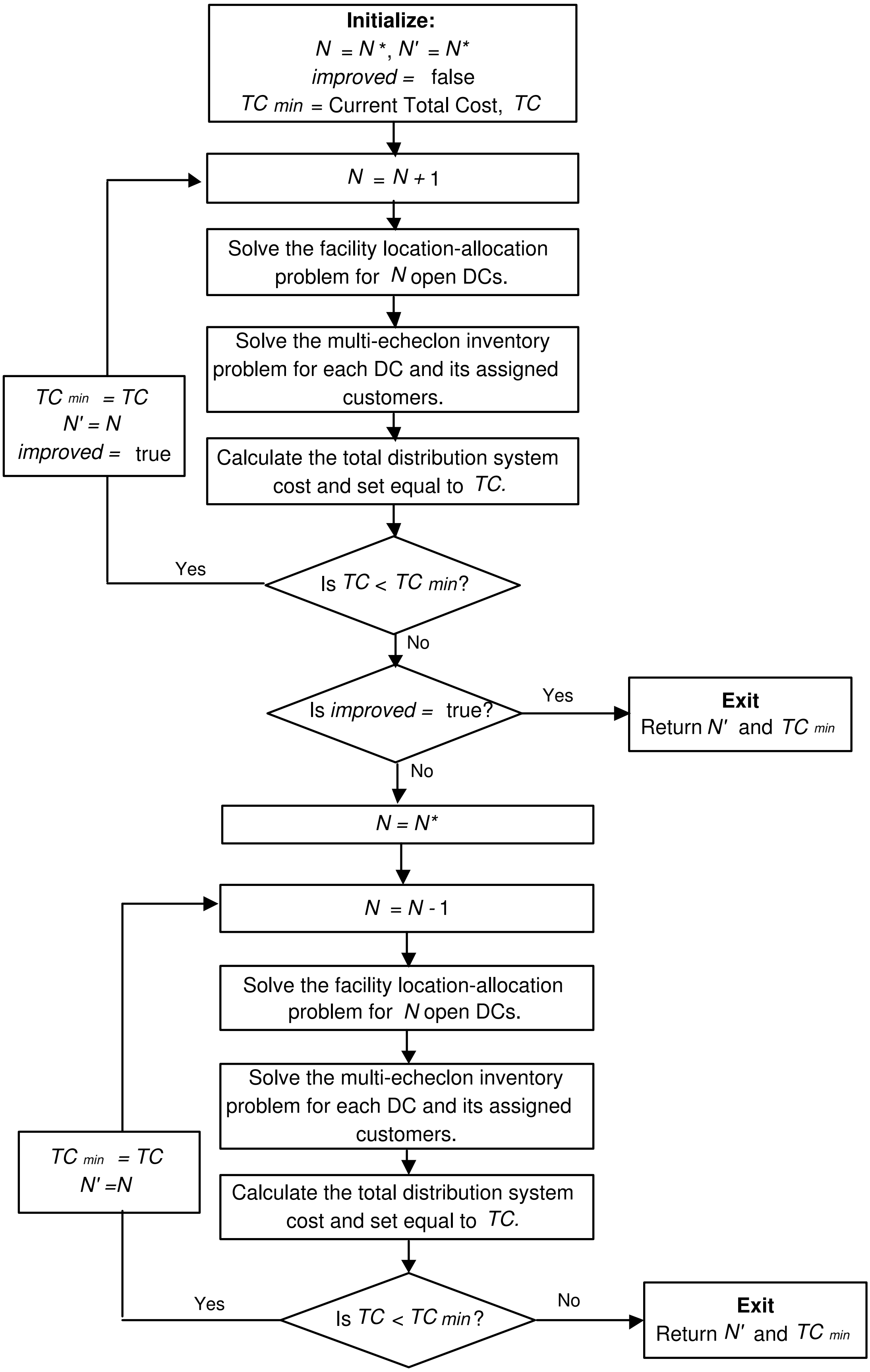


Figure 4.4: Improvement Algorithm for N.

4.2.2 Heuristic Approach #2

The second heuristic procedure uses a very different philosophy than the first heuristic. The first heuristic focuses on solving one problem (facility location), then solving another problem (inventory) based on the solution of the first problem. The philosophy of this heuristic is different because it concentrates on optimizing as much of the problem as possible before solving the facility location-allocation problem. In addition, this heuristic uses an iterative procedure to adjust the inventory and location solutions until they converge to the optimal or near-optimal solution. The procedure behind this heuristic is very similar to the procedure used by Ballou [4] is his facility location heuristic, DISPLAN (Refer to Section 2.2.2 for more details on the DISPLAN method).

Rather than approaching this problem by solving for the best locations first, this heuristic solves for the optimal inventory policies for the candidate DC locations first. This is be a good first step because it allows us to perform the location analysis knowing the true potential of each candidate location. Next, the location problem is solved considering the optimal inventory policy for each DC. This sequence iterates back and forth until the solution fails to improve by more than a certain percentage.

Figure 4.5 presents a flowchart that illustrates the steps in this heuristic procedure in more detail. The TC variable for the total distribution cost is also used in this flow diagram. However, t is a new variables and acts as a counter for the number of iterations that are performed throughout the heuristic procedure. Other new variables are M, which represents an infinitely large number and p, which is the threshold improvement percentage that must be reached in order justify additional iterations of the heuristic.

We begin with $TC_0 = M$ to guarantee that the heuristic does not end with the initial solution. This ensures at least a second iteration because the percent improvement of the first iteration, $\left(1 - \left(\frac{(TC_1)}{TC_0}\right)\right)$, will be very large because TC_0 is infinite. Therefore, the improvement will be greater than the threshold percentage, p, and the procedure continues.

This heuristic procedure begins by calculating the optimal multi-echelon inventory policy for each candidate DC location, assuming that the only open DC is located there and all the demand is assigned to it. Using this inventory policy, the inventory, land and land-related overhead costs are calculated and converted into linear unit costs. Next, the facility location-allocation problem is solved based on a linear program that optimizes the transportation, labor, inventory, land, and total overhead costs. The nonlinear cost components (inventory, land and land-related overhead) are estimated for each DC using the linear unit costs calculated in the previous step. Unlike the previous heuristic procedure, we solve for the number of DCs to open during the facility location problem.

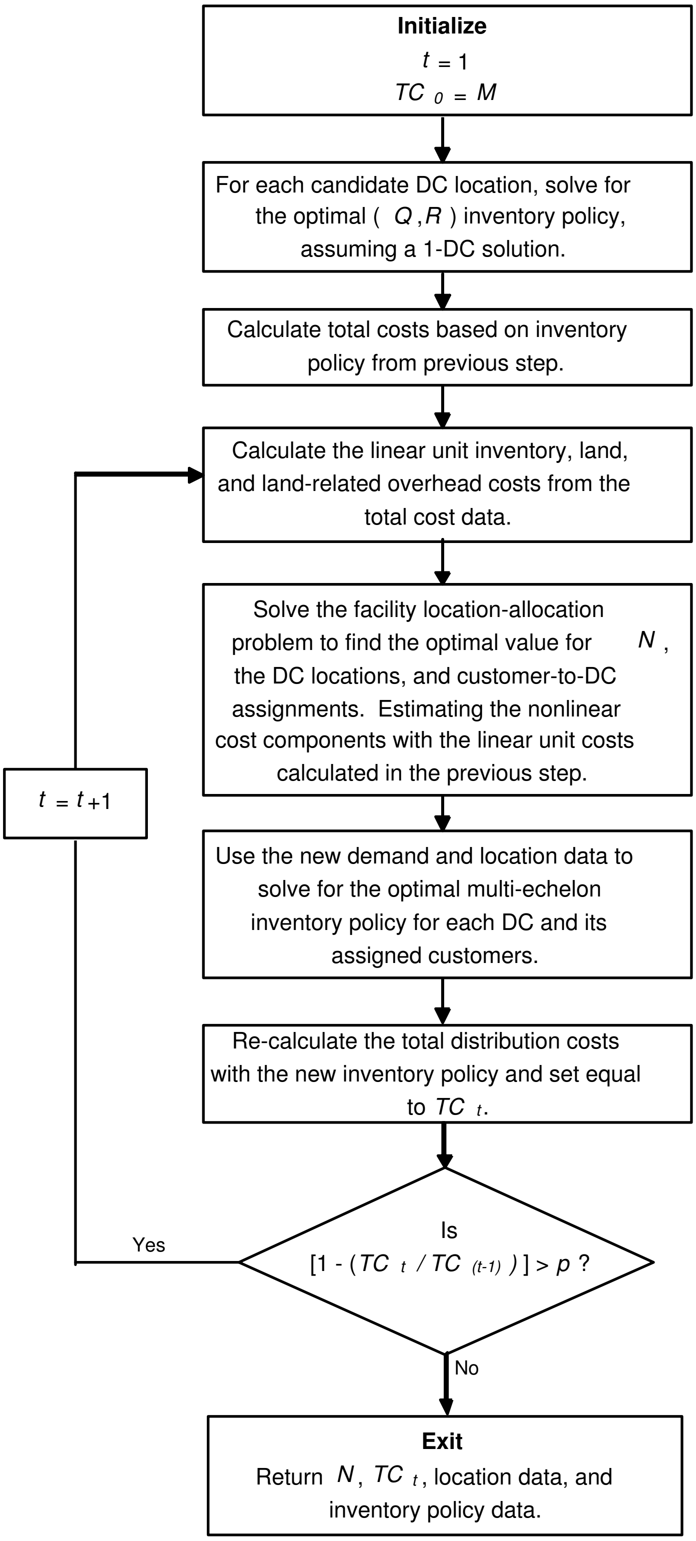


Figure 4.5: Heuristic #2 Flow Diagram.

After the facility location-allocation problem has been solved, the multi-echelon inventory policies must be optimized again for each DC and its assigned customers. Then, the total distribution system cost are calculated based on the locations, demand assignments and inventory policy. If the percent improvement is less then the user-chosen threshold, p, than the procedure ends. Otherwise, the new unit costs for the nonlinear cost components are calculated for use in the facility location problem optimization in the next iteration.

These two heuristic methods are similar in that they both attempt to improve on an initial solution. However, they approach the inventory-location problem from different points-of-view (i.e. the location or inventory problem dominates). The first heuristic solves the location problem and then expands on the solution by incorporating the optimal inventory policy. The second heuristic does the opposite by optimizing the inventory policy first, followed by the facility location problem. We test both of these heuristics on several different sample problems to analyze their respective strengths and weaknesses in solving the inventory-location problem.

4.3 Heuristic Performance Measurement

In order to truly understand the performance for each heuristic method applied to the inventory-location problem, we must have some means for comparison, such as an upper or lower bound. We are capable of obtaining an upper bound using the current facility location tool that has been developed for Thermo King. Thus, for each sample problem, we can use the Thermo King tool to calculate an upper bound. We can then use this to determine how much each heuristic method used is able to improve on the original facility location solution. This improvement measurement is also the measure for determining what heuristic methods are most effective in finding good solutions for the inventory-location problem.

Because we are not solving the exact problem, we are not be able to obtain the true optimal solution for the inventory-location model. However, there are other means of obtaining a lower bound. We could assume all the demand goes through one DC to minimize the inventory costs or open many DCs to obtain a minimum transportation cost solution. We could also choose the locations with the lowest land and/or labor rates to minimize these costs. However, none of these solutions would be very close to the optimal solution because optimizing one cost will inevitably sub-optimize another. Therefore, we do not see the value in using this sort of solution as a lower bound. For this reason, we only consider an upper bound in measuring the performance of the heuristic methods.

4.4 Experimental Design

The heuristic methods must be tested thoroughly to address the two research questions presented in Section 4.1. We plan to do this by testing many sample problems, varying several test parameters to represent different types of distribution systems and supply chain networks. All other parameters (i.e., fixed order cost, number of product families, service level, etc.) are considered common parameters and remain constant for all sample problems. The values for these common parameters can be found in Appendix C.

We vary the values of 5 different test parameters to create different data sets for testing. These test parameters include the number of customers in the system, the number of manufacturers in the system, the average product value which has an impact on the average unit inventory holding cost, the average unit transportation cost per mile, and the customer demand level. Rather than test all possible combinations, we focus on testing certain combinations of the extreme values for each test parameter. These different combinations are presented in Table 4.1 below. As the table describes, the focus is to compare the medium values for various test parameters as well as the high-low and low-high extremes. These combinations are chosen to maximize the different test results obtained. High-high and low-low combinations were excluded from this analysis because it is assumed they would not provide any additional information than the comparison of the medium values.

Table 4.1: Test Data Combinations.

Balance between the number of customers and the number of manufacturers: High number of customers, Low number of manufacturers Low number of customers, High number of manufacturers Moderate number of customers, Moderate number of manufacturers
Ratio of product value and unit transportation cost: High product value, Low unit transportation cost Low product value, High unit transportation cost Moderate product value, Moderate unit transportation cost
Customer demand Level: High customer demand Moderate customer demand Low customer demand

Table 4.2: Test Data Extremes.

Parameter	Low	Moderate	High
Number Customers	20	50	100
Number Manufacturers	5	10	20
Avg. Product Value ($/unit)	$10	$50	$100
Avg. Unit Transportation Cost ($/unit/mile)	$0.0002	$0.0023	$0.0117
Avg. Customer Demand Level (# units/year)	5,000	20,000	50,000

Data from one company that faces this problem was used to set the low, moderate, and high levels for each of the test parameters. These values are shown in Table 4.2. Given these settings, the individual parameter values need to be generated for each data set. The methods we used to generate the test parameter values and the data sets are discussed in the following sections. First we discuss our sources of land and labor cost data for the candidate DCs in Section 4.4.1. Next, we discuss our methods for generating the customer and manufacturer locations in Section 4.4.2. We then discuss the various unit cost test parameters in Section 4.4.3, followed by our method for calculating the customer demand levels in Section 4.4.4. In Section 4.4.5 we discuss our method for determining the type and percentage of supplied goods for each manufacturer. Finally, our testing methods are discussed in Section 4.4.6.

4.4.1 DC Locations

When solving the inventory-location heuristics, there are a total of 326 candidate locations to consider for DC locations. These 326 candidate locations include all customer and manufacturer locations and are used for all tests. For each of these locations, we use land and labor costs representative of the area. The land and labor cost information for the 326 locations is presented in Appendix D. This information is based primarily on government statistics and cost of living factors. These data were obtained from a number of online resources. Resources for material handling labor rates for different locations were obtained through the bureau of labor statistics at http://www.bls.gov/oes/2001/oessrcma.htm. Specific land cost information for some locations was obtain at the following websites:

http://www.avatarproperties.com/index.shtml

http://www.nctimes.net/news/2002/20020922/53834.html

http://www.vanport-intl.com/landprice.htm

Land and labor costs for some locations were estimated using cost of living factors found at http://list.realestate.yahoo.com/re/neighborhood/.

4.4.2 Customer and Manufacturer Locations

In generating the customer and manufacturer location data sets, it was first necessary to determine what number of customers and manufacturers would represent small, moderate and large distribution systems. We again used information from a reference company to determine these values. We chose 20 customers to represent a small supply chain, 50 customers to represent a moderate supply chain, and 100 customers to represent a large supply chain. With regards to manufacturers, the different sizes were chosen based on the number of product families. A small supply chain is represented by 1 manufacturer per product family, a moderate supply chain is 2 manufacturers per product family, and a large supply chain is 4 manufacturers per product family. The size of a supply chain with respect to the number of customers and manufacturers can grow to be much larger than the high values we have chosen here; however, we feel these numbers are sufficient to indicate the difference in behavior of different sized supply chains.

The next step in this process was to generate the data sets that would represent the customer and manufacturer locations. Industry data was used once again for generating this data. A total of 210 different customer locations and 232 manufacturer locations in the continental U.S. were used to determine the customer and manufacturer data sets. For each size value (20, 50, 100 customers or 5, 10, 20 manufacturers), ten location data sets were randomly generated from the industry data for both the customer and manufacturer locations. In doing so, each location was assigned an equal probability of being chosen. The resulting customer and manufacturer location data sets are presented in Appendices E–H.

4.4.3 Unit Costs

In Section 4.4 we discussed that the unit transportation cost and product value parameters are test parameters and are varied for different sample problems. Again, industry data were used to determine appropriate values for low, moderate and high unit transportation costs and product values.

Unit transportation cost parameter: The industry data provided an average transportation cost in units of \$/pound/mile. We used this to calculate the unit transportation cost for products of different weights (small – 1 lb., moderate – 10 lb., large – 50 lb.). These calculations resulted in low, moderate and high unit transportation costs of \$0.0002, \$0.0023, and \$0.0117.

Product value parameter: The product value parameter is chosen because it is directly correlated to the inventory holding costs, which has a significant effect on the total unit holding costs in the calculation of the order quantity, Q. Low, moderate, and high product values were chosen in order to obtain low, moderate, and high inventory holding costs. The different product values we used were \$10, \$50, and \$100 as shown in Table 4.2. The product values for 4 of the 5 product families were generated randomly, while the value for the last product family was chosen to obtain the specified product value average. These values are presented in Appendix I. We then calculated the unit inventory holding costs by applying the industry standard of 10% to the product value. These calculations resulted in unit inventory holding costs of \$1, \$5, and \$10 for the low, moderate, and high parameter values.

Unit holding cost parameter: Note that the unit inventory holding costs based on the product values explained above are only a portion of the total unit holding costs used to calculate the order quantity, Q. The unit land and unit land-related overhead cost components are also included in the holding cost formulation (see Section 3.3.3 for the exact formulation and an explanation). The total unit holding cost is found in the denominator of the formulation for Q_{jk}^{DC}:

$$Q_{jk}^{DC} = \sqrt{\frac{2\sum_{i=1}^{M}[(d_{ik}y_{ji})(A_j + S_j)]}{h_k + \left(\frac{C_j^{ld}}{r^{ld}}\right) + \left(\frac{OH^{ld}}{inv}\right)\left(\frac{C_j^{ld}}{land}\right)}} \quad \forall j, k \tag{4.1}$$

$$. \tag{4.2}$$

Although the land and land-related overhead costs are also included, the inventory holding cost, h_k, is the most significant factor in the total unit holding cost and therefore, has the largest effect in determining the value for the order quantity, Q.

4.4.4 Customer Demand

One of the test parameters defined in Table 4.2 is the customer demand level. We vary this parameter to test supply chains of different size. Again, we use low, moderate and high values for the average customer demand (5,000; 20,000; 50,000) in the sample problems. The values for these average demand levels have been chosen based on industry data and are designed to portray a representative range in demand levels for different types of products.

In order to represent a realistic demand pattern, not all customers are assigned the average demand. Rather, the customers are divided into three different classes: A, B, and C customers that represent large, medium and small demand levels. Each of these classes represent a given percentage of the customer population and has its own average demand level and standard deviation. The details for each class are presented in Table 4.3.

The individual customer demand values are randomly generated from a uniform distribution based on the average demand and standard deviation for each class. An example is given

Table 4.3: Customer Class Details.

	Class A	**Class B**	**Class C**
%age of Customers	20%	30%	50%
Mean Demand	2 × mean	mean	$\frac{3}{5}$ × mean
Standard Deviation	± 25%	± 20%	± 15%

below in Table 4.4 to demonstrate our calculations.

Table 4.4: Demand Example: Avg. Demand = 5,000; 20 Customers.

	Class A	**Class B**	**Class C**
# Customers	4	6	10
Mean Demand	10,000	5,000	3,000
Minimum Demand Value	7,500	4,000	2,550
Maximum Demand Value	12,500	6,000	3,450

Given an average demand of 5,000 units and 20 customers, this example shows the minimum and maximum demand values for each customer class. For example, the demand values for Class A are uniformly distributed between 7,500 (10,000 - (0.25)×10,000) and 12,500 (10,000 + (0.25)×10,000). Demand for Class B is uniformly distributed between 4,000 and 6,000 and so on. The complete data sets for each demand level are presented with the customer location data in Appendices E, F, and G. These demand data sets have been assigned randomly to the customer location data sets to ensure that the low, moderate, and high demand customers are spread evenly throughout the supply chain region.

4.4.5 Manufacturer Supply

The supply from manufacturers to DCs is based on a simple calculation. It is assumed that every manufacturer produces one product family and provides a given percentage of the demand for that particular product family. These data are randomly assigned to each manufacturer with equal probability as the manufacturer locations are generated.

The assignment of product families to manufacturers is fairly straightforward. In Section 4.4.2 we state that the number of manufacturers for the different sized supply chains are based on the number of product families. Therefore, we randomly assign one of each product family for a small supply chain, two of each product family for a moderate-sized supply chain, and 4 of each product family for a large supply chain.

The distribution of supply percentages for each manufacturer is similar to the customer demand data sets in that not all manufacturers are assigned the same supply percentages. The supply percentages are assigned to the manufacturers to allow for one large manufacturer and one or more smaller manufacturers. The supply assignments for a small supply chain are very easy - all manufacturers provide 100% of the demand for their assigned product family. In a moderate-sized supply chain, one manufacturer is randomly assigned 80% of the supply and one is assigned 20% of the supply for each product family. Finally, manufacturers are randomly assigned 50%, 20%, 20%, and 10% of the supply for each product family in a large supply chain. These assignments are presented with the manufacturer location data sets in Appendix H.

4.4.6 Testing Methods

Values for the common parameters (i.e., fixed order cost, number product families, service level, etc.) were also chosen based on common industry practices and remain fixed for all sample problems. This ensures that any changes in the results for the different sample problems can be attributed to a change in one of the test parameters presented in Table 4.2. The values for the common parameters are presented in Appendix C.

In Table 4.1, we presented three different categories we plan to examine in order to test the behavior of each heuristic. For each of these three categories, there are three different data combinations we plan to test. This results in $3 \times 3 \times 3 = 27$ different data combinations. Furthermore, for each data combination, we run 10 sample problems, using different customer and manufacturer location data sets. This results in 270 sample problems for each heuristic, with a total of 540 test runs. The resulting data from these sample problems is then analyzed to address our two research questions.

4.5 Inventory-Location Tool

The best heuristic method used for the inventory-location problem are implemented in an Excel-based decision support tool, similar to the Thermo King facility location tool. This Excel-based Inventory-Location Tool provides detailed output to the user for an inventory allocation system and distribution center locations that complement each other. The output of this tool provides the following as optimized output:

- The location for each open DC.

- The customer-to-DC assignments.
- The amount of each product shipped to each DC from each manufacturer.
- Optimal order quantities for each customer for each product.
- Optimal order quantities for each open DC for each product.
- Optimal reorder points for each customer for each product.
- Optimal reorder points for each open DC for each product.

Other output will include:

- Demand levels satisfied at each open DC.
- Inventory levels to be held at each open DC.
- Required land size for each open DC.
- Transportation costs for each manufacturer-DC and DC-customer channel.
- Detailed cost summary for each open DC.

Chapter 5

Research Results Analysis

In Chapter 4 the research questions and goals were presented. In this chapter the results of this research are discussed along with the complete data analysis for each heuristic method. In Section 5.1 we first review the Experimental Design for the test data and discuss the data sets that were run for each model. We then briefly discuss some of the initial assumptions for the common test parameters in Section 5.2. Next, the results and analysis for the first research question are discussed in Section 5.3. The analysis for the second research question is presented in Section 5.4. Many examples for specific results are presented in these sections — more complete summarized data can be found in Appendix J.

5.1 Experimental Design

The experimental design for the data sets used in this research was discussed in detail in Section 4.4. This discussion included information on the three test parameters used in this research — the customer demand level, the ratio of the number of customers to the number of manufacturers, and the ratio of product value to the product transportation cost. Low, medium, and high values were defined for each test parameter to show that the different extremes considered in the data sets. Next, a plan was created to determine which values for each test parameter would be tested together. Originally, seven unique combinations were chosen, using different extremes for the value of each test parameter. The first combination uses the medium value for all three test parameters while the six remaining combinations are chosen by keeping two test parameters at their medium value and changing the third test parameter to its low and high extreme.

For each unique combination of test parameters, 10 data sets were tested using different customer and manufacturer locations and customer demand data. This resulted in 70 planned data sets to be run on each model (the location model with a fixed inventory policy, Heuristic 1, and Heuristic 2), totalling 210 different test runs.

As the testing proceeded, the seven planned test parameter combinations were run on each model as planned. A few of these combinations resulted consistently in 1-DC solutions. In these cases, all three models resulted in the same solution; thus, this data was not useful for comparing the performance of any of the models. Towards the end of the testing period, some slight modifications were made to the chosen test parameter combinations in an attempt to decrease the number of 1-DC solutions. In addition, three unplanned test parameter combinations were also tested in order to generate more data sets where multiple DCs were opened. These modifications and test sets were determined based on what test parameter values seemed to be resulting in solutions that opened more than just 1 DC. In the end, a total of 10 test parameter combinations were run, resulting in 100 data sets for each heuristic. Out of these 10 test parameter combinations, 6 resulted in distribution systems with more than 1 open DC. Thus, 60 data sets for each heuristic method are available for data analysis performed in the remaining sections of this chapter.

5.2 Common Parameter Assumptions

The initial formulation for the inventory-location model originally included Backorder Inventory Costs as a part of the total inventory costs. This cost was calculated as a fixed percentage (5%) of the total demand. This parameter was based on the research performed for the Thermo-King model described in Section 1.4.3. However, this assumption for backorder costs did not fit well with the other assumptions made in the model. To summarize, the inventory levels calculated in the inventory-location model turned out to be much lower than what we actually see in a spare-parts distribution center. Due to this, the backorder inventory costs seemed very large compared to the inventory holding costs, which we believe are not representative of a realistic inventory scenario. Thus, it was decided to remove this cost from the results in an attempt to make the inventory cost breakdown more realistic. The backorder inventory cost component is not included in the optimization of either heuristic method so doing this had no effect on the performance of either method. The only effect was on the magnitude of the total costs provided.

5.3 Research Question 1: Location Model with Fixed vs. Flexible Inventory

In Section 4.1, the research questions were defined. The first research question was defined as:

Research Question 1: *To what extent will the solutions from the combined inventory-location model improve on the solutions from the location model with a fixed inventory policy?*

It is already known that the inventory-location model will not perform any worse than the location model with a fixed inventory policy because the same cost factors are being optimized in each model. The primary difference between these two models is the addition of the nonlinear cost components in the inventory-location model. Therefore, the purpose of this research question was to determine how much better the inventory-location model would perform, based on the inclusion of the nonlinear cost components. Two heuristic methods were used to solve the inventory-location model — the analysis performed in this section compares the results of the location model with a fixed inventory policy with the results from the heuristic that performed best for each data set. The details pertaining to which heuristic performed best are discussed in Section 5.4, where we discuss Research Question 2.

It is already known that in situations where only 1 DC is opened, the inventory-location model performs the same as the location model with A fixed inventory policy. The nonlinear costs in 1-DC networks will reduce to linear costs so both models have the same solving capability. However, the test runs where more than 1 DC is opened do show that the inventory-location model results in a lower total cost than the location model with a fixed inventory policy. These results are summarized and presented in Table 5.1 below.

Table 5.1: Inventory Location Model Results vs. Fixed Inventory Model Results.

# Cust vs. # Manf Ratio	**Demand Level**	**Product $ vs. Transp. $ Ratio**	**Avg. # of DCs Opened**	**Min{H1, H2} Total Cost**	**Fixed Inv. Policy Total Cost**
Med	Med	Med	2.0	$5,715,697	$5,721,319
Med	Low	Med	1.0	$1,731,918	$1,731,918
Med	High	Med	3.5	$13,310,154	$13,338,243
Med	Med	Low	1.0	$2,331,349	$2,331,349
Med	Med	High	6.1	$19,665,834	$19,675,904
High	Med	Med	2.8	$10,708,905	$10,715,509
Low	Med	High	1.0	$1,109,092	$1,109,092
Med	High	High	10.8	$46,345,927	$46,361,915
High	Med	Low	1.0	$4,344,443	$4,344,443
High	High	Low	2.7	$10,192,706	$10,480,249
Total Average:				**$11,545,602**	**$11,580,994**
> 1DC Average:				**$17,656,537**	**$17,715,523**

Each entry in Table 5.1 represents the average total cost for the ten data sets run for the given test parameter combination. A total of 100 runs were completed — 40 of these test runs resulted in 1-DC solutions, leaving 60 sets of test results where improvements could potentially be made by the inventory-location model. The level of improvements made in the average total cost can be seen for each of the data sets in Table 5.1. For more detailed results, refer to Appendix K or L. Appendix K shows an example of the detailed output of the inventory-location model and Appendix L presents the cost summary for each test set tested for each test parameter combination.

In order to gain a better understanding of the improvement realized by the inventory-location model, two different averages are given at the bottom of Table 5.1. Recall the comment made previously that the inventory-location model will not perform any worse than the location model with a fixed inventory policy — rather, it will perform at least as good or better. The information in Table 5.1 illustrates this and shows that the inventory-location model resulted in an average lower cost that is approximately $35,000 lower than the location model with a fixed inventory policy. The second average presented in Table 5.1 only considers test results where more than 1 DC is opened. Based on the second average, the inventory-location model performs even better in situations where more than 1 DC is opened. In these cases, the inventory-location model is able to improve the average total cost by approximately $59,000.

5.3.1 Cost Component Analysis

To begin the analysis for Research Question 1, the data results were studied to determine which cost components appeared to be affected most by including the nonlinear costs in the optimization of the inventory-location model. Figure 5.1 portrays the difference in performance for each cost component, based on the solutions with greater than 1 DC opened. The values in the bar chart represent the results for the location model with a fixed inventory policy minus the results for the inventory-location model. The cases where the bar lies to the right of the center line represent cost components where the inventory-location model resulted in a cost savings. The bars to the left of the centerline show the cost components where the location model with a fixed inventory policy performed better.

Table 5.2: Cost Component Performance Comparison — Research Question 1.

	Min {H1,H2}	**Location Model w/ Fixed Inv.**	**Cost Difference**	**Average %-age of Total Cost**
Labor Cost	$2,840,940	$2,782,211	-$58,730	15.9%
Land Cost	$63,572	$61,297	-$2,275	0.4%
Transportation Cost	$13,044,141	$13,082,837	$38,696	73.9%
Inventory Cost	$464,781	$607,243	$142,462	3.0%
OH Cost	$1,243,103	$1,181,936	-$61,167	6.9%
Total Cost	**$17,656,537**	**$17,715,523**	**$58,986**	100.0%

Figure 5.1 shows that the inventory location model performed notably better with regards to the inventory and the transportation cost components. On the other hand, the location

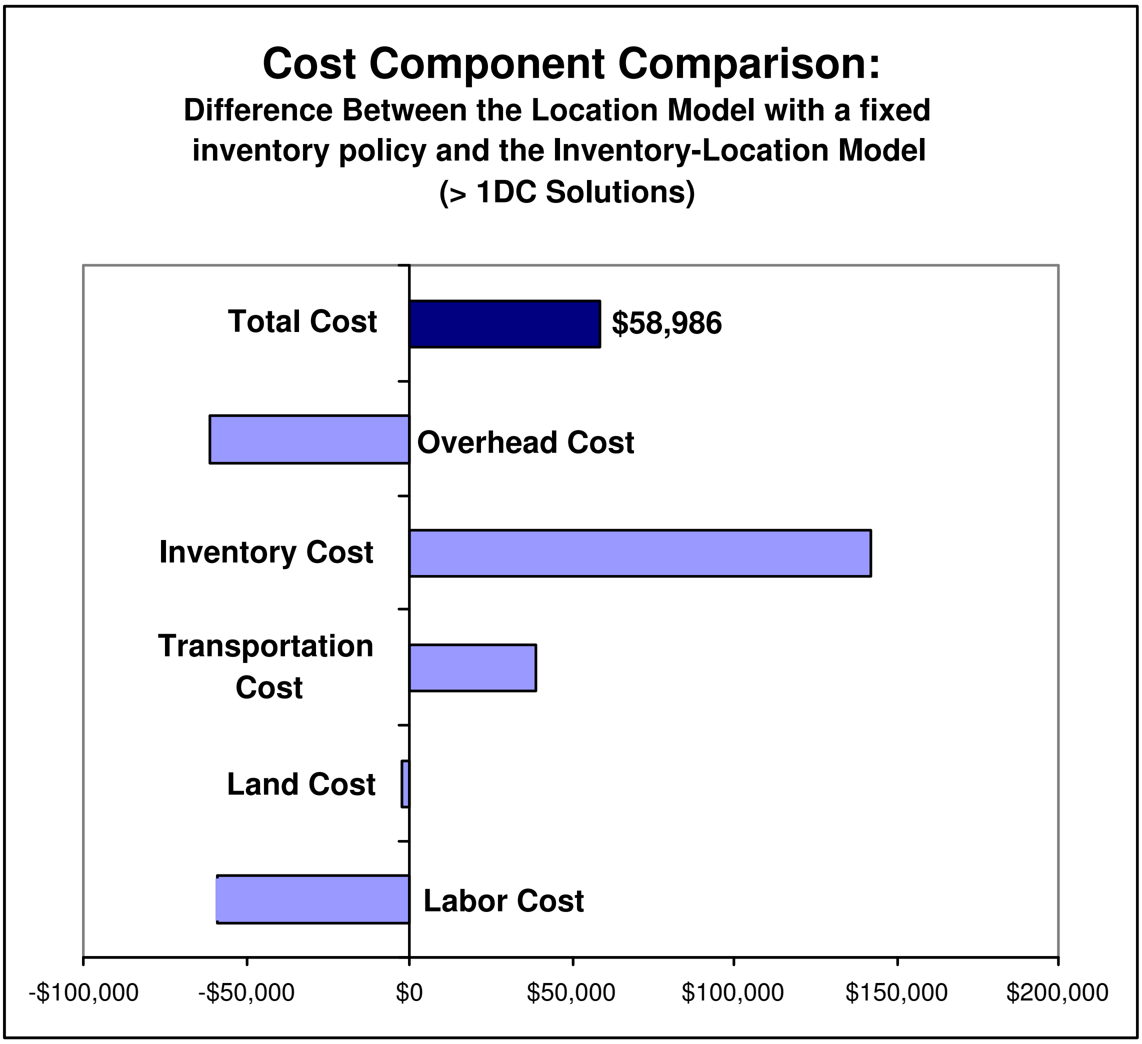


Figure 5.1: Cost Component Performance Comparison — Research Question 1.

model with a fixed inventory policy performed better with regards to the overhead costs, labor costs and slightly better with the land cost. Recall that the total overhead cost is based on three cost components — a fixed overhead cost, a land-related overhead cost and a labor-related overhead cost. Thus, if the location model with a fixed inventory policy performs better with regards to land and labor costs, it will also perform better at reducing the total overhead cost. However, the inventory-location model performed better in the end, resulting in an average total cost reduction of approximately $59,000.

One surprising observation from Figure 5.1 is the performance comparison of the Land cost component. Although the improvement is small, it is interesting that the location model with a fixed inventory policy performs better for this cost component when it has no capability for considering non-linear costs. It would seem more logical that the inventory-location model would perform better for this cost component because it has this capability. Due to this inconsistency, the data was analyzed in more detail. One important thing that was found in doing this is that in many situations (particularly those with high test parameter values) the location model with a fixed inventory policy sometimes opens less DCs than the inventory-location model does. In these situations the land costs, inventory costs, and overhead costs are lower for the location model with a fixed inventory policy. Thus, if only data sets where the same number of DCs were opened could be analyzed, the results would most likely show that the inventory-location model performs better with respect to all non-linear cost components. In addition, the location model with a fixed inventory policy would probably not have as good of performance with the labor and overhead cost components. However, it is not logical to throw out the data sets where the number of DCs opened is unequal. This data is important in showing the difference in the behavior of the two models. Thus, these results are included in all analysis reported in this chapter.

Table 5.2 also presents information regarding the average %-age each cost component is of the total cost. Note that the largest cost factor on average for all data runs is the transportation cost. This cost alone accounts for over 70% of the total cost. Based on this, we can expect that the inventory-location model may have an advantage because Figure 5.1 shows that it is more capable of reducing the transportation than the location model with a fixed inventory level. For the same reason, we can expect to see a similar relationship with the inventory costs. Although it is a smaller percentage of the total cost, the cost component comparison in Figure 5.2 shows that the inventory location model was much better at finding better inventory costs. In fact, when we look closely at the inventory cost component, we notice that the inventory-location model performs very well in making improvements. On average, a savings of approximately $142,500 is gained. This may seem small in comparison to the total cost, but the improved cost is about 23% less than the original inventory cost. Thus, we can be confident that the inventory-location model will perform well in terms of %-reduction of the original cost.

By including the nonlinear costs in the optimization, the flexible inventory-location model was able to recognize situations where small sacrifices could be made with some cost factors to gain larger improvements in the inventory and transportation cost. This tradeoff seems to occur most often between the labor and land costs and the transportation and inventory costs. A general example of this can be seen in the values for the data sets with a low transportation cost to inventory cost ratio, high value of average customer demand, and high customer-to-manufacturer ratio. This test parameter combination is the one in which the inventory-location model was able to improve the most upon. Data Set 3 will be used to portray an example of how each model behaves. The detailed costs for this data set for each heuristic method are shown in Table 5.3.

Table 5.3: Fixed Inv. Location Model vs. Inventory-Location Model.

	Location Model w/ Fixed Inventory	**Inventory-Location Model: Min{H1, H2}**
Number Iterations Completed	1	2
Number DCs Opened	1	3
Labor Cost	\$5,649,934	\$5,809,477
Land Cost	\$38,419	\$67,537
Transportation Cost	1,838,073	1,811,336
Inventory Cost	\$2,334,147	\$1,408,623
OH Cost	\$297,823	\$827,583
Total Cost	**\$10,158,395**	**\$9,924,555**
Average Customer Distance (miles):	904	499
Maximum Customer Distance (miles):	2,261	1,101

In this example, the inventory-location model resulted in 3 open DCs in Poplar Bluff, MO; Well, NV; and Hubbard, OH. The location model with a fixed inventory policy resulted in only 1 DC located in Poplar Bluff, MO. By opening only 1 DC, the solution for the location model with a fixed inventory policy resulted in reduced labor, land, and overhead cost. The labor and land costs are cheaper because all the demand is centralized in one inexpensive DC location. Although these costs are higher for the inventory-location model, this increase is offset by the additional savings in the transportation and inventory costs. The inventory-location model has a slight edge in finding reduced transportation cost and is significantly better at reducing the inventory cost component. This model is better able to balance the trade-offs between these various cost factors because they are all included in the optimization criteria in some way. In addition, the customer service level is also improved in the inventory-location model solution. Due to having a larger number of DCs open, both the average and maximum customer distances are approximately half that of the location model with a fixed inventory policy.

5.3.2 Test Parameter Analysis

In addition to performing analysis on the individual cost factors, additional analysis was performed on each of the test parameter values. The purpose of this analysis was to identify any trends in the behavior of the inventory-location model or the location model with a fixed inventory policy with respect to any specific test parameter.

Two metrics in particular are used to analyze the behavior of the two models. The first metric looks at which model performs better and by what percentage (test parameter vs. %-improvement). The second metric is focused on which model performs better on more occasions (test parameter vs. %-improved solutions). Both metrics will be portrayed in various figures in the following sections. In each figure, sub-figure (a) will represent the %-improvement while sub-figure (b) will represent the %-improved solutions for each test parameter.

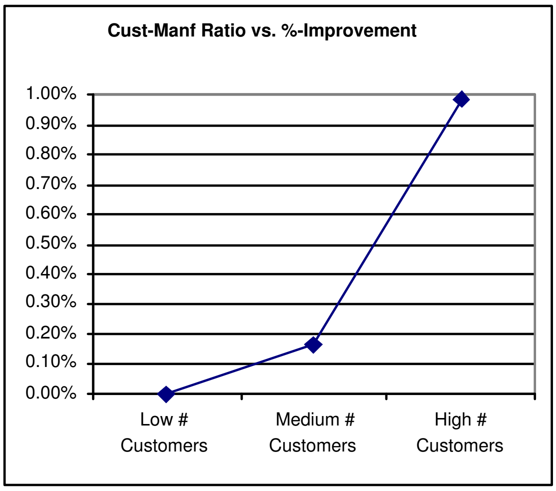
Test Parameter # 1: # Customer vs. # Manufacturer Ratio

The first test parameter analyzed is the ratio of the number of customers to the number of manufacturers. The three ratio values used in the data sets are (20:20) for low, (50:10) for medium, and (100:5) for a high ratio. Of the six test parameter combinations resulting in more than 1 DC being opened, 0 were for the low ratio value, 5 were for the medium ratio value and 1 was for the high ratio value. The metrics for the %-improvement and %-improved solutions are shown in Figure 5.2 and Table 5.4 below.

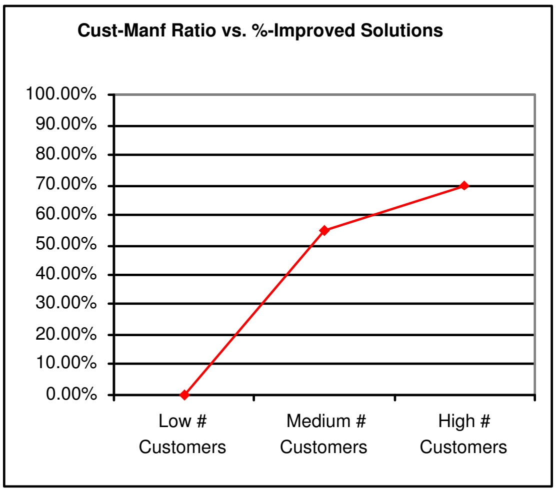
Table 5.4: Comparison by # Customer to # Manufacturer Ratio.

%-Wins by Customer/Manf Ratio	**# Ties**	**# Improvements**	**%-Improvement**	**%-Improved Solutions**
Low # Customers	0	0	0.00%	0.00%
Medium # Customers	18	22	0.16%	55.00%
High # Customers	6	14	0.98%	70.00%

Based on these results, there seems to be a slight trend with the ratio for the number of customers vs. the number of manufacturers. As the ratio increases (number of customers increases, number of manufacturers decreases), the percentage of solutions improved by the flexible inventory-location model increases. This is shown in Figure 5.2(b). The amount by which the inventory-location model is able to improve on the location model with a fixed inventory policy also increases as the number of customers increases. Despite this, it is difficult to tell if a trend exists here due to the poor balance of data. It is apparent that a relationship may exist, but it is not certain how significant the relationship is.



(a) %-Improvement.



(b) %-Improved Solutions.

Figure 5.2: # Customer to # Manufacturer Ratio Analysis.

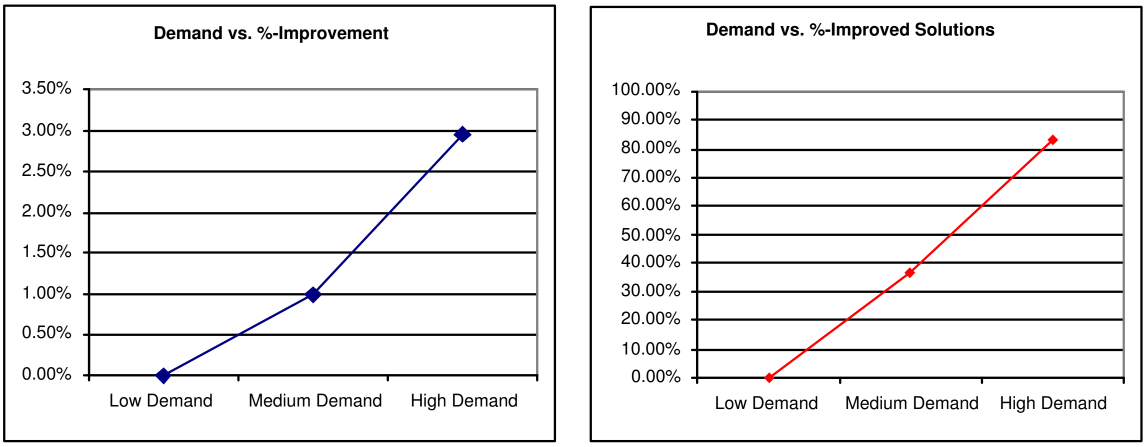
Another point worth noting in these graphs is the magnitude of the improvements made. Although it appears the flexible inventory-location model is very effective in finding better solutions, the magnitude of these improvements is not very large. In the best case (large customer to manufacturer ratio), the largest average improvement is only about 1%. A very large supply chain would be needed for this level of improvement to be substantial. This will be discussed in more detail throughout the chapter.

Test Parameter # 2: Average Customer Demand Level

The next test parameter to be analyzed is the demand test parameter. The metrics for the %-improvement and %-improved solutions are shown in Figure 5.3 and Table 5.5. The spread of data for this test parameter has a much better balance. None of the six test parameter combinations are for low demand. Rather, these 6 combinations are spread evenly for the medium and high demand test parameters (3 each).

It is clear in Figure 5.3 that the demand parameter seems to have a strong correlation with both the number of improvements and the amount of improvement. It is clear in both graphs above that there is an upward trend that exists as the average customer demand increases. In fact, the %-improvement is at its peak value when the average customer demand level is high.

These figures show that as the average customer demand level increases, the inventory location model is more effective in solving the problem. This can be explained by the fact that



(a) %-Improvement. (b) %-Improved Solutions.

Figure 5.3: Demand Analysis.

Table 5.5: Comparison by Demand.

% Wins by Demand Level	**# Ties**	**# Improvements**	**%-Improvement**	**%-Improved Solutions**
Low Demand	0	0	0.00%	0.00%
Medium Demand	19	11	0.91%	36.67%
High Demand	5	25	2.01%	83.33%

as the demand increases, the total cost as well as all of the individual cost components will increase. Depending on what the test parameter values are, different cost components will comprise most of the total cost. For example, when the # Customer vs. # Manufacturer ratio and the Transportation $ vs. Inventory $ ratio are both set to a medium value, the transportation cost component is consistently the largest cost component proportionately, followed by the labor cost and the inventory cost components. The inventory-location model is able to find lower cost solutions by improving the most on these cost components.

The example presented in Figure 5.6 shows more detail on the behavior of the inventory-location model and how it is more capable of obtaining cost savings by focusing on the largest cost components. The test parameter values for the data set in this example are high # Customer vs. # Manufacturer ratio, high Customer Demand, and low Transportation $ vs. Inventory $ ratio. The results for the data set with the largest %-improvement for this test parameter combination are shown in this example. The results of this example match up very closely with what we saw in the cost component analysis. The land, labor,

Table 5.6: Test Parameter #2 Analysis.

HHL — Data Set 9	Fixed Inventory-Location Model	Inventory-Location Model	Avg. %-age of Total Cost	%-Improvement
DCs Opened	3	1		
Labor	$5,988,359	$5,580,511	53.3%	-6.8%
Land	$70,264	$22,504	0.4%	-68.0%
Transportation	$2,193,477	$2,368,860	21.0%	8.0%
Inventory	$1,567,524	$2,813,371	20.2%	79.5%
Overhead	$830,213	$272,371	5.1%	-67.2%
Total	**$10,649,838**	**$11,057,617**	100.0%	3.8%

and overhead costs components are lower for the location model with the fixed inventory policy. However, the inventory-location model is able to make significant improvements for the inventory and transportation cost components - both of which are substantial %-ages of the total cost. These savings outweigh the savings made with respect to land, labor, and overhead and result in an overall cost savings of approximately $400,000 or 3.8%.

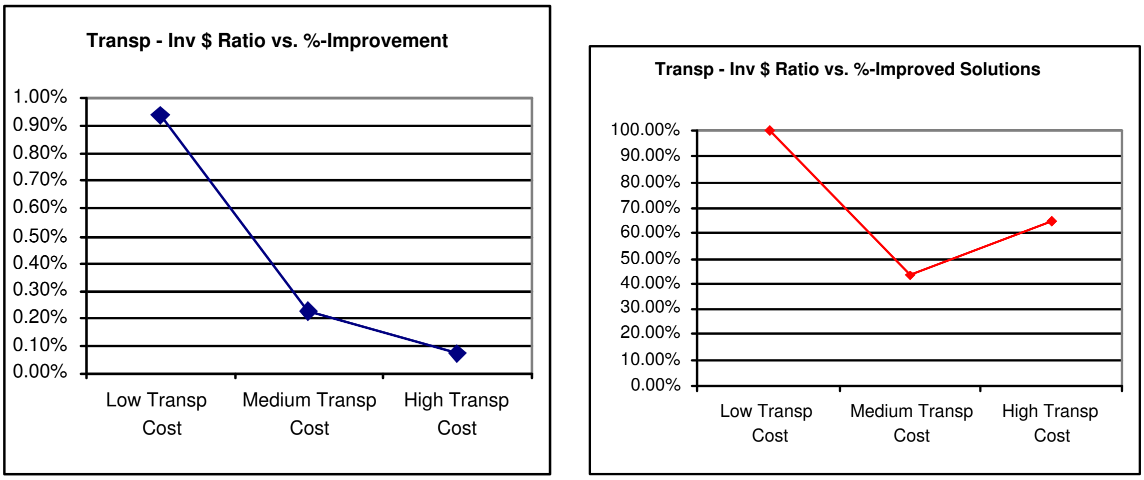
Test Parameter # 3: Transportation $ vs. Inventory $ Ratio

The last test parameter analyzed is the ratio between the unit transportation cost and the product value (which is directly proportional to the unit inventory cost). The metrics for the %-improvement and %-improved solutions are shown in Figure 5.4 and Table 5.7. Of the six test parameter combinations resulting in more than 1 DC being opened, 1 was for the low ratio value, 3 were for the medium ratio value and 2 were for the high ratio value.

Table 5.7: Comparison by Transportation and Inventory Cost Ratio.

% Wins by Transp/Inv $ Ratio	**# Ties**	**# Improvements**	**%-Improvement**	**%-Improved Solutions**
Low Transp Cost	0	10	0.94%	100.00%
Medium Transp Cost	17	13	0.23%	43.33%
High Transp Cost	7	13	0.07%	65.00%

The effect of the Transportation $ vs. the Inventory $ ratio parameter on the results of the inventory-location model behaves opposite of the trend seen for the # customer vs. #



(a) %-Improvement. (b) %-Improved Solutions.

Figure 5.4: Transportation $ to Inventory $ Ratio Analysis.

manufacturer ratio for the %-improvement metric. The best performance for the inventory-location model is seen at the lowest value of the ratio (low transportation cost, high inventory cost). As the ratio increases, the inventory-location model becomes more capable of finding better solutions; however, the amount by which these solutions improve on the location model with a fixed inventory policy is less significant.

From this information, we observe that the inventory cost seems to have an increased effect on the performance of the results of the inventory-location model. Overall the inventory cost component is only about 3% of the total cost, but in situations where the unit inventory cost is high, the average %-age increases to about 20%. In this case, it becomes much more important to balance the inventory costs with the other cost components. The inventory-location model is able to account for the inventory cost in the optimization criteria and thus, is much more capable of achieving results with a lower total cost in situations where the inventory costs are high.

5.3.3 Comparison Notes

Several trends have been identified in the last few sections through the cost component and test parameter analyses. The analysis performed makes it clear that the inventory-location model consistently performs better than the location model with a fixed inventory policy. Due to incorporating the nonlinear cost components, the inventory-location model is usually able to create a solution where the largest cost components (transportation and inventory) are balanced better with the other cost components.

It is important to note that although several cost improvements were made by the inventory-location model, the magnitude of these improvements is not significant. On average, the inventory-location model resulted in a savings of approximately $59,000 when more than 1 DC is opened. This is only about 0.34% of the total cost. An explanation for this small improvement is found by looking at a breakdown of each of the cost component to see what percentage of the total cost each component is. When doing this, the average inventory cost consists of only 3% of the total costs. This does not leave much room for improvement. Even if the inventory-location model were to improve this cost by 60%, that would only be about 2% of the total cost — not to mention that this improvement would inevitably cause an increase in other cost components. However, if this model were applied to a supply chain having similar demand, but much higher product values (higher inventory costs), the improvement using the inventory-location model would be much more substantial. In this case, it would be much more valuable to use the inventory-location model to optimize the supply chain locations and inventory policies together. In fact, the next section portrays this type of example to show the capability of the inventory-location model under these conditions.

5.3.4 High Inventory Cost Performance

In order to test how the model performs in high-inventory cost situations, a few extra data sets were tested on both models. The inventory cost is greatly increased in these tests to determine how capable the inventory-location model is for making improvements under these conditions. It was stated in previous sections that the reason for the small improvement is the fact that the inventory costs are only a small percentage of the total cost. Thus, if the inventory cost is a larger portion of the total cost, the amount that the inventory-location model can improve on the solution should increase as well.

The first data set increases the unit product value substantially to $1,000 per unit. This gives us a unit holding price of $100/unit/year. The demand test parameter for this data set was set at the maximum value (100 units/customer/year) and the # Customer to # Manufacturer ratio was set at the medium value (50 Customers, 10 Manufacturers). The unit transportation cost parameter was set to the lowest value ($0.0023/unit/mile). The results for the location model with a fixed inventory policy and the inventory location model are shown in Table 5.8.

The inventory %-age in this example has increased to approximately 20% of the total cost and appears to have a significant effect on the performance of the inventory-location model. The level of improvement made by the model increases to approximately 9.5%. This level of improvement can no longer be considered negligible — this can add up to a substantial dollar amount for many supply chains. In the example above, the dollar amount saved by the inventory-location model is almost $2,000,000.

The second data set tested increases the unit product value drastically to $1,000,000 per unit.

Table 5.8: Data Set 1 — Unit Product Value = $1,000/unit.

DC Node:	Fixed Inventory-Location Model	Inventory-Location Model	% of Total Cost
DC Node:	3 DCs Opened	9 DCs Opened	
Quantity:	2,423,466	2,423,466	
Percent Demand:	1.00	1.00	
Labor Cost:	$2,931,803	$3,128,282	17.08%
Land Cost:	$19,533	$44,409	0.24%
Total Transportation Cost:	$9,705,089	$9,117,707	49.78%
Total Inventory Cost:	$6,806,431	$3,732,139	20.38%
Total OH Cost:	$761,227	$2,291,936	12.51%
Total Cost:	**$20,224,082**	**$18,314,473**	100.00%

The purpose of this test is to verify the performance of the inventory-location model. In extreme conditions such as this, the inventory costs should approach 100% of the total costs because the other cost components will comprise only a small percentage of the total cost. With the inventory costs comprising such a large amount of the total costs, this provides the perfect opportunity for the inventory-location model to make improvements. This is portrayed in the example shown in Table 5.9. The inventory costs here consist of 94.26% of the total costs. When applying the inventory-location model, this solution is improved by 84% as compared to the location model with a fixed inventory policy.

Table 5.9: Data Set 2 — Unit Product Value = $1,000,000/unit.

	Fixed Inventory-Location Model	Inventory-Location Model	% of Total Cost
DC Node:	3 DCs Opened	50 DCs Opened	
Quantity:	2,423,466	2,423,466	
Percent Demand:	1.00	1.00	
Labor Cost:	$2,931,803	$3,937,386	0.37%
NL Land Cost:	$8,613	$48,305	0.00%
Total Transportation Cost:	$24,003,439	$44,042,763	4.15%
Total Inventory Cost:	$6,492,504,065	$1,001,551,150	94.26%
Total OH Cost:	$745,034	$12,925,052	1.22%
Total Cost:	**$6,520,192,954**	**$1,062,504,656**	100.00%

The result of this example proves that the inventory-location model does perform as we expect it to. When the inventory costs are very large, the inventory-location model is much more capable of making significant improvements in the total cost. So, although the improvements shown in the data analysis for Research Question #1 are very small, we can assume that this is due to the inventory costs being such a small portion of the total costs. The two examples discussed in this section show that as the inventory costs increase, the inventory-location model has increasingly better performance than the location model with a fixed inventory policy.

5.4 Research Question 2: Heuristic 1 vs. Heuristic 2

The purpose of the second research question defined in Section 4.1 was to find an effective way to obtain good results using different heuristic methods for the inventory-location problem. More specifically, this question was defined as:

Research Question 2: *What type of heuristic method is the most effective in finding good solutions for the inventory-location problem?*

To answer this question, two different heuristic methods were proposed. These two methods will be referred to as H1 for the first heuristic method and H2 for the second heuristic method. The philosophy behind the first heuristic method was to fist solve the location model for a given number of open DCs and then improve on this initial solution with two different improvement algorithms. The first step of the methodology for H1 is to calculate an initial estimate for the number of DCs to be opened, N, using the method discussed in Erlebacher and Meller [9]. See Appendix B for details on the calculation of this estimate. After solving the location model, a multi-echelon inventory model is applied to the results, which is then followed by two improvement algorithms. The first algorithm uses a pair-wise exchange for each open DC with its neighboring cities to see if surrounding cities will improve the solution. This algorithm calculates the actual inventory costs for each exchange, unlike the location model used for the initial solution. The second improvement algorithm conducts a search on other local values of N to determine if the initially calculated value correlates with the minimum cost solution. If a different value for N is found to result in a lower cost, the steps of this heuristic are repeated using the new value of N.

The approach of the second heuristic is different than that of the first heuristic. Rather than try to improve a solution from the location model, H2 attempts to solve both the location and inventory model together in an iterative process. Initially, linear estimates for the nonlinear costs are calculated based on the optimal 1-DC solution to the given problem. The inventory-location model is then solved, followed by the multi-echelon inventory policy. Next, new linear estimates for the nonlinear costs are estimated based on the number of DCs opened in the new solution. The inventory-location model is then solved again, using the new linear estimates for the nonlinear costs. This process is repeated until the %-improvement between iterations is below a pre-defined value.

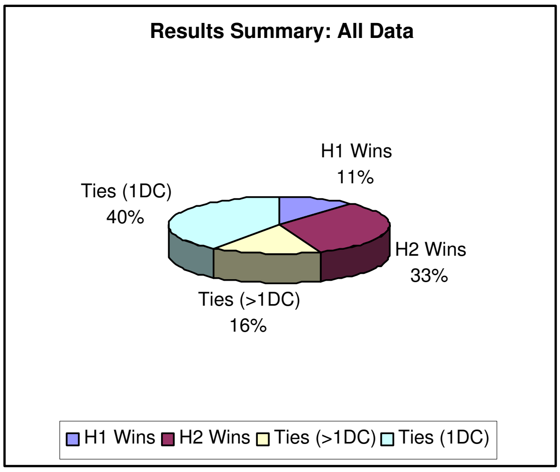
Similar to the first research question, several data sets were run on each heuristic model to obtain different results to compare. A total of 100 test results were obtained for each heuristic; however, 40 of these resulted in only 1 DC being opened. In situations where only 1 DC is open, both heuristics performed the same because the optimal solution can be found by total enumeration — no LP is necessary. Therefore, only 60 of the 100 test results can be used to compare the performance of Heuristic 1 and Heuristic 2.

The first analysis performed to compare the performance of H1 and H2 was to compile and summarize the results for each type of test parameter combination. This results summary is shown in Table 5.10. For each test parameter combination tested, the average number of DCs opened and the averages of the total resulting costs are shown. Similar to Table 5.1, two overall averages are given. The first includes the results for all 100 data sets and the second only includes results from the 60 test runs that resulted in more than 1 DC opening.

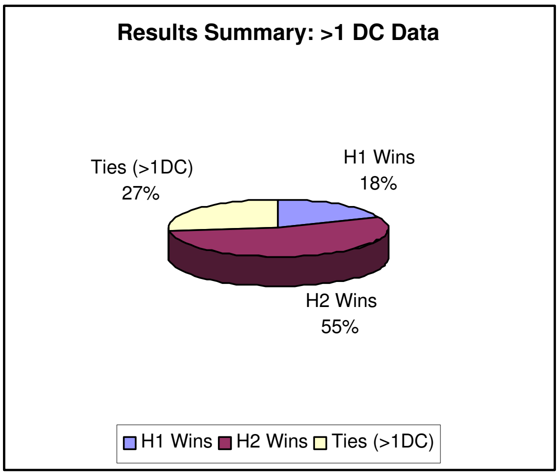
Table 5.10: Heuristic 1 Results vs. Heuristic 2 Results.

Product \$ vs. Transp \$ Ratio	**Demand Level**	**# Cust vs. # Manf Ratio**	**Avg. # DCs-H1**	**Avg. # DCs-H2**	**Heuristic 1 Total Cost**	**Heuristic 2 Total Cost**
Med	Med	Med	2.00	2.00	\$5,719,720	\$5,715,697
Med	Low	Med	1.00	1.00	\$1,733,433	\$1,731,918
Med	High	Med	3.40	3.70	\$13,328,864	\$13,310,154
Med	Med	Low	1.00	1.00	\$2,331,346	\$2,331,349
Med	Med	High	6.00	6.00	\$19,669,545	\$19,665,834
High	Med	Med	2.70	2.90	\$10,714,545	\$10,708,905
Low	Med	High	1.00	1.00	\$1,109,092	\$1,563,884
Med	High	High	10.40	11.00	\$46,356,421	\$46,345,927
High	Med	Low	1.00	1.00	\$4,344,443	\$4,344,443
High	High	Low	2.50	2.80	\$10,192,706	\$10,199,070
Total Avg:					**\$11,549,860**	**\$11,546,239**
> 1DC Avg:					**\$17,663,633**	**\$17,657,598**

Based on these results, Heuristic 2 resulted in an average cost savings (over H1) of approximately \$6,000 in situations where more than 1 DC was open. This results summary shows that Heuristic 2 not only results in a total cost savings, but also performs as good or better than Heuristic 1 in most cases. When looking at more detailed data, this is apparent once again. The 100 data sets were compared individually to determine which method performed best. The results summary of this analysis is shown in Figure 5.5. The pie chart on the left shows that the performance of H1 and H2 were equal in 56% of the solutions. Overall, H2 resulted in a better solution in 33% of the test runs, while H1 only performed better for 11% of the test runs. The performance of H2 over H1 is even more evident in the second pie chart where the 1-DC solutions are omitted from the data. Now the results show that H2 resulted



(a) Summary for All Data.



(b) Summary for Data with more than 1 DC.

Figure 5.5: Transportation \$ to Inventory \$ Ratio Analysis.

in a better solution over half the time, while H1 was able to improve the solution in only 18% of the test runs. In addition, further statistical analysis in the sections to follow will show that the improvements made by H2 have more of an impact than the improvements made by H1.

5.4.1 Cost Component Analysis

Similar to the study performed for Research Question 1, a cost component analysis was also performed for Research Question 2 to determine which heuristic method performed better with respect to each of the cost components. In order to show the true difference in the performance of each heuristic, only the data resulting in more than 1 DC is included in this analysis.

Figure 5.6 portrays a bar chart that summarizes the performance of each primary cost component. The values shown in this chart are the averages of each cost component for H1 minus the averages of the H2 cost components. Thus, the bars on the left side of the chart represent cost components where H1 resulted in a lower value and the bars on the right side of the chart are those which were better handled by H2. The values on the x-axis show the magnitude of the difference between the H1 and H2 average values. At a glance, this figure shows us that H2 performed better in terms of optimizing the transportation costs, inventory costs, and the total costs overall while H1 performed slightly better in optimizing the labor cost and significantly better at optimizing the overhead cost. The land cost component seems to be affected very little by either heuristic method.

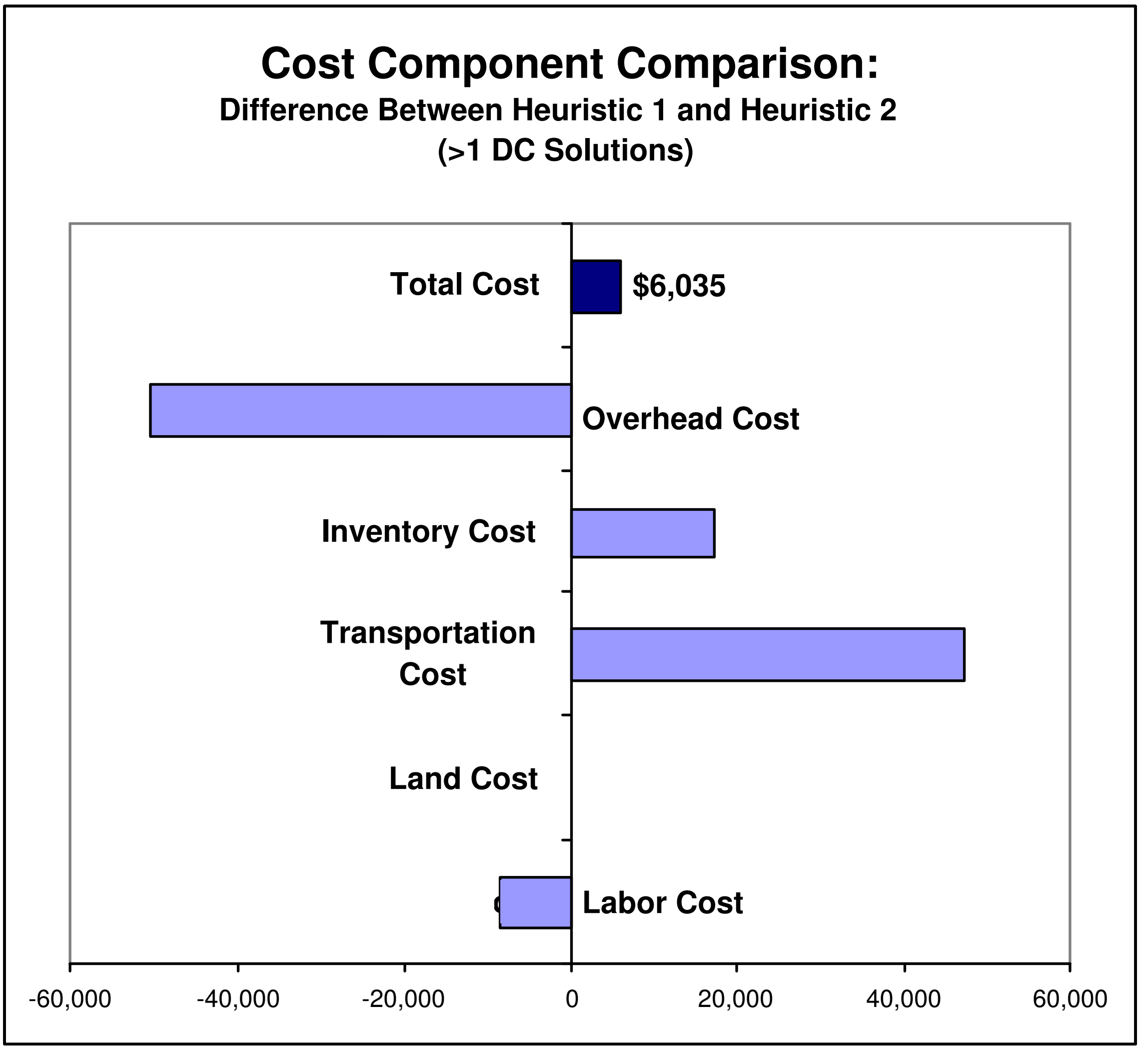


Figure 5.6: Cost Component Performance Comparison — Research Question 2.

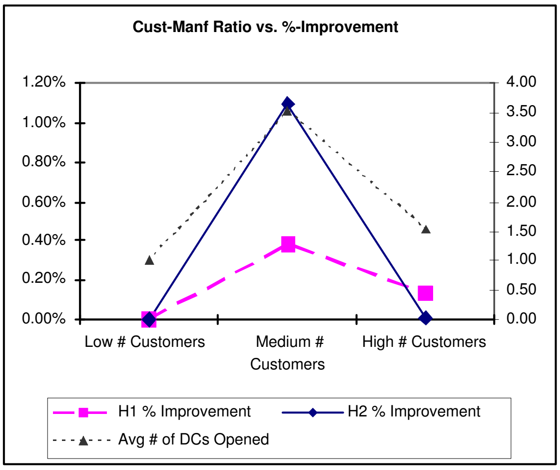
Table 5.11: Cost Component Performance Comparison — Research Question 2.

	H1	**H2**	**H1-H2**	**Average %-age of Total Cost**
Labor Cost	2,833,315	2,841,791	-8,476	16%
Land Cost	64,716	64,545	171	0%
Transportation Cost	13,091,093	13,043,830	47,262	74%
Inventory Cost	468,196	450,715	17,481	3%
OH Cost	1,206,313	1,256,715	-50,402	7%
Total Cost	17,663,633	17,657,598	6,035	100%

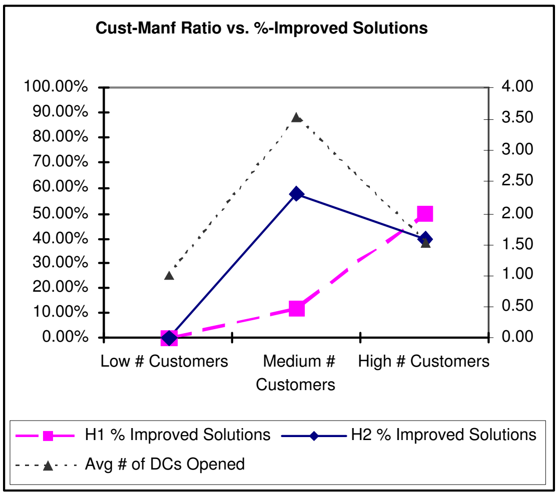
It is evident in Figure 5.6 that the trade-off in performance between the transportation cost and the overhead costs are comparable in magnitude. Although H2 performs significantly better than H1 in optimizing the transportation cost, this savings is balanced out by the savings in the overhead cost from H1. The overhead costs in H1 are lower than H2 for two reasons. First, H1 tends to either open fewer DCs or it opens DCs at lower land and labor cost locations. The overhead cost is related to both of these costs; therefore, if H1 results in lower land and labor costs, the overhead cost will inevitably be lower as well. Second, there are some situations with high demand where H2 tends to open more DCs than H1. By doing this, H2 is better able to balance all cost components to result in a lower total cost. However, because H1 has less DCs open, the overhead cost is lower than that of H2. Overall, it is the inventory costs savings in H2 that causes it to perform better than H1. This is a direct result of the capability H2 has to include an estimate for the inventory and other nonlinear costs in the optimization criteria of the inventory-location problem. Thus, it is this capability that gives H2 its apparent edge in performance over H1.

5.4.2 Test Parameter Analysis

The analysis in Sections 5.4.1 and 5.4 showed the relative performance of each heuristic method overall as well as for each cost component. The intent of the analysis in this section is to learn more about the behavior of each heuristic method and to find what test parameters have the most significant effect on the outcome of each method. This is accomplished by comparing the different values for each of the test parameters individually to see if there are any apparent effects on the behavior of either heuristic method. The same two metrics from Section 5.3.2 will be used to analyze the behavior of the heuristics. The first metric looks at which heuristic method performs better and by what percentage (test parameter vs. %-improvement). The second metric is focused on which heuristic method performs better on more occasions (test parameter vs. %-improved solutions). For both metrics, the average number of DCs opened is also shown for reference. In cases where specific trends



(a) %-Improvement.



(b) %-Improved Solutions.

Figure 5.7: # Customer to # Manf. Ratio Metrics.

or behaviors are observed, examples are given to shed some light on the behavior of each heuristic method.

Test Parameter # 1: # Customer vs. # Manufacturer Ratio

The first test parameter analyzed is the ratio of the number of customers to the number of manufacturers. The three ratio values used in the data sets are (20:20) for low, (50:10) for medium, and (100:5) for a high ratio. Of the six test parameter combinations resulting in more than 1 DC being opened, 0 were for the low ratio value, 5 were for the medium ratio value and 1 was for the high ratio value. The metrics for the %-improvement and %-improved solutions are shown in Figure 5.7 and Table 5.12.

It is difficult to make any strong inferences based on these graphs due to the poor spread of data across the three categories. However, some patterns and behaviors can be observed from this information. First, H2 seems to be more capable of both finding better solutions than H1 and finding more of them as the ratio of # customers to # manufacturers increases. H1 seems to follow the same basic pattern as H2 for both metrics but with less drastic performance improvements. H2 performs best according to both metrics when the medium value for the ratio is used. However, when the high value of the ratio is used (large # of customers vs. small # manufacturers) H1 becomes increasingly competitive by almost meeting the %-improved solutions and just barely improving on the %-improvement by %0.03.

One observation that may explain the behavior of the two heuristic methods is the number

Table 5.12: Comparison by Customer to Manufacturer Ratio.

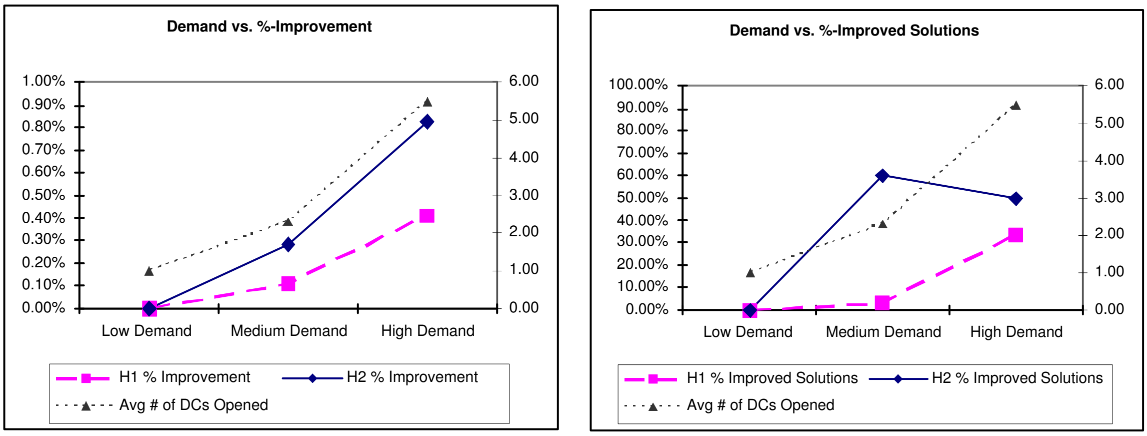
% Wins by Customer/Manf Ratio	**H1 Wins**	**H2 Wins**	**Ties (> 1DC)**
Low # Customers	0	0	0
Medium # Customers	6	29	15
High # Customers	5	4	1
% Wins (Low # Customers)	0%	0%	0%
% Wins (Medium # Customers)	12%	58%	30%
% Wins (High # Customers)	50%	40%	10%

of DCs opened. In both situations where the ratio of the # customers to # manufacturers is high, H2 often resulted in solutions with a higher number of DCs opened than H1. However, the solution for H1 proves that a lower cost solution is attainable by opening fewer DCs. This overestimation of the appropriate number of DCs can most likely be attributed to the linear estimation methods for H2. At low and medium cost solutions, these estimates are effective in helping H2 find good solutions. However, as the total cost increases, these costs are not as accurate and sometimes result in H2 underestimating the actual inventory costs and opening an extra DC. On some occasions, this does result in a lower cost solution. Most of the time however, we see that this is not the best solution to the problem because the solution found by H1 with less open DCs results in a lower cost. Future research possibilities for this portion of the inventory-location model are discussed in more detail in Section 6.3 of Chapter 6.

Another clear pattern here is that the number of DCs opened does not seem to follow any trend that is correlated to the ratio of the number of customers vs. manufacturers. This is a logical observation — neither of these variables play a role in the objective of the MIP described in Section 3.3 of Chapter 3. Thus, any trends or behaviors found for either heuristic in this particular test parameter analysis can not reasonably be linked with the number of DCs opened.

Test Parameter # 2: Average Customer Demand Level

The next test parameter analyzed is the demand test parameter. This parameter appears multiple times in the objective statement of the MIP from Section 3.3 — in fact, it is tied to every cost component in some way. Thus, it is no surprise to see that the demand test parameter seems to cause a clear upward trend in the number of DCs opened. The average number of DCs opened begins at 1 for low demand and increases to almost 6 for high demand. Again, this is important because any trend in the behavior for either heuristic could possibly be linked with the increasing number of open DCs.



(a) %-Improvement. (b) %-Improved Solutions.

Figure 5.8: Demand Metrics.

The metrics for the %-improvement and %-improved solutions are shown in Figure 5.8 and Table 5.13. The spread of data for the demand test parameter is much more balanced. None of the six test parameter combinations are for low demand. Rather, the 6 combinations are spread evenly for for the medium and high demand test parameters (3 each).

Table 5.13: Comparison by Demand.

% Wins by Demand Level	**H1 Wins**	**H2 Wins**	**Ties (>1DC)**
Totals (Low Demand)	0	0	0
Totals (Medium Demand)	1	18	11
Totals (High Demand)	10	15	5
%Wins (Low Demand)	0%	0%	0%
%Wins (Medium Demand)	3%	60%	37%
%Wins (High Demand)	33%	50%	17%

It appears that the performance of H1 and H2 are quite similar for low and medium values of demand (despite the fact that H2 still performs slightly better on a large number of occasions). It is when the demand grows to a large value that H2 is able to out-perform H1. When the demand grows to this level, it becomes increasingly important to be able to balance the different cost components.

An example is presented in Table 5.14 — this example is similar to the example given for test parameter #2 for Research Question 1. The test parameter values for the data set in this example are medium # Customer vs. # Manufacturer ratio, high Customer Demand, and medium Transportation $ vs. Inventory $ ratio. The results for the data set with one of the larger %-improvement are shown in this example. We can see here that H1 performs better with respect to land and overhead costs because less DCs are opened (3 as opposed to 4). However, H2 performs better overall because it is able to balance all of the cost components more effectively. In this case, one extra DC is opened and results in a 4% savings in Transportation Cost. This savings can be expected because the average customer distance in this case is much less than what is found in Heuristic 1. A savings of approximately 7.9% is seen here for the Inventory Costs. Although the inventory holding costs are increased by having an extra DC, the pipeline inventory costs are reduced because the travel time has decreased. This example shows how the inventory-location model is better able to judge the impacts of minor decisions on all cost factors (rather than just the linear costs).

Table 5.14: Test Parameter #2 Analysis.

MHM — Data Set 4	H1	H2	Avg. %-age of Total Cost	%-Improvement
DCs Opened:	3	4		
Labor:	$3,080,294	$3,040,551	24.0%	1.31%
Land:	$50,157	$65,753	0.4%	-23.72%
Transportation:	$8,449,764	$8,120,600	65.9%	4.05%
Inventory:	$429,044	$397,569	3.3%	7.92%
Overhead:	$804,638	$1,070,666	6.3%	-24.85%
Total:	**$12,813,896**	**$12,695,139**	100.0%	0.94%
Avg. Cust. Distance (miles):	594	513	13.6%	
Max Cust. Distance (miles):	1,390	1,390	0.0%	

This example leads to another valuable observation. While H2 does perform better than H1 here, the difference between the two solutions in terms of both cost and customer service is not substantial. However, the solutions provided are very different in terms of what type of supply chain is recommended. Thus, instead of just comparing H1 and H2 in terms of cost and service, it is also a good idea to consider non-quantitative factors. For example, the total costs for H1 may be slightly higher but the location is such that a company can use an already existing corporate facility for the DC. In this case, using the H1 solution may be preferable. Therefore, the fact that H1 and H2 provide many solutions of equal objective function values means that there are many “good” solutions to consider in the larger context of the problem.

Test Parameter # 3: Transportation $ vs. Inventory $ Ratio

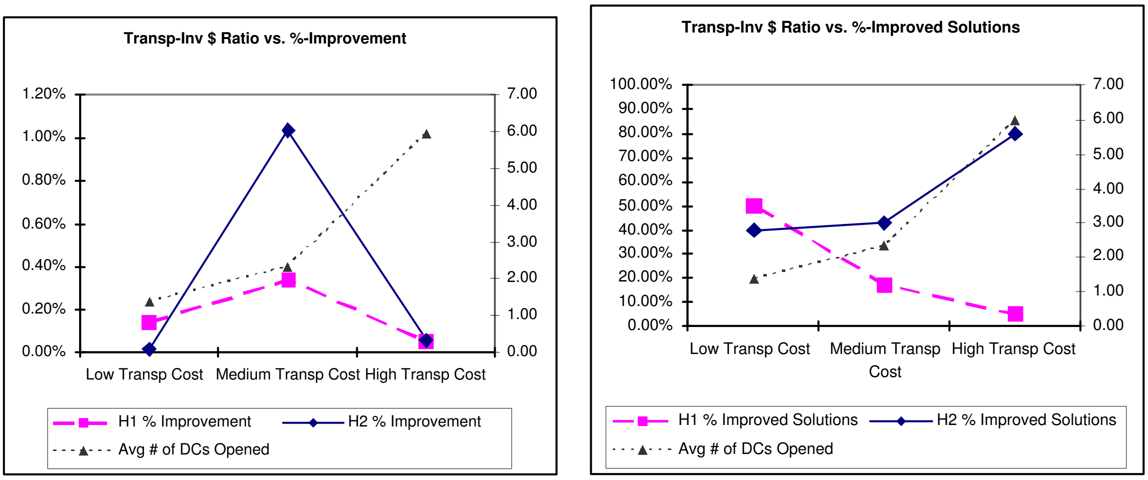
The last test parameter analyzed is the ratio between the unit transportation cost and the product value (which is directly proportional to the unit inventory holding cost). This ratio is interesting because these costs have opposite effects on the number of DCs opened. As the transportation cost increases, it becomes more desirable to have more DCs opened to decrease the travel distance between the DC and the customer; however, as the inventory cost increases, it is better to have less DCs opened to minimize the inventory holding cost. This pattern is evident in the number of DCs opened as the ratio increases. When the ratio is low (low transportation cost, high inventory cost), very few DCs are opened on average. As the ratio increases to a medium or high value (high transportation cost, low inventory cost), the average number of DCs opened steadily increases. From this, two assumptions can be made. The first assumption is that there is a correlation between these unit costs and the number of DCs opened. This is important because any trends in the behavior of H1 or H2 may possibly be linked with the increasing number of open DCs. The second assumption is that the unit inventory cost has a stronger affect on the number of open DCs than the transportation cost (given the values that are being used in our test data). If the effect was equal, the number of DCs opened would be similar because the two costs would balance each other.

The metrics for the %-improvement and %-improved solutions are shown in Figure 5.9 and Table 5.15. Of the six test parameter combinations resulting in more than 1 DC being opened, 1 was for the low ratio value, 3 were for the medium ratio value and 2 were for the high ratio value.

Table 5.15: Comparison by Transportation and Inventory Cost Ratio.

% Wins by Transp/Inv Ratio	**H1 Wins**	**H2 Wins**	**Ties (>1DC)**
Low Transp Cost	5	4	1
Medium Transp Cost	5	13	12
High Transp Cost	1	16	3
% Wins (Low Transp Cost)	50%	40%	10%
% Wins (Medium Transp Cost)	17%	43%	40%
% Wins (High Transp Cost)	5%	80%	15%

The most notable observation from these graphs is the large differences in the performance of H1 and H2 when moving from a low to a medium to a high transportation/inventory cost ratio. At the low ratio value, H1 and H2 perform in a very similar fashion. This is most likely due to there being several 1 DC solutions included in the results for this category. When moving on to the medium ratio value, the performance of H2 increases significantly. This is not surprising, due to the added capability that H2 has of being able to include an estimate



(a) %-Improvement. (b) %-Improved Solutions.

Figure 5.9: Transportation $ to Inventory $ Ratio Metrics.

for the inventory cost component in the optimization criteria of the inventory-location model. Although H1 applies several improvement algorithms to the initial location solution, these are not as effective in determining the best trade-off between the inventory cost component and other costs that effect the number or size of DCs. In high ratio scenarios, H2 is still able to perform better than H1 in most occasions. However, because the inventory costs are lower (due to the low product value), H2 no longer has the same advantage over H1.

5.4.3 Wilcoxon Signed-Rank Test

A statistical analysis was also performed to learn more about the performance of Heuristic 1 vs. Heuristic 2. The test chosen for this was the Wilcoxon Signed-Rank Test. This is a nonparametric test that is useful in analyzing the performance of paired data sets. This test takes into account the magnitude of the performance differences between the paired data sets, rather than only looking at which one performed better. The first step in the Wilcoxon Signed-Rank test is to calculate the difference between each data set (H1-H2) and then rank the pairs according to the magnitude of these differences. A mean rank is used in the case of equal performance. A sign is then attached to each rank according to the sign of the difference. If H1 performed better a negative sign (-) will be given to the ranking and vice versa.

The Wilcoxon Signed-Rank test is used to test the null hypothesis that the sum of the differences between the pairs is equal to zero. If the null hypothesis is true, the sum of the ranks of the positive differences should be the same as the sum of the ranks of the negative differences.

In this case, the test will be applied to the average total cost of each heuristic for each unique set of test parameters. The notation for the rank of each data set is shown below. For this analysis, all ten test parameter combinations are accounted for, including the 1-DC solutions. In other words, $n = 10$.

$i = \#$ of unique sets of test parameters ($i = 1, \ldots, n$).

$\mu_D = \sum_{i=1}^{n}(\mu_{H1} - \mu_{H2})$ = The average difference between H1 and H2 will be the sum of the differences for each test parameter combination.

The null hypothesis states that μ_D will equal zero, implying that any difference in H1 and H2 is due to random variation. The alternative hypothesis states that the sum of all the rankings will be either greater than or less than zero, depending on which heuristic performed better. The notation for both hypotheses is as follows:

Null hypothesis: $H_0 : \mu_D = 0$

Test Statistic Value: s_+ = the sum of the positive ranks

Alternative Hypothesis:	Rejection Region for Level α Test:
$H_{a1} : \mu_D > 0$	$s_+ \geq c_1$
$H_{a1} : \mu_D < 0$	$s_+ \leq c_2$, where $c_2 = n(n+1)/2 - c_1$

The values for α and the critical value c_1 are obtained from a table containing the Upper-Tail Critical Values and Probabilities for the Null Distribution of the Wilcoxon Signed-Rank Statistic S_+. This table is found in Appendix A.9 of [7].

After defining our null and alternative hypotheses, we can begin the test by assigning the rank of each pair by looking at the difference of the average total costs (H1-H2). The rankings for these ten combinations are shown in Table 5.16 for each test parameter combination. The test parameter combinations are shown by giving an L, M, or H for each test parameter. For example, a test parameter combination of LMH implies a low # Customer to # Manufacturer Ratio, a medium average Customer Demand level, and a High Transportation $ to Inventory $ Ratio, respectively.

Based on the rankings calculated in Table 5.16, we can solve for the value for the test statistic, s_+, as follows:

$s_+ = 2.5 + 2.5 + 2.5 + 5 + 6 + 7 + 9 + 10 = 47$

In order to accept or reject the null hypothesis, we must obtain the value for c_1. Table 5.16

Table 5.16: Ranking of Pairs.

	Difference	**Rank**	**Signed Rank**
MMM	$5,622	5	5
MLM	$0	2.5	2.5
MHM	$28,089	9	9
MML	$0	2.5	2.5
MMH	$10,070	7	7
MHH	-$15,988	8	-8
HML	$0	2.5	2.5
HHL	$281,179	10	10
HMM	$6,604	6	6
LMH	$0	2.5	2.5

shows ten unique test parameter combinations ($n = 10$). The critical values and α values from the table in [7] for $n = 10$ are shown in Table 5.17.

Table 5.17: Critical Values for n=10.

n	c_1	α	Reject H_0?
10	41	0.194	Yes
	44	0.106	Yes
	47	0.048	Yes
	50	0.020	No
	52	0.010	No

The test statistic value for this problem is 47. Thus, we can reject the null hypothesis for approximate levels of $\alpha = 0.048$ and above. However, Table 5.17 shows us that any level smaller than $\alpha = 0.48$ does not fall within the rejection region for the null hypothesis. Based on this analysis, we can be 95.2% confident that the difference in performance that we observe between H1 and H2 is due to a statistically significant difference in the results, as opposed to random variation.

The Wilcoxon Signed-Rank test was also performed for the individual H1 and H2 test results rather than for the average of each test parameter combination. When the test is performed with all the detailed data, the results are much more supportive of H2. There are 100 test results available for this test — because n is greater than 20, we can approximate μ_D using the normal distribution. We calculate the standard z-value as follows:

$$Z = \frac{s_+ - n(n+1)/4}{\sqrt{n(n+1)(2n+1)/24}}$$

Table M.1 in Appendix M shows the difference and ranking of all test results for H1 and H2. Two different rank columns are shown in the table. The first rank column represents the ranking of all 100 data sets, which includes all the 1 DC solutions. There are 57 tied solutions in the 100 test sets — the rank for each of these is 29 (the average rank for 1-57). The second rank column represents only the solutions where more than 1 DC was opened. Here, there are 60 data sets to work with and 17 ties. The average rank for the tied solutions is 9.

At the bottom of table M.1, we see that the sum of the positive signed ranks is 4132 for the 100 data sets. Using this information and the formula above, we calculate the Z value for the 100 data sets as follows:

$$Z = \frac{4132 - 100(101)/4}{\sqrt{100(101)(201)/24}}$$

$$Z = 5.5254$$

This value for Z is very high and relates to a 99.99% probability that the difference between H1 and H2 is statistically significant rather than being due to random variation. One reason for this value being so large is because all the ties were included in the analysis. This is misleading because H2 did not actually perform better than H1 in these solutions; yet, the rank in these cases is positive.

In order to obtain a more accurate measure of the performance of H2, another Wilcoxon Signed-Rank test is performed — this time only on the 60 test sets resulting in more than one open DCs. The ranks for these solutions are also shown in M.1 in Appendix M. When adding the positive-signed ranks, we obtain a total of 1199 for s_+. We then calculate the Z value as follows:

$$Z = \frac{1199 - 60(61)/4}{\sqrt{60(61)(121)/24}}$$

$$Z = 2.0907$$

This value for Z relates to a 98.17% probability that the difference between H1 and H2 is statistically significant. This is a more accurate measure for the performance of H2 because the only test sets considered are those where H2 has an opportunity to improve upon H1.

5.4.4 Customer Service Performance

One intangible factor that is worthwhile to track is the customer service level provided with each resulting distribution system. We attempt to measure this by looking at the average and maximum distance to the customers. These factors correlate with the average and maximum delivery time. These data are shown for each unique test parameter combination in Tables 5.18 and 5.19.

Table 5.18: Customer Service Comparison — Average Customer Distance.

Test Parameter Combination	**H1 Average Cust. Dist.** (miles)	**H2 Average Cust. Dist.** (miles)
MMM	675	670
MLM	923	923
MHM	541	513
MML	920	920
MMH	391	391
HMM	613	597
LMH	901	901
MHH	258	256
HML	910	910
HHL	604	560
Average:	**674**	**664**
> 1 DC Average:	**514**	**498**

Notice that there is not a large difference between H1 and H2 for either of these metrics. In some cases, there are distinct differences (e.g., MHM and HHL), but for most test parameter combinations, the difference in customer service is not significant. This is explained by the fact that the solutions for H1 and H2 often resulted in the same (or at least similar) locations for DCs to be opened. In fact, 73% of the test sets resulted in the same locations for open DCs. Additionally, 13% of the solutions resulted in at least similar solutions where DCs where opened in the same regions. Only 14 % of the test sets resulted in different solutions with very different DC locations — this is primarily due to the number of DCs opened being different for H1 and H2. Of the solutions with the same DC locations, the factor driving the cost savings for H2 is the amount of inventory chosen to be stored at each DC.

5.4.5 Runtime Performance

Another factor that is worth looking into is the runtime of the model — e.g., how much time was needed to find the best solution for each heuristic method? Heuristic 1 did not perform nearly as well as Heuristic 2 with regards to this measure. This was partially due to the manner in which Heuristic 1 was implemented. An initial optimization of the system was performed, but was followed by several iterations of an improvement algorithm. In many cases, these improvement iterations required an optimization run that resulted in

Table 5.19: Customer Service Comparison — Maximum Customer Distance.

Test Parameter Combination	H1 Maximum Cust. Dist. (miles)	H2 Maximum Cust. Dist. (miles)
MMM	1,580	1,614
MLM	1,925	1,925
MHM	1,402	1,363
MML	1,964	1,964
MMH	1,135	1,259
HMM	1,552	1,522
LMH	1,800	1,800
MHH	1,096	1,030
HML	2,014	2,014
HHL	1,486	1,383
Average:	**1,595**	**1,587**
> 1 DC Average:	**1,375**	**1,362**

longer run times to find the best solution. The average number of iterations to find the best solution for the data sets we tested was 6 iterations. Depending on the computer used to execute the model, each iteration can take up to 1 hour to set-up and run. Thus, Heuristic 1 took approximately 6 hours to run on average (on a computer with a 1.0 GHz Pentium 3 processor).

Heuristic 2 performed much better than Heuristic 1 with regard to runtime performance. In most cases, this heuristic ran 2 iterations, but was able to find the best solution on the first iteration. In situations with high total costs, an extra iteration was sometimes required. However, only 2 iterations were needed in 90% of the test problems. Furthermore, the first iteration had the best solution in 95% of the test runs. Thus, Heuristic 2 could be used without the implementation of the iterative process and still find the best solution 95% of the time. This is a notable advantage — being able to run a model one iteration for approximately 1 hour and be confident in the solution it provides. This is much more convenient that running a model for several iterations.

One aspect of the algorithm performance that could be improved is reducing the runtime of the algorithm. For large location problems like the ones we solve, the location-inventory problem has to consider facility locations that are not very good solutions to the problem. One way to improve the algorithm then is to include a pre-processing step to eliminate some locations from consideration. In such a step, potentially good locations are suggested through a heuristic search and then the location-inventory problem is solved with a smaller set of locations, which decreases the overall runtime. Recent work by Meller, Chen and Hodgdon

[13] showed that implementing such an approach returned heuristic solutions within 1% of optimal with only 20% of the computational effort of obtaining the optimal solution (for 100 customers and 5 facilities). Applying such a pre-processing step to our location-inventory heuristics then is likely to reduce the runtime of the heuristics by a factor of five without sacrificing very much in the way of solution quality.

Chapter 6

Conclusions

6.1 Thesis Overview

We began in Chapter 1 by giving an introduction of the classic problems addressed in this research — the Inventory Control Problem and the Facility Location Problem. The background and mathematical models were presented for each of these problems. Different forms of the Inventory Control Problem was discussed in Section 1.2, including the Deterministic EOQ and Stochastic EOQ models, followed by a discussion on how a Multi-Echelon Inventory Model is formulated. Next, the Facility-Allocation Model was presented in Section 1.4 where we also reviewed the complications of including nonlinear costs such as inventory holding costs and land costs in the model. Finally, we discussed how these two models affect each other and the motivation driving this research. Reasons were given to show why a combined inventory-location model would likely be valuable and an outline of the research performed for this topic was presented.

In Chapter 2 we presented a literature review and summarized much of the previous research performed in three fields pertaining to this research. To begin with, a review of Multi-Echelon Inventory Models was presented for both exact and heuristic models. Next, research for the Facility Location Model was presented. Exact and heuristic methods were presented once again for this problem. Finally, a review on the limited current literature for the combined inventory-location models was presented. This research showed what type of analysis had already been performed and outlined the best direction for future research in this area.

Next, the problem statement was presented in Chapter 3. In this chapter we defined all the details for the inventory-location model — including what cost components were included, our assumptions, and a detailed problem formulation. The parameters for the problem were presented and followed by the decision variables and the mathematical formulation of the mixed-integer program. We also explained in this chapter that this problem would be very complicated to solve optimally. Thus, it was d etermined that heuristic methods would be created to solve the inventory-location problem.

Once we defined our problem formulation and stated that we would use a heuristic approach for the inventory-location problem, Chapter 4 elaborated by presenting more details on the research performed. Here we defined two research questions. The first research question was to determine how much better the inventory-location model would perform in comparison to the location model with a fixed inventory policy. The second research question addressed our heuristic approaches for solving the inventory-location problem to determine which method would perform better. We then continued by explaining the general philosophy and flow for each heuristic method used. An in-depth experimental design was also presented in Section 4.4 of this chapter. Here we defined how our test data parameters and data sets were obtained, as well as a complete description of the type of data sets that were tested and how the test parameters were altered to produce different types of results.

Finally, in Chapter 5 we summarized the results for all the research performed by presenting data and analysis for each research question presented in Chapter 4. This included a results summary for each test parameter combination, a detailed cost component analysis, and an analysis for each test parameter. We found in this chapter that the inventory-location model performed better than the location model with a fixed inventory policy. Furthermore, we learned that the second heuristic method defined in Chapter 4 performed better than the first heuristic method. Several examples were used to explain both research questions and the nature of the results. The examples and discussion in this chapter helped to explain the behavior and to show the performance of the models. One important note made is that although the second heuristic performs better, the solutions are relatively similar in terms of cost and customer service. Thus, the results from both methods could be used to make a final recommendation. The ability to offer multiple "good" solutions is valuable because there may be non-quantitative factors to consider in such a decision. Having multiple good solutions allows management to more easily include these non-quantifiable factors in the decision.

6.2 General Observations

Recall that our first research question was to determine how much better the inventory-location model would perform in comparison to the location model with a fixed inventory policy. Based on the data analysis alone, we determined that the inventory-location model performed consistently better, but the cost improvement was not significant. The inventory-location tool improved the solution by only 0.33%. However, when the data were analyzed in more detail, some valuable information was discovered. First, the inventory cost in the data sets tested was only approximately 3% of the total cost of the distribution system. This does not leave much room for the inventory-location model to improve the solution. To prove that the inventory-location model does in fact perform as we originally expected it to, some extra data sets were tested and presented in Section 5.3.4. These data sets incorporated higher product values, which lead to an increase in unit inventory holding costs and overall inventory costs. Two examples were presented where the inventory costs were increased to approximately 20% and 95% of the total system cost. Through this analysis, we found that the inventory-location model did, in fact, perform drastically better than the location model with a fixed inventory policy. In the first example where the inventory was 20% of the total cost, the inventory-location model resulted in a 9.5% improvement in total cost over the location model with a fixed inventory policy. The second example showed an even more impressive performance by the inventory-location model. The total cost using the inventory-location model was 84% less than the resulting cost using the location model with a fixed inventory policy. This analysis was quite valuable in illustrating that the inclusion of the nonlinear costs in the optimization criteria actually do make a big difference in the outcome of a facility location model for those cases with high inventory costs.

The next research question analyzed pertained to which heuristic method performed better at finding good solutions for the inventory-location model. Here we looked at two heuristic methods (the details of each are described in Chapter 4). The data analysis showed that Heuristic 2 consistently performed better than Heuristic 1. In fact H2 was able to find an equal or better solution than H1 in 82% of the test problems run. However, the average magnitude of the improvement was not significant — only improvements of 0.18% were made over H1. In cases with larger total costs, the magnitude of improvement achieved by H2 increased to as much as 1.33%. This is still only a small improvement, but demonstrates that in high inventory situations, we can expect the improvement for Heuristic 2 to be somewhat greater than the improvement for Heuristic 1.

Aside from the total cost improvement, there were some additional attributes of the second heuristic method that made it perform better than the first method. Section 5.4.4 in Chapter 5 showed us that the second heuristic performed better in terms of both customer service metrics (average and maximum distance to customers). This improvement was not quantified in dollars, but is nevertheless a very important consideration in any supply chain. We saw a third advantage to using the second heuristic method in Section 5.4.5 of Chapter 5. This section compared the runtime details for the two heuristic methods and showed that Heuristic 2 was able to find the best solution in much less time than Heuristic 1. Due to the design of Heuristic 1, several iterations were performed, causing it to take approximately 6 hours on average to run to completion. On the other hand, Heuristic 2 was able to run to completion in approximately 2 hours. In fact, we found that Heuristic 2 was able to find the best solution in only 1 hour 95% of the time. This is another intangible factor that is difficult to quantify monetarily. However, the added value of convenience in terms of a short runtime should not be ignored.

6.3 Future Research Recommendations

The limited literature review in Chapter 2 for the combined inventory-location model showed us that this field of research is still very young. Thus, there are still many opportunities for future research on this subject. In fact, many stem directly from the results of the research discussed in this thesis.

We have seen in this research that not all of the assumptions made are consistent for a spare-parts inventory system. In order to represent this type of supply chain configuration in the inventory-location model, more research would be needed in two areas in particular. To begin with, it is important to understand the true values for many of the parameters defined in Appendix C. Thus, it would be extremely useful to conduct research to understand what these values should be — this information is critical to understand what type of supply chain is being modeled. On the same note, it is also important to know how many product family categories are needed to obtain a model for the desired type of supply chain. We used five product families in this research; however, this may not necessarily be an accurate portrayal of a spare-parts supply chain. More than likely, this number would be much higher.

After more accurate data are researched for the parameter values and the product families needed, it would be very informative to run more tests using the inventory-location model. The research presented here showed that the inventory-location model performed better when inventory costs were a higher percentage of the total cost. However, it would be worthwhile to verify this by running a balanced set of test problems. Furthermore, it would be interesting to re-examine which heuristic method performs better for the new test problems. The research performed here showed that Heuristic 2 performed better most of the time, but not by a large percentage. It is possible that the %-improvement of H2 over H1 may increase in cases where the inventory cost were a higher percentage of the total cost.

Another area for future research lies in how to improve the performance of the second heuristic method. Several things could potentially be altered in this heuristic that may result in improved solutions. For example, research on how to better estimate the nonlinear costs would be very helpful. We discussed briefly that as the total system cost increases, the error between our estimates for the nonlinear cost and the actual cost increases as well. If this error could be reduced, the inventory-location model would be able to perform even better because the trade-off relationships between different cost components would be represented more accurately.

Finally, in Chapter 1 we discussed that this project was motivated originally by a location model created for Thermo King that was created for the purpose of solving the facility location-allocation problem. Now that we have defined and explored the capabilities of two heuristics to the location-inventory problem, an improved Thermo King location tool can be created to enhance the tool with respect to inventory decisions.

Appendix A

Pipeline Inventory Derivation

The pipeline inventory is the inventory that is in transit between the DC and the customers. Note that pipeline inventory between the manufacturers and the DCs is not considered in this problem.

The calculation for the pipeline inventory is based on the fact that all of the demand for a customer must be transported from the DC that customer is assigned to. Therefore, for each customer-to-DC assignment, we can calculate the pipeline inventory by multiplying the total demand for the customer by the number of days to travel from the DC to the customer. This can modeled mathematically using the following parameters:

d_{ik} = average annual demand of customer i for product k; Total Demand $(D) = \sum_{i=1}^{M}\sum_{k=1}^{P} d_{ik}$

$$y_{ji} = \begin{cases} 1 & \text{if DC } j \text{ is assigned to customer } i, \\ 0 & \text{otherwise} \end{cases}$$

m_{ji} = mileage from DC j to customer i

avg = average mileage travelled in one day (miles/day)

ND = number of business days in one year

$trav_{ji}$ = number of days necessary to travel from DC j to customer i $\left(trav_{ji} = \lceil \frac{m_{ji}}{avg} \rceil\right)$

h_k = inventory holding cost for product k (\$/unit/year)

Using these parameters, we can define the pipeline inventory as follows:

$$\text{Pipeline Inventory} = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{k=1}^{P}\left(\frac{d_{ik}y_{ij}}{ND}\right) trav_{ji}.$$

This expression will give us the average number of units in pipeline inventory per day. We can calculate the total pipeline inventory costs from this by multiplying this expression by the inventory holding cost per day. In this case the pipeline inventory costs can be formulated as follows:

$$\text{Pipeline Inventory Costs} = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{k=1}^{P} h_k \left(\frac{d_{ik} y_{ij}}{ND} \right) trav_{ji}.$$

Appendix B

Initial N Formulation for Heuristic 1

The first step of the methodology for Heuristic 1 is to calculate an initial estimate of the number of DCs to be opened, N, using the method discussed in Erlebacher and Meller [9]. This appendix will discuss the details of this formulation for N by presenting the general formulation for N in Section B.1 and showing a detailed cost breakdown and formulation in Section B.2.

B.1 General Formulation

Determining the optimal number of open DCs is as difficult as solving the original problem. Therefore, Erlebacher and Meller provide an alternative method of calculating an estimate for N based on some simplifying assumptions. In particular, it is assumed that:

1. Customer demand is entirely homogeneous.
2. Customer properties (land cost, labor cost, etc.) are identical for all customers.
3. Any amount of demand can be assigned to any DC.
4. All open DCs must serve the same size demand.
5. Each DC serves an "optimally-shaped region."

Given these assumptions, the optimization problem is reformulated using N as a decision variable. In this formulation, each cost component will fall under one of the following four cost categories:

1. F' = Costs that increase linearly as the number of open DCs, N, increases.

2. I' = Costs that increase nonlinearly as the number of open DCs, N, increases.
3. T' = Costs that decrease nonlinearly as the number of open DCs, N, increases.
4. Costs that are not effected by the number of open DCs, N.

The optimization problem is then modeled as shown in (C.1):

$$\text{Minimize} \quad g(N) = F'N + I'\sqrt{N} + \frac{T'}{\sqrt{N}}. \tag{B.1}$$

Differentiating g and setting the result equal to 0 we obtain the following formulation for N:

$$g'(N) = 0 \Longrightarrow 4F'^2N^3 - I'^2N^2 + 2T'I'N - T'^2 = 0. \tag{B.2}$$

We use (C.2) to search for the value of N resulting in $g'(N) = 0$. This value for N is then rounded to the nearest integer value and used as a starting point for the inventory-location analysis.

B.2 Cost Organization

The cost components described in Chapter 3 are organized into the four cost categories presented in Section B.1. The results are summarized in Table B.1 below.

Table B.1: Cost Component Categories.

F': **Linear Increase**	I': **Nonlinear Increase**	T': **Nonlinear Decrease**	**No Effect**
Fixed Overhead Costs	Fixed Transportation Costs	Variable Transportation Costs	Labor Costs
Labor-related Overhead Costs	Fixed Inventory Order Costs	Pipeline Inventory Costs	
	Inventory Holding Costs		
	Land Costs		
	Land-related Overhead Costs		

All cost components in the first three categories, F', I', and T' are then modeled assuming a 1-DC solution. Each cost component will be scaled accordingly based on the number of open DCs using the formulation in (C.1). Some parameters for this formulation are new or have a slightly different meaning than the parameters described in Section 3.3.1. This is due to the fact that the characteristics for all customers and DCs are identical in this formulation. The new parameters used are:

C_{ld} = Land cost at all locations (\$/acre). This is based on the minimum land cost value in the location database.

C_{lb} = Burdened labor rate at all locations (\$/person/year). This is based on the minimum burdened labor rate value in the location database.

Q_k^{DC} = Order quantity for product k at all open DCs.

Q_k^{C} = Order quantity for product k at all customers.

R_k^{DC} = Reorder point for product k at all open DCs.

R_k^{C} = Reorder point for product k at all customers.

m_{DC} = Average mileage from DC to manufacturers.

m_C = Average mileage from customers to DC.

$trav_{DC}$ = Average travel time from manufacturers to DC $\left(trav_{DC} = \lceil \frac{m_{DC}}{avg} \rceil\right)$.

LT_{DC} = Leadtime for orders being sent to DC ($LT_{DC} = L + trav_{DC}$).

S_{DC} = Fixed shipment cost at DC (\$/shipment).

S_C = Fixed shipment cost at customers (\$/shipment).

A_{DC} = Fixed order cost at DC (\$/order).

Using the parameters above, the cost components are formulated as follows:

Category 1 (F'): Linear Increase

Fixed Overhead Costs: F

Labor-related Overhead Costs: $OH^{LB}\frac{C_{lb}}{lab}$

Category 2 (I'): Nonlinear Increase

Fixed Transportation Costs: $\sum_{k=1}^{P} \left[S_{DC} \left(\frac{D}{Q_k^{DC}} \right) + S_C \left(\frac{D}{Q_k^C} \right) \right]$

Fixed Inventory Order Costs: $\sum_{k=1}^{P} \left[A_{DC} \left(\frac{D}{Q_k^{DC}} \right) \right]$

Inventory Holding Costs: $\sum_{k=1}^{P} \left[h_k \left(\frac{Q_k^{DC}}{2} + R_k^{DC} + LT_{DC} \left(\frac{D}{ND} \right) \right) \right]$

Land Costs: $\sum_{k=1}^{P} \left[\frac{C_{ld}}{r^{ld}} \left(\frac{Q_k^{DC}}{2} + R_k^{DC} + LT_{DC} \left(\frac{D}{ND} \right) \right) \right]$

Land-related Overhead Costs: $OH^{ld} \left[\frac{C_{ld}}{land} \right] \left[\frac{\left(\frac{Q_k^{DC}}{2} \right) + R_k^{DC} + LT_{DC} \left(\frac{D}{ND} \right)}{inv} \right]$

Category 3 (T'): Nonlinear Decrease

Variable Transportation Costs: $\sum_{k=1}^{P} [(TC_k m_{DC} D) + (TC_k m_C D)]$

Pipeline Inventory Costs: $\sum_{k=1}^{P} \left[(h_k \left(\frac{D}{ND} \right) trav_{DC} \right]$

We combine these individual formulations for each cost component to obtain the following for F', I', and T':

$$F' = \left(F + OH^{LB} \frac{C_{lb}}{lab} \right) \tag{B.3}$$

$$I' = \sum_{k=1}^{P} \left[S_{DC} \left(\frac{D}{Q_k^{DC}} \right) + S_C \left(\frac{D}{Q_k^C} \right) + A_{DC} \left(\frac{D}{Q_k^{DC}} \right) \right]$$

$$+ \sum_{k=1}^{P} \left[\left(h_k + \frac{C_{ld}}{r^{ld}} + \left(\frac{OH^{LD}}{inv} \right) \left(\frac{C_{ld}}{land} \right) \right) \left(\frac{Q_k^{DC}}{2} + R_k^{DC} + LT_{DC} \left(\frac{D}{ND} \right) \right) \right] \tag{B.4}$$

$$T' = \sum_{k=1}^{P} \left[(TC_k D)\,(m_C + m_{DC}) + \left[(h_k \left(\frac{D}{ND} \right) trav_{DC} \right] \right] \tag{B.5}$$

These values for F', I', and T' are substituted into (C.2) to calculate the value of N that results in $g'(N) = 0$. This value will then be rounded to the nearest integer and used as the initial value of N to begin Heuristic 1.

Appendix C

Common Parameters

Indices:

P = number of Product Families = **5**

Demand/Supply Parameters:

d_{ik} = average annual demand of customer i for product k = **See Table 4.2**

ND = number of business days in one year = **250 days**

μ_{ik} = average daily demand $\left(\mu_{ik} = \dfrac{d_{ik}}{(ND)(P)}\right)$ = **varies based on demand**

σ_{ik} = standard deviation of daily demand = **25% of daily demand**

v_{lk} = percentage of annual supply from manufacturer l of product k = **See Section 4.4.5**

Transportation Parameters:

S_i = fixed shipment cost for customer i = **$50/shipment**

S_j = fixed shipment cost for DC j = **$50/shipment**

TC_k = variable unit transportation cost = **See Table 4.2**

m_{ji} = mileage from DC j to customer i = **varies**

m_{lj} = mileage from manufacturer l to DC j = **varies**

avg = average mileage travelled in one day = **400 miles/day**

$trav_{ji}$ = number of days necessary to travel from DC j to customer i $\left(trav_{ji} = \lceil \frac{m_{ji}}{avg} \rceil\right)$ = **varies based on mileage**

Land and Labor Parameters:

C_j^{lb} = burdened labor wage at DC j = **varies based on location**

r^{lb} = inventory processing rate per person = **150,000 units/person/year**

C_j^{ld} = land cost at DC j (\$/acre/year) = **varies based on location**

r^{ld} = inventory holding capability per acre = **1,500,000 units/acre/year**

Inventory Parameters:

h_k = unit inventory holding cost = **See Section 4.4**

A_i = order placement cost at customer i = **\$10/order for all i**

A_j = order placement cost at DC j = **\$10/order for all j**

Overhead Parameters:

F = annual fixed cost for an open DC = **\$200,000**

OH^{lb} = labor-related overhead cost for a reference city with labor-rate lab = **\$75,000**

lab = burdened labor rate for overhead reference city (\$/person/year) = **\$45,000/person/year**

OH^{ld} = land-related overhead cost for a reference city with land rate $land$ and inv units of inventory = **\$75,000**

$land$ = burdened labor rate for overhead reference city (\$/acre/year) = **\$15,000/acre/year**

inv = # units of inventory for overhead reference city = **6,500,000 units**

Service Level Parameter:

α = Type 1 service level = **95%**

z = z-value from a normal distribution corresponding to α = **1.645**

Leadtime Parameters:

L = fixed lead time parameter **= 2 days**

Appendix D

Location Cost Details

Table D.1: Location Land and Labor Costs.

Index	Location	Latitude	Longitude	Land Cost ($/Acre/Year)	Labor Cost ($/Employee/Year)
1	Alexander Cy, AL	32.93008	85.80503	$17,606	$20,721
2	Anniston, AL	33.75977	85.79233	$17,606	$27,040
3	Birmingham, AL	33.45641	86.80190	$17,606	$25,661
4	Dothan, AL	31.14812	85.37185	$17,606	$23,092
5	Huntsville, AL	34.71843	86.55644	$17,606	$23,741
6	Mobile, AL	30.70114	88.10318	$17,606	$25,607
7	Montgomery, AL	32.35699	86.25782	$17,606	$26,905
8	Fort Smith, AR	35.23125	94.33941	$13,100	$24,850
9	Lake Village, AR	33.33191	91.29770	$13,100	$18,311
10	Little Rock, AR	34.75600	92.28483	$13,100	$23,714
11	Lowell, AR	36.29589	94.12368	$13,100	$19,485
12	Paragould, AR	36.11322	90.55109	$13,100	$18,919
13	Russellville, AR	35.29465	93.07289	$13,100	$19,254
14	Springdale, AR	36.16722	94.24011	$13,100	$19,715
15	Texarkana, AR	33.43104	93.87649	$13,100	$22,011
16	Flagstaff, AZ	35.93212	111.59785	$11,947	$24,471
17	Nogales, AZ	31.46327	110.88190	$11,947	$20,134
18	Page, AZ	36.91080	111.50201	$11,947	$21,978
19	Phoenix, AZ	33.70397	112.35184	$11,947	$25,174
20	Tucson, AZ	32.21798	110.97087	$11,947	$24,552
21	Williams, AZ	35.91556	112.36603	$11,947	$20,553
22	Yuma, AZ	32.61531	114.64872	$11,947	$24,039
23	Bakersfield, CA	35.48350	119.00766	$29,868	$28,500
24	Barstow, CA	34.69361	115.85182	$29,868	$20,972
25	Bishop, CA	37.02602	118.33439	$29,868	$25,058

Table D.2: Location Land and Labor Costs.

Index	**Location**	**Latitude**	**Longitude**	**Land Cost ($/Acre/Year)**	**Labor Cost ($/Employee/Year)**
26	Blythe, CA	33.75675	115.72300	$29,868	$22,774
27	Eureka, CA	40.64632	124.02577	$29,868	$22,166
28	Fresno, CA	36.84110	119.80102	$29,868	$23,525
29	Hayward, CA	37.68018	121.92150	$29,868	$29,814
30	Los Angeles, CA	33.97395	118.24841	$29,868	$26,121
31	Modesto, CA	37.66946	121.01680	$29,868	$27,040
32	Needles, CA	34.64210	115.55873	$29,868	$20,763
33	Redding, CA	40.67574	122.45698	$29,868	$27,797
34	Sacramento, CA	38.38046	121.55541	$29,868	$29,338
35	Salinas, CA	36.44177	121.41660	$29,868	$26,210
36	San Diego, CA	32.72110	117.17437	$29,868	$35,324
37	San Francisco, CA	37.78483	122.72780	$29,868	$32,034
38	San Luis Obispo, CA	35.26557	120.62122	$29,868	$29,772
39	Stockton, CA	37.67220	121.29879	$29,868	$33,097
40	Westlake Village, CA	34.03238	119.13430	$29,868	$37,461
41	Craig, CO	40.61242	108.00978	$6,707	$22,271
42	Denver, CO	39.72630	104.85681	$6,707	$29,960
43	Durango, CO	37.31836	107.88037	$6,707	$24,450
44	Estes Park, CO	40.62811	105.56925	$6,707	$25,498
45	Grand Junction, CO	39.06902	108.58313	$6,707	$25,526
46	Kit Carson, CO	38.82717	102.59814	$6,707	$23,633
47	Lamar, CO	37.95549	102.43642	$6,707	$20,930
48	Pueblo, CO	38.34412	104.42778	$6,707	$25,985
49	East Windsor, CT	41.90335	72.59288	$69,168	$22,648
50	North Haven, CT	41.38438	72.86264	$69,168	$23,801
51	Warehouse Point, CT	41.90990	72.60295	$69,168	$21,530
52	Washington, DC	38.91194	77.01672	$73,360	$28,203
53	Bridgeville, DE	38.66030	75.33002	$29,868	$19,380
54	Bartow, FL	27.91845	81.79079	$25,152	$18,479
55	Cocoa, FL	28.31509	80.72345	$25,152	$19,275
56	Daytona Beach, FL	29.14616	81.05337	$25,152	$22,876
57	Fort Myers, FL	26.56436	81.92507	$25,152	$22,011
58	Gainesville, FL	29.68041	82.34574	$25,152	$24,255
59	Jacksonville, FL	30.33754	81.76862	$25,152	$26,851
60	Miami, FL	25.77908	80.19782	$25,152	$28,311
61	Orlando, FL	28.54518	81.37329	$25,152	$24,282
62	St Augustine, FL	29.84951	81.33255	$25,152	$21,530
63	Tallahassee, FL	30.41851	84.20338	$25,152	$23,046
64	Tampa, FL	27.99610	82.58204	$25,152	$23,444
65	Vero Beach, FL	27.63801	80.40294	$25,152	$19,212
66	West Palm Beach, FL	26.67264	80.07061	$25,152	$24,688
67	Atlanta, GA	33.84437	84.47405	$18,864	$27,986
68	Augusta, GA	33.45669	81.96918	$18,864	$22,984
69	Fort Valley, GA	32.55481	83.88866	$18,864	$18,647
70	Gainesville, GA	34.29407	83.83497	$18,864	$19,652
71	Hazlehurst, GA	31.80687	82.62699	$18,864	$18,793
72	Savannah, GA	32.07226	81.13562	$18,864	$28,635
73	Tifton, GA	31.48544	83.50362	$18,864	$19,359
74	Vidalia, GA	32.19868	82.39208	$18,864	$20,029
75	Cedar Rapids, IA	41.97661	91.65758	$18,340	$27,905

Table D.3: Location Land and Labor Costs.

Index	Location	Latitude	Longitude	Land Cost ($/Acre/Year)	Labor Cost ($/Employee/Year)
76	Davenport, IA	41.52723	90.57369	$18,340	$25,877
77	Decorah, IA	43.29425	91.78958	$18,340	$19,610
78	Des Moines, IA	41.67269	93.57217	$18,340	$29,149
79	Dubuque, IA	42.45888	90.87714	$18,340	$29,041
80	Emmetsburg, IA	43.11835	94.69076	$18,340	$18,395
81	Mt Pleasant, IA	40.99460	91.57371	$18,340	$20,008
82	Sioux City, IA	42.49475	96.39936	$18,340	$25,958
83	Spencer, IA	43.13291	95.17791	$18,340	$19,967
84	Sumner, IA	42.78792	92.30926	$18,340	$18,605
85	Boise, ID	43.60377	116.27292	$12,262	$27,635
86	Bonners Ferry, ID	48.81408	116.39820	$12,262	$20,427
87	Idaho Falls, ID	43.51670	111.69154	$12,262	$23,193
88	Twin Falls, ID	42.44322	114.62950	$12,262	$19,401
89	Byron, IL	42.09198	89.32263	$23,266	$20,448
90	Cairo, IL	37.02880	89.19275	$23,266	$18,018
91	Chicago, IL	41.81193	87.68732	$23,266	$26,797
92	Peoria, IL	40.69314	89.58985	$23,266	$30,582
93	Ringwood, IL	42.40483	88.30544	$23,266	$24,303
94	Robinson, IL	39.00456	87.75178	$23,266	$20,386
95	Springfield, IL	39.82084	89.59898	$23,266	$28,095
96	Woodstock, IL	42.32027	88.46283	$23,266	$26,357
97	Evansville, IN	37.99713	87.57496	$23,161	$25,688
98	Fort Wayne, IN	41.09376	85.07071	$23,161	$29,744
99	Indianapolis, IN	39.77509	86.13216	$23,161	$30,150
100	Madison, IN	38.80455	85.42061	$23,161	$19,464
101	Michigan City, IN	41.59419	86.75699	$23,161	$20,532
102	Muncie, IN	40.24798	85.43322	$23,161	$27,364
103	Rensselaer, IN	40.99479	87.10368	$23,161	$19,149
104	Rochester, IN	41.04099	86.25427	$23,161	$18,626
105	Dodge City, KS	37.69053	99.90242	$6,183	$19,191
106	Fort Scott, KS	37.82163	94.71479	$6,183	$17,494
107	Great Bend, KS	38.39357	98.77507	$6,183	$18,542
108	Hays, KS	38.87820	99.33480	$6,183	$19,045
109	Kansas City, KS	39.10305	94.63038	$6,183	$27,716
110	Oakley, KS	38.94581	100.97018	$6,183	$19,652
111	Salina, KS	38.82367	97.64211	$6,183	$19,149
112	Wichita, KS	37.65197	97.25900	$6,183	$23,795
113	Lexington, KY	38.03785	84.61645	$16,663	$24,769
114	Louisville, KY	38.18896	85.67682	$16,663	$31,448
115	Park City, KY	36.96515	86.01386	$16,663	$19,087
116	Alexandria, LA	31.17589	92.43118	$13,100	$21,643
117	Baton Rouge, LA	30.44924	91.18561	$13,100	$25,037
118	Hammond, LA	30.54904	90.46447	$13,100	$19,988
119	Lake Charles, LA	30.23336	93.21490	$13,100	$23,957
120	New Orleans, LA	29.95830	90.07700	$13,100	$23,795
121	Shreveport, LA	32.49820	93.75023	$13,100	$22,470
122	Auburn, MA	42.18484	71.94718	$61,832	$25,121
123	Boston, MA	42.37057	71.02696	$61,832	$37,482
124	Fall River, MA	41.75621	71.06706	$61,832	$17,892
125	Baltimore, MD	39.29654	76.62349	$36,680	$26,499

Table D.4: Location Land and Labor Costs.

Index	**Location**	**Latitude**	**Longitude**	**Land Cost ($/Acre/Year)**	**Labor Cost ($/Employee/Year)**
126	Bangor, ME	45.06174	68.87889	$12,681	$24,958
127	Calais, ME	45.18825	67.38910	$12,681	$21,517
128	Houlton, ME	46.12135	67.83301	$12,681	$22,313
129	Hulls Cove, ME	44.64187	68.39148	$12,681	$24,471
130	Portland, ME	43.65878	70.26239	$12,681	$27,716
131	Detroit, MI	42.23993	83.15082	$22,008	$34,422
132	Escanaba, MI	45.85134	87.05705	$22,008	$20,532
133	Grand Rapids, MI	42.98423	85.62910	$22,008	$29,852
134	Imlay City, MI	43.06564	83.06089	$22,008	$18,898
135	Kalamazoo, MI	42.24541	85.52986	$22,008	$34,260
136	Mackinaw City, MI	45.75302	84.69175	$22,008	$19,841
137	Marquette, MI	46.59344	87.61528	$22,008	$21,517
138	Muskegon, MI	43.29549	86.46885	$22,008	$20,407
139	Saginaw, MI	43.41242	83.88687	$22,008	$40,046
140	Saint Johns, MI	42.97967	84.58196	$22,008	$19,904
141	Sturgis, MI	41.84291	85.47827	$22,008	$20,637
142	Albert Lea, MN	43.68629	93.38984	$13,310	$20,344
143	Crookston, MN	47.70508	96.41200	$13,310	$18,751
144	Duluth, MN	47.00557	92.00193	$13,310	$30,068
145	International Falls, MN	48.23249	93.64038	$13,310	$22,355
146	Lake City, MN	44.42175	92.23222	$13,310	$21,915
147	Merrifield, MN	46.53931	94.13439	$13,310	$21,706
148	Minneapolis, MN	44.97927	93.27302	$13,310	$32,232
149	Chillicothe, MO	39.79523	93.58888	$12,471	$19,673
150	Cuba, MO	38.10008	91.36891	$12,471	$18,772
151	Hannibal, MO	39.73699	91.45683	$12,471	$19,317
152	Jefferson City, MO	38.49403	92.16519	$12,471	$20,721
153	Poplar Bluff, MO	36.77876	90.44069	$12,471	$17,557
154	Saint Joseph, MO	39.75749	94.83660	$12,471	$27,797
155	Saint Louis, MO	38.63150	90.19231	$12,471	$31,583
156	Springfield, MO	37.25807	93.34367	$12,471	$27,743
157	Washington, MO	38.52348	91.02355	$12,471	$19,149
158	Columbus, MS	33.51626	88.46132	$12,366	$18,898
159	Corinth, MS	34.87589	88.59158	$12,366	$19,359
160	Grenada, MS	33.78602	89.84546	$12,366	$18,332
161	Gulfport, MS	30.39628	89.06410	$12,366	$19,694
162	Jackson, MS	32.29110	90.19269	$12,366	$24,525
163	Meridian, MS	32.38161	88.66349	$12,366	$17,830
164	Billings, MT	45.68697	108.38739	$3,144	$21,713
165	Butte, MT	45.99790	112.59877	$3,144	$24,010
166	Great Falls, MT	47.40202	111.42295	$3,144	$25,120
167	Havre, MT	48.66300	110.09437	$3,144	$20,427
168	Helena, MT	46.70934	112.19762	$3,144	$21,412
169	Livingston, MT	45.53066	110.36905	$3,144	$20,197
170	Miles City, MT	46.44781	105.79534	$3,144	$20,700
171	Missoula, MT	46.85361	113.90912	$3,144	$20,805
172	West Glacier, MT	48.43296	114.06220	$3,144	$21,517
173	Asheville, NC	35.60271	82.56728	$25,152	$28,960
174	Charlotte, NC	35.26002	80.80415	$25,152	$26,878
175	Greensboro, NC	36.05529	79.83169	$25,152	$26,851

Table D.5: Location Land and Labor Costs.

Index	**Location**	**Latitude**	**Longitude**	**Land Cost ($/Acre/Year)**	**Labor Cost ($/Employee/Year)**
176	Raleigh, NC	35.77376	78.60418	$25,152	$25,958
177	Shelby, NC	35.31201	81.55678	$25,152	$19,967
178	Washington, NC	35.51927	76.88920	$25,152	$20,427
179	Wilmington, NC	34.16350	77.95481	$25,152	$32,583
180	Bismarck, ND	46.98121	100.50272	$4,349	$25,688
181	Fargo, ND	46.92536	96.99062	$4,349	$27,229
182	Grand Forks, ND	47.90410	97.43150	$4,349	$25,715
183	Gwinner, ND	46.15273	97.76774	$4,349	$19,170
184	Minot, ND	48.08463	101.41901	$4,349	$19,422
185	Williston, ND	48.22573	103.64905	$4,349	$19,610
186	Grand Island, NE	40.87227	98.36870	$7,284	$19,631
187	Kearney, NE	40.75141	99.12905	$7,284	$19,443
188	Lincoln, NE	40.86514	96.82313	$7,284	$28,635
189	North Platte, NE	41.10256	100.74907	$7,284	$19,757
190	Omaha, NE	41.29174	96.17110	$7,284	$28,203
191	Concord, NH	43.23031	71.53610	$24,104	$24,681
192	Atlantic City, NJ	39.48685	74.64301	$74,408	$27,013
193	Albuquerque, NM	35.19959	106.64483	$2,253	$24,688
194	Carlsbad, NM	32.41690	104.46539	$2,253	$21,936
195	Clovis, NM	34.49724	103.29498	$2,253	$21,643
196	Gallup, NM	35.65153	108.31950	$2,253	$19,862
197	Lordsburg, NM	32.31595	108.72305	$2,253	$21,203
198	Raton, NM	36.66267	104.81504	$2,253	$22,690
199	Roswell, NM	33.34667	104.59369	$2,253	$21,328
200	Santa Fe, NM	35.69747	105.98215	$2,253	$35,345
201	Socorro, NM	34.03598	107.03802	$2,253	$22,544
202	Tucumcari, NM	35.11420	103.61551	$2,253	$20,218
203	Vaughn, NM	34.60084	105.20583	$2,253	$19,485
204	Ely, NV	39.31416	114.84043	$4,611	$20,930
205	Las Vegas, NV	36.17372	115.10647	$4,611	$30,717
206	Reno, NV	39.65558	119.70461	$4,611	$27,851
207	Wells, NV	41.54392	114.82176	$4,611	$19,045
208	Winnemucca, NV	41.21348	117.70680	$4,611	$22,229
209	Albany, NY	42.61485	73.97081	$14,777	$28,311
210	Binghamton, NY	42.16563	75.89069	$14,777	$26,202
211	Bohemia, NY	40.76902	73.11337	$14,777	$28,745
212	Buffalo, NY	42.92930	78.83271	$14,777	$31,069
213	Elmira, NY	42.08259	76.71857	$14,777	$24,823
214	Middletown, NY	41.39011	74.34040	$14,777	$23,780
215	New York, NY	40.75042	73.99633	$14,777	$42,552
216	Newport, NY	43.20331	74.97189	$14,777	$20,616
217	Rochester, NY	43.28602	77.68426	$14,777	$29,176
218	Syracuse, NY	43.02143	76.19770	$14,777	$27,148
219	Watertown, NY	44.07254	76.01659	$14,777	$20,155
220	Bucyrus, OH	40.83267	82.97388	$23,580	$19,149
221	Cincinnati, OH	39.16676	84.53822	$23,580	$28,771
222	Cleveland, OH	41.52340	81.59965	$23,580	$28,987
223	Columbus, OH	40.04011	82.89722	$23,580	$29,284
224	Delphos, OH	40.79444	84.31160	$23,580	$19,736
225	Gallipolis, OH	38.79376	82.26920	$23,580	$18,353

Table D.6: Location Land and Labor Costs.

Index	**Location**	**Latitude**	**Longitude**	**Land Cost ($/Acre/Year)**	**Labor Cost ($/Employee/Year)**
226	Hubbard, OH	41.23609	80.73697	$23,580	$18,165
227	Lykens, OH	41.04655	82.96876	$23,580	$18,437
228	N Canton, OH	40.89561	81.43304	$23,580	$18,437
229	Toledo, OH	41.72068	83.56936	$23,580	$32,259
230	Urbana, OH	40.12172	83.79731	$23,580	$21,140
231	Atoka, OK	34.35825	96.08250	$6,644	$16,761
232	Guymon, OK	36.72971	101.42615	$6,644	$18,290
233	Oklahoma City, OK	35.49161	97.56282	$6,644	$24,012
234	Tulsa, OK	36.03915	95.86867	$6,644	$28,040
235	Astoria, OR	46.14221	123.79600	$10,690	$22,690
236	Bend, OR	44.08204	121.22713	$10,690	$23,465
237	Biggs, OR	45.59745	120.73036	$10,690	$21,530
238	Burns, OR	43.55429	118.87427	$10,690	$21,328
239	Coos Bay, OR	43.21514	124.19836	$10,690	$21,349
240	Eugene, OR	44.11787	123.07419	$10,690	$28,284
241	Grants Pass, OR	42.40214	123.41612	$10,690	$21,726
242	Klamath Falls, OR	42.29329	121.81687	$10,690	$22,523
243	Lakeview, OR	42.18076	120.36961	$10,690	$21,936
244	Newport, OR	44.55241	124.02443	$10,690	$23,612
245	Pendleton, OR	45.71181	118.63797	$10,690	$23,549
246	Portland, OR	45.49893	122.69316	$10,690	$29,095
247	Allentown, PA	40.60750	75.47003	$27,458	$28,149
248	Altoona, PA	40.50177	78.41004	$27,458	$24,066
249	Harrisburg, PA	40.26459	76.86964	$27,458	$35,855
250	Philadelphia, PA	40.00181	75.11787	$27,458	$30,285
251	Pittsburgh, PA	40.43444	80.02482	$27,458	$31,529
252	Scranton, PA	41.40188	75.63763	$27,458	$28,419
253	Youngstown, PA	40.27934	79.36607	$27,458	$18,940
254	Charleston, SC	32.78033	79.94084	$16,768	$25,255
255	Columbia, SC	33.98745	81.02486	$16,768	$27,824
256	Florence, SC	34.04985	79.68536	$16,768	$23,254
257	Greenville, SC	34.84857	82.40287	$16,768	$28,311
258	Myrtle Beach, SC	33.71174	78.85201	$16,768	$24,904
259	Aberdeen, SD	45.47617	98.41041	$3,982	$21,077
260	Pierre, SD	44.33407	100.09420	$3,982	$21,349
261	Rapid City, SD	44.00436	103.24002	$3,982	$23,065
262	Sioux Falls, SD	43.54636	96.69063	$3,982	$25,174
263	Watertown, SD	44.95564	97.17795	$3,982	$19,485
264	Chattanooga, TN	35.01782	85.20643	$22,008	$27,229
265	Crossville, TN	35.96235	85.05143	$22,008	$19,149
266	Knoxville, TN	36.03233	83.88480	$22,008	$31,177
267	Memphis, TN	35.16926	89.99042	$22,008	$27,851
268	Morrison, TN	35.62137	85.87597	$22,008	$18,395
269	Nashville, TN	36.16569	86.77810	$22,008	$27,392
270	Amarillo, TX	35.20545	101.79551	$6,602	$22,578
271	Austin, TX	30.32637	97.77126	$6,602	$25,742
272	Brownsville, TX	26.05216	97.51447	$6,602	$21,362
273	Brownwood, TX	31.77539	98.99153	$6,602	$17,830
274	Cisco, TX	32.28648	98.97332	$6,602	$18,018
275	Corpus Christi, TX	27.75940	97.64816	$6,602	$22,578

Table D.7: Location Land and Labor Costs.

Index	**Location**	**Latitude**	**Longitude**	**Land Cost ($/Acre/Year)**	**Labor Cost ($/Employee/Year)**
276	Dallas, TX	32.78118	96.79033	$6,602	$25,985
277	Del Rio, TX	29.41020	100.89320	$6,602	$18,626
278	El Paso, TX	31.76361	106.48459	$6,602	$21,821
279	Fort Stockton, TX	30.88637	102.89049	$6,602	$17,788
280	Fort Worth, TX	32.77142	97.29148	$6,602	$25,877
281	Freeport, TX	29.16192	95.34239	$6,602	$18,332
282	Houston, TX	29.81314	95.30979	$6,602	$26,175
283	Laredo, TX	27.51588	99.49408	$6,602	$21,605
284	Lubbock, TX	33.60770	101.84206	$6,602	$23,687
285	Marathon, TX	29.81874	103.06072	$6,602	$19,401
286	Mcallen, TX	26.26931	98.22436	$6,602	$19,883
287	Muenster, TX	33.69067	97.34502	$6,602	$20,218
288	Nederland, TX	29.99225	94.19545	$6,602	$19,736
289	Odessa, TX	31.76516	102.35435	$6,602	$25,742
290	San Angelo, TX	31.44451	100.53340	$6,602	$22,254
291	San Antonio, TX	29.39993	98.53750	$6,602	$23,552
292	Snyder, TX	32.74507	100.91748	$6,602	$18,123
293	Vernon, TX	34.15552	99.28400	$6,602	$18,668
294	Victoria, TX	28.77737	97.02668	$6,602	$21,794
295	Green River, UT	39.02008	110.21386	$9,432	$21,643
296	Saint George, UT	37.30685	113.35542	$9,432	$21,530
297	Salina, UT	38.92140	111.90816	$9,432	$19,254
298	Salt Lake City, UT	40.75610	111.90072	$9,432	$28,013
299	Spanish Fork, UT	40.06995	111.64909	$9,432	$21,161
300	Springdale, UT	37.18625	113.01392	$9,432	$21,530
301	Harrisonburg, VA	38.42278	78.87714	$22,322	$21,831
302	Norfolk, VA	36.89591	76.20852	$22,322	$26,175
303	Richmond, VA	37.52425	77.49316	$22,322	$25,742
304	Roanoke, VA	37.27418	79.95786	$22,322	$26,824
305	Ellensburg, WA	47.02808	120.48998	$12,052	$20,847
306	Everett, WA	47.98866	122.19980	$12,052	$32,664
307	Pasco, WA	46.42066	118.89945	$12,052	$27,364
308	Port Angeles, WA	48.05111	123.36041	$12,052	$22,816
309	Seattle, WA	47.43225	121.80339	$12,052	$32,664
310	Spokane, WA	47.66264	117.43600	$12,052	$28,635
311	Wenatchee, WA	47.57382	120.35188	$12,052	$20,909
312	Eau Claire, WI	44.75653	91.47310	$15,720	$26,607
313	Green Bay, WI	44.49439	87.97605	$15,720	$29,852
314	La Crosse, WI	43.85456	91.13207	$15,720	$28,284
315	Madison, WI	43.06956	89.42386	$15,720	$30,582
316	Milwaukee, WI	43.01126	87.95841	$15,720	$29,555
317	Oshkosh, WI	44.00566	88.55756	$15,720	$27,121
318	Plover, WI	44.41394	89.56551	$15,720	$21,098
319	Walworth, WI	42.56154	88.59715	$15,720	$22,271
320	Bluefield, WV	37.33273	81.16007	$11,109	$19,631
321	Charleston, WV	38.32895	81.60509	$11,109	$20,929
322	Casper, WY	42.85988	106.31256	$2,463	$25,580
323	Cheyenne, WY	41.25173	104.56264	$2,463	$25,201
324	Cody, WY	44.54164	109.43659	$2,463	$22,062
325	Rawlins, WY	41.53808	106.92196	$2,463	$20,951
326	Sheridan, WY	44.78038	106.83756	$2,463	$22,083

Appendix E

Customer Location and Demand Data — Average Demand of 5,000

Table E.1: Customer Data Sets — Average Demand = 5,000; 20 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Tallahassee, FL	9,891	Oklahoma City, OK	10,875	Grand Island, NE	8,309
	Salina, UT	12,435	Hubbard, OH	9,787	Walworth, WI	11,923
	Idaho Falls, ID	9,357	Nashville, TN	9,662	Carlsbad, NM	8,564
	Gallup, NM	8,785	Nogales, AZ	11,560	Vernon, TX	10,446
B	Binghamton, NY	4,216	Youngstown, PA	5,823	Cairo, IL	5,083
	Plover, WI	4,395	Amarillo, TX	4,054	St Augustine, FL	4,879
	Oshkosh, WI	5,640	Saint Johns, MI	5,713	Knoxville, TN	5,631
	Nogales, AZ	4,829	Watertown, SD	4,595	Lincoln, NE	5,644
	Westlake Village, CA	4,223	Pueblo, CO	4,087	Sheridan, WY	4,747
	Boston, MA	4,724	Asheville, NC	5,473	Marathon, TX	4,570
C	Rochester, IN	3,433	Rochester, IN	2,755	Lykens, OH	2,773
	Pueblo, CO	3,056	Crossville, TN	2,571	Grand Junction, CO	2,576
	Aberdeen, SD	3,020	Houston, TX	2,660	Snyder, TX	2,571
	Charlotte, NC	2,746	Elmira, NY	3,088	Pasco, WA	2,780
	Portland, ME	2,892	Westlake Village, CA	2,684	Needles, CA	3,189
	Greenville, SC	3,155	Minot, ND	2,781	Roswell, NM	3,147
	Omaha, NE	3,159	Baton Rouge, LA	3,105	Chattanooga, TN	3,047
	Charleston, SC	3,022	Plover, WI	2,978	North Platte, NE	3,413
	Laredo, TX	3,045	Minneapolis, MN	2,872	Eugene, OR	3,291
	Corinth, MS	3,089	Des Moines, IA	2,691	Missoula, MT	2,623

Table E.2: Customer Data Sets — Average Demand = 5,000; 20 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Ely, NV	9,508	Lubbock, TX	11,081	Binghamton, NY	12,154
	Bonners Ferry, ID	8,913	Byron, IL	10,143	Tucumcari, NM	10,678
	Hays, KS	10,468	Fresno, CA	8,978	Chattanooga, TN	12,306
	Bakersfield, CA	10,024	Lake City, MN	7,904	Watertown, NY	9,492
B	Lamar, CO	5,610	Corpus Christi, TX	5,160	Woodstock, IL	5,139
	Birmingham, AL	4,975	Hays, KS	4,789	Stockton, CA	4,397
	Cedar Rapids, IA	5,018	Calais, ME	4,308	Vaughn, NM	5,315
	Pierre, SD	4,062	Spanish Fork, UT	4,174	Urbana, OH	5,533
	Plover, WI	4,042	Springfield, MO	5,676	Eau Claire, WI	4,387
	Tucson, AZ	5,341	Livingston, MT	4,474	Toledo, OH	4,191
C	Miami, FL	3,255	Jefferson City, MO	3,448	Little Rock, AR	2,581
	Alexander Cy, AL	2,615	Gulfport, MS	2,719	Sheridan, WY	3,286
	Nogales, AZ	2,768	Greensboro, NC	2,704	Philadelphia, PA	2,814
	Lakeview, OR	2,873	Birmingham, AL	2,644	Greensboro, NC	3,089
	Minneapolis, MN	2,772	Fort Valley, GA	2,840	Salina, UT	2,758
	Fort Stockton, TX	3,422	Orlando, FL	2,579	Billings, MT	2,807
	Myrtle Beach, SC	3,355	Wilmington, NC	2,690	Gwinner, ND	2,615
	Great Bend, KS	2,704	Estes Park, CO	2,749	Hulls Cove, ME	3,193
	Green Bay, WI	2,975	Florence, SC	2,892	Alexandria, LA	3,058
	Toledo, OH	2,905	Needles, CA	2,959	Marquette, MI	2,712
	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Newport, OR	7,522	Roswell, NM	10,590	Vernon, TX	8,236
	Hayward, CA	7,616	Cleveland, OH	11,819	Minot, ND	12,322
	Lowell, AR	8,116	Havre, MT	11,623	Harrisonburg, VA	10,012
	Paragould, AR	9,387	Pittsburgh, PA	10,690	Port Angeles, WA	12,317
B	Indianapolis, IN	5,635	Davenport, IA	5,915	Hubbard, OH	4,985
	Omaha, NE	5,848	Williams, AZ	5,448	Mt Pleasant, IA	4,561
	Pierre, SD	5,614	Helena, MT	4,392	Green River, UT	4,802
	Gainesville, GA	5,823	Watertown, SD	5,760	Brownsville, TX	5,184
	Oklahoma City, OK	4,109	Bishop, CA	4,594	Calais, ME	4,505
	Knoxville, TN	4,501	Meridian, MS	4,336	Sioux Falls, SD	4,319
C	Oakley, KS	3,286	Baltimore, MD	2,763	Tucumcari, NM	2,599
	Crossville, TN	2,616	Grants Pass, OR	3,362	Robinson, IL	2,757
	Wichita, KS	2,994	Fort Wayne, IN	3,119	Newport, NY	3,051
	Austin, TX	2,874	Bangor, ME	2,794	Alexander Cy, AL	3,039
	Hays, KS	2,898	Raton, NM	3,166	Fort Wayne, IN	2,994
	Minneapolis, MN	2,676	Washington, DC	3,336	Los Angeles, CA	2,934
	New York, NY	3,097	Alexander Cy, AL	2,883	Barstow, CA	3,233
	Sioux City, IA	2,791	Louisville, KY	2,764	Albuquerque, NM	3,398
	Pittsburgh, PA	3,422	West Glacier, MT	3,378	Bridgeville, DE	2,811
	Charlotte, NC	3,395	Gallup, NM	2,982	Vidalia, GA	2,603

Table E.3: Customer Data Sets — Average Demand = 5,000; 20 Locations.

	Set 10	d_i
A	Kearney, NE	9,322
	Charleston, SC	11,423
	Dubuque, IA	9,541
	Klamath Falls, OR	12,109
B	Idaho Falls, ID	5,691
	Vaughn, NM	5,496
	Tulsa, OK	4,905
	Miles City, MT	4,712
	Chicago, IL	4,835
	Shreveport, LA	4,876
C	Gwinner, ND	2,576
	Pasco, WA	3,179
	Newport, OR	3,273
	Boise, ID	2,662
	N Canton, OH	2,602
	Madison, IN	3,436
	Estes Park, CO	2,992
	Milwaukee, WI	3,202
	El Paso, TX	2,581
	Memphis, TN	3,428

Table E.4: Customer Data Sets — Average Demand = 5,000; 50 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Minneapolis, MN	11,772	Jacksonville, FL	12,462	Shreveport, LA	8,362
	West Glacier, MT	12,296	Las Vegas, NV	12,451	Salinas, CA	8,537
	Burns, OR	9,364	Watertown, SD	8,032	Portland, ME	9,321
	Savannah, GA	8,490	Minneapolis, MN	9,763	North Haven, CT	11,981
	North Haven, CT	12,288	Great Falls, MT	11,802	Chattanooga, TN	12,216
	Park City, KY	8,984	Binghamton, NY	11,492	Fort Stockton, TX	7,878
	Modesto, CA	11,949	Grand Rapids, MI	11,725	Plover, WI	12,273
	Rawlins, WY	10,062	Fort Scott, KS	11,401	Crossville, TN	9,179
	N Canton, OH	7,968	West Palm Beach, FL	7,950	Bishop, CA	9,396
	Plover, WI	9,400	Little Rock, AR	8,807	Kansas City, KS	9,886
B	Chicago, IL	4,301	Fort Smith, AR	5,445	Altoona, PA	5,834
	Lexington, KY	5,436	Wenatchee, WA	4,324	Evansville, IN	5,533
	New York, NY	4,593	New Orleans, LA	4,921	Seattle, WA	5,717
	Salt Lake City, UT	4,808	Gainesville, FL	4,850	Montgomery, AL	5,848
	Marquette, MI	5,370	Concord, NH	4,976	Las Vegas, NV	5,416
	San Diego, CA	5,732	Spanish Fork, UT	5,947	Miami, FL	4,037
	Bismarck, ND	5,478	Emmetsburg, IA	5,409	Butte, MT	5,886
	New Orleans, LA	5,662	Gwinner, ND	4,010	Minot, ND	5,107
	Lake City, MN	5,274	Evansville, IN	5,801	Hammond, LA	4,631
	Portland, OR	4,337	Hulls Cove, ME	5,811	Aberdeen, SD	4,858
	Corinth, MS	4,631	Orlando, FL	4,273	Sioux Falls, SD	4,636
	Hubbard, OH	5,923	Chattanooga, TN	4,723	Roanoke, VA	5,420
	Charlotte, NC	5,721	Tampa, FL	4,270	Gainesville, FL	5,647
	Seattle, WA	4,961	Snyder, TX	5,133	Amarillo, TX	5,103
	Salina, UT	4,255	Park City, KY	4,413	Charleston, WV	4,667
C	Texarkana, AR	3,294	Coos Bay, OR	3,021	Fall River, MA	2,613
	Lincoln, NE	3,337	Poplar Bluff, MO	2,642	Coos Bay, OR	2,948
	Billings, MT	2,805	Mackinaw City, MI	3,354	Alexander Cy, AL	3,200
	Florence, SC	3,252	Great Bend, KS	3,444	Rapid City, SD	2,942
	Columbus, MS	2,970	Baltimore, MD	2,873	Des Moines, IA	3,384
	Vidalia, GA	2,951	Hammond, LA	2,964	Washington, MO	3,076
	Cody, WY	2,716	Madison, IN	3,402	Columbia, SC	2,791
	Des Moines, IA	2,617	Michigan City, IN	3,095	Watertown, SD	3,344
	Fort Stockton, TX	3,323	Imlay City, MI	2,607	Cincinnati, OH	3,334
	Guymon, OK	2,565	Urbana, OH	2,985	Morrison, TN	3,228
	Myrtle Beach, SC	2,714	Syracuse, NY	3,072	Gwinner, ND	3,248
	Dodge City, KS	3,329	Washington, DC	3,315	New York, NY	3,271
	San Angelo, TX	3,384	San Angelo, TX	2,809	Corinth, MS	3,434
	Fargo, ND	3,131	Salinas, CA	3,244	Bluefield, WV	3,412
	Louisville, KY	3,291	Elmira, NY	3,032	Gallup, NM	2,662
	Pendleton, OR	3,421	Grants Pass, OR	3,382	Jefferson City, MO	3,052
	Miami, FL	2,896	Escanaba, MI	3,007	Rensselaer, IN	3,121
	Craig, CO	3,078	Louisville, KY	3,138	Socorro, NM	3,388
	Oshkosh, WI	3,443	Newport, OR	2,669	Page, AZ	2,666
	Hays, KS	3,357	Watertown, NY	2,616	Milwaukee, WI	2,696
	Mackinaw City, MI	2,936	Knoxville, TN	3,371	Michigan City, IN	3,095
	Toledo, OH	2,823	Lincoln, NE	3,023	Miles City, MT	3,150
	Saint George, UT	3,160	Newport, NY	2,571	Bartow, FL	3,423
	Springfield, MO	3,288	Youngstown, PA	2,639	Lake Charles, LA	2,682
	Memphis, TN	2,849	North Platte, NE	3,084	Decorah, IA	3,137

Table E.5: Customer Data Sets — Average Demand = 5,000; 50 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Rochester, IN	8,369	Rapid City, SD	10,219	Great Bend, KS	12,189
	Meridian, MS	10,969	Gainesville, FL	7,714	Peoria, IL	8,420
	Tulsa, OK	9,685	Saginaw, MI	11,931	Vernon, TX	11,639
	Pasco, WA	9,014	Bakersfield, CA	7,850	Odessa, TX	8,685
	Tucson, AZ	11,876	Fort Worth, TX	11,997	Ellensburg, WA	11,519
	Madison, WI	12,484	Green Bay, WI	11,610	Pittsburgh, PA	9,255
	Raton, NM	9,884	Oakley, KS	11,844	Columbia, SC	10,954
	Woodstock, IL	7,585	Warehouse Point, CT	11,924	Missoula, MT	11,140
	N Canton, OH	7,522	Miami, FL	9,861	Kansas City, KS	10,427
	Grand Island, NE	11,723	Fall River, MA	7,589	Altoona, PA	12,224
B	Barstow, CA	4,105	Eau Claire, WI	4,368	Lykens, OH	5,549
	Brownwood, TX	5,282	Minot, ND	4,907	Baltimore, MD	4,333
	Corpus Christi, TX	5,823	Amarillo, TX	4,734	Biggs, OR	4,490
	Springfield, MO	4,148	Milwaukee, WI	4,226	Del Rio, TX	4,805
	Gallup, NM	4,295	Walworth, WI	5,355	Port Angeles, WA	5,224
	Phoenix, AZ	5,974	Billings, MT	5,673	Robinson, IL	4,998
	Albuquerque, NM	5,033	Wells, NV	5,017	Gallup, NM	5,613
	Livingston, MT	5,190	Saint Johns, MI	4,471	Houlton, ME	4,044
	Eugene, OR	4,319	Williams, AZ	5,188	Everett, WA	4,309
	Washington, DC	4,649	Fort Stockton, TX	4,407	Rensselaer, IN	4,693
	Norfolk, VA	4,293	Shelby, NC	4,867	Atoka, OK	4,527
	Russellville, AR	4,380	Hulls Cove, ME	5,965	Lake City, MN	4,234
	Winnemucca, NV	5,514	El Paso, TX	4,517	Craig, CO	5,863
	Freeport, TX	5,389	Calais, ME	5,088	Toledo, OH	4,803
	Nederland, TX	5,910	Raton, NM	4,093	Green Bay, WI	4,784
C	Merrifield, MN	3,359	Chillicothe, MO	3,090	Daytona Beach, FL	2,933
	Mt Pleasant, IA	2,829	Huntsville, AL	3,341	New York, NY	2,947
	Washington, NC	2,742	Springfield, MO	3,003	Cuba, MO	3,240
	Port Angeles, WA	3,249	Chattanooga, TN	2,799	Warehouse Point, CT	3,212
	Estes Park, CO	2,929	Jefferson City, MO	3,325	Portland, ME	3,391
	San Diego, CA	3,148	Las Vegas, NV	3,430	Baton Rouge, LA	3,368
	Baltimore, MD	3,194	Watertown, NY	3,269	Durango, CO	2,849
	Grand Junction, CO	2,879	Idaho Falls, ID	3,284	New Orleans, LA	3,307
	Eureka, CA	2,688	Decorah, IA	3,392	Eau Claire, WI	2,870
	East Windsor, CT	2,959	San Antonio, TX	2,738	Wilmington, NC	2,993
	Plover, WI	3,402	Meridian, MS	3,434	Brownsville, TX	2,838
	Los Angeles, CA	2,686	Carlsbad, NM	3,433	Alexandria, LA	3,372
	Pittsburgh, PA	3,309	Marquette, MI	3,444	Grand Rapids, MI	3,308
	Hazlehurst, GA	2,789	San Luis Obispo, CA	3,021	Bucyrus, OH	3,131
	Roanoke, VA	3,299	North Platte, NE	2,861	Duluth, MN	2,883
	Hubbard, OH	3,349	Lake Charles, LA	3,075	Madison, WI	3,346
	Springdale, AR	3,394	Delphos, OH	3,398	Muskegon, MI	2,630
	Muskegon, MI	3,288	Guymon, OK	2,696	Washington, NC	2,635
	Tallahassee, FL	2,712	Birmingham, AL	3,429	Denver, CO	3,052
	Cocoa, FL	3,152	Redding, CA	3,267	Allentown, PA	2,779
	Cincinnati, OH	3,045	Baton Rouge, LA	3,102	Modesto, CA	3,158
	Rapid City, SD	3,377	Mackinaw City, MI	3,040	Marquette, MI	2,717
	Middletown, NY	3,331	Boise, ID	3,280	Victoria, TX	2,795
	Greensboro, NC	2,859	Davenport, IA	3,038	Watertown, NY	3,328
	Nashville, TN	2,805	Sioux City, IA	2,679	Meridian, MS	2,811

Table E.6: Customer Data Sets — Average Demand = 5,000; 50 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Muncie, IN	11,215	Socorro, NM	8,964	Burns, OR	11,977
	Barstow, CA	8,561	Richmond, VA	11,902	Reno, NV	11,001
	Daytona Beach, FL	9,596	San Francisco, CA	12,169	Michigan City, IN	10,557
	Gainesville, FL	11,094	Bakersfield, CA	11,517	Bangor, ME	11,901
	Spencer, IA	8,221	Seattle, WA	9,094	Atlantic City, NJ	10,076
	Sheridan, WY	8,953	Coos Bay, OR	9,628	Gallipolis, OH	10,127
	Fort Valley, GA	9,507	Denver, CO	11,767	Hubbard, OH	7,522
	Robinson, IL	10,659	Charlotte, NC	10,173	Fort Smith, AR	11,211
	Columbia, SC	9,642	Tucson, AZ	8,503	Corinth, MS	11,457
	Madison, WI	11,239	Saint Louis, MO	10,861	Muncie, IN	9,841
B	Grand Island, NE	5,704	Louisville, KY	4,404	Jackson, MS	4,608
	Needles, CA	5,891	Paragould, AR	5,863	Lincoln, NE	4,881
	Portland, OR	4,512	St Augustine, FL	4,457	Spokane, WA	5,742
	Green Bay, WI	5,293	Pasco, WA	5,797	Birmingham, AL	5,677
	Middletown, NY	5,903	Saint George, UT	5,115	Tulsa, OK	5,173
	Bismarck, ND	4,565	North Haven, CT	4,790	Saint Johns, MI	5,026
	Corinth, MS	5,685	Salt Lake City, UT	5,750	Binghamton, NY	4,217
	Green River, UT	5,639	Fresno, CA	5,085	Newport, NY	5,385
	Saint Johns, MI	4,600	Chicago, IL	5,731	Winnemucca, NV	5,756
	Salinas, CA	5,295	West Palm Beach, FL	4,554	Charlotte, NC	5,982
	Washington, NC	5,401	Charleston, SC	5,931	Nederland, TX	5,387
	Decorah, IA	5,433	Portland, ME	5,989	Kearney, NE	4,815
	Clovis, NM	4,816	Fargo, ND	5,306	Redding, CA	4,104
	Estes Park, CO	5,398	Winnemucca, NV	4,284	Chattanooga, TN	5,553
	Chattanooga, TN	5,331	Des Moines, IA	5,090	Fort Worth, TX	5,899
C	Birmingham, AL	2,635	Allentown, PA	2,756	Lakeview, OR	2,963
	Gwinner, ND	3,356	Urbana, OH	2,945	New Orleans, LA	2,661
	Detroit, MI	3,256	Kit Carson, CO	2,775	Richmond, VA	3,129
	Portland, ME	3,198	Biggs, OR	2,739	Columbia, SC	3,426
	Sacramento, CA	2,876	Fort Smith, AR	2,667	Augusta, GA	2,933
	Wenatchee, WA	2,551	Dallas, TX	2,998	Byron, IL	2,836
	Lake Charles, LA	3,077	Lincoln, NE	2,757	Rochester, NY	2,600
	International Falls, MN	3,273	Cocoa, FL	3,255	Kalamazoo, MI	2,893
	Missoula, MT	2,867	Mobile, AL	3,400	Mcallen, TX	2,984
	Cedar Rapids, IA	3,353	Spokane, WA	2,713	Billings, MT	3,075
	Vaughn, NM	2,897	Butte, MT	3,334	Toledo, OH	2,951
	Salt Lake City, UT	3,044	Rawlins, WY	3,292	Pasco, WA	3,061
	Vernon, TX	3,178	Watertown, SD	3,431	Scranton, PA	2,835
	Lordsburg, NM	3,220	Davenport, IA	3,339	Mackinaw City, MI	3,315
	Mackinaw City, MI	2,944	Sioux City, IA	2,817	Nogales, AZ	3,018
	Gallipolis, OH	2,995	Jacksonville, FL	2,809	Indianapolis, IN	2,920
	Albany, NY	3,113	Muskegon, MI	2,795	Huntsville, AL	3,203
	Urbana, OH	3,070	Vernon, TX	2,732	Carlsbad, NM	3,264
	Washington, MO	3,278	N Canton, OH	2,736	Emmetsburg, IA	3,095
	Carlsbad, NM	3,151	Columbia, SC	3,027	Ringwood, IL	3,123
	Cheyenne, WY	3,118	Modesto, CA	2,642	Great Bend, KS	2,642
	San Luis Obispo, CA	2,641	Bonners Ferry, ID	3,171	Bakersfield, CA	2,640
	Calais, ME	3,276	Everett, WA	3,192	Park City, KY	2,870
	Huntsville, AL	2,855	Park City, KY	2,871	Syracuse, NY	2,817
	Buffalo, NY	3,214	Chattanooga, TN	3,290	Salt Lake City, UT	3,323

Table E.7: Customer Data Sets — Average Demand = 5,000; 50 Locations.

	Set 10	d_i
A	Missoula, MT	9,448
	Augusta, GA	8,464
	Philadelphia, PA	11,620
	Davenport, IA	10,683
	Hulls Cove, ME	9,047
	Rensselaer, IN	11,231
	Livingston, MT	10,236
	Fort Valley, GA	7,977
	St Augustine, FL	12,426
	Lake Village, AR	8,317
B	Baton Rouge, LA	4,691
	Saint George, UT	5,498
	Fall River, MA	4,971
	Amarillo, TX	5,241
	Cleveland, OH	5,095
	Del Rio, TX	5,464
	Morrison, TN	5,391
	Tucumcari, NM	4,636
	San Diego, CA	4,252
	Freeport, TX	4,637
	Page, AZ	5,756
	Estes Park, CO	5,737
	Victoria, TX	5,067
	Flagstaff, AZ	5,869
	Atoka, OK	5,905
C	Nederland, TX	2,667
	Bohemia, NY	3,376
	Bakersfield, CA	2,642
	Warehouse Point, CT	2,976
	Fargo, ND	2,647
	Bismarck, ND	3,099
	Tulsa, OK	2,742
	Biggs, OR	2,917
	Shelby, NC	2,890
	Clovis, NM	3,082
	Green River, UT	3,114
	Fort Wayne, IN	3,418
	Cocoa, FL	2,864
	Savannah, GA	3,344
	Casper, WY	3,068
	Lincoln, NE	2,807
	Shreveport, LA	3,233
	Grand Forks, ND	3,030
	Alexandria, LA	3,405
	Nogales, AZ	2,910
	N Canton, OH	3,398
	Saint Louis, MO	2,597
	Columbus, OH	3,230
	Lakeview, OR	2,799
	Stockton, CA	3,239

Table E.8: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Miami, FL	9,722	Austin, TX	9,032	Shreveport, LA	12,115
	Harrisonburg, VA	11,247	Knoxville, TN	10,303	Dubuque, IA	8,344
	Everett, WA	11,700	El Paso, TX	11,119	Park City, KY	9,133
	Lubbock, TX	10,818	Portland, ME	8,034	Cleveland, OH	10,098
	Columbia, SC	9,472	Bluefield, WV	9,271	Gulfport, MS	11,655
	Hubbard, OH	12,371	Lake Charles, LA	8,352	Kit Carson, CO	9,902
	Bohemia, NY	8,706	Craig, CO	7,530	Auburn, MA	10,388
	Meridian, MS	8,086	Fall River, MA	8,523	Binghamton, NY	11,448
	Cisco, TX	11,575	New York, NY	10,032	Guymon, OK	10,492
	Green River, UT	10,451	Gulfport, MS	9,596	Coos Bay, OR	9,257
	Marathon, TX	10,403	Birmingham, AL	7,626	Evansville, IN	12,002
	Jacksonville, FL	10,209	Los Angeles, CA	10,804	Woodstock, IL	8,860
	Tifton, GA	11,127	Everett, WA	8,663	Tifton, GA	7,778
	Lake Charles, LA	8,083	Madison, IN	12,185	Marquette, MI	10,246
	Gainesville, GA	8,603	Louisville, KY	11,092	Atlanta, GA	10,425
	Charlotte, NC	10,948	Laredo, TX	7,605	Spanish Fork, UT	8,534
	Williston, ND	9,718	Hazlehurst, GA	10,459	Livingston, MT	9,770
	Burns, OR	7,679	Pueblo, CO	12,232	Indianapolis, IN	9,100
	Lamar, CO	8,975	Snyder, TX	10,755	Cody, WY	10,567
	Seattle, WA	10,837	Eugene, OR	11,365	Spokane, WA	10,295
B	Paragould, AR	4,799	Rochester, NY	4,110	Redding, CA	5,587
	Fort Stockton, TX	5,070	Houston, TX	4,534	Eau Claire, WI	4,622
	Emmetsburg, IA	4,400	Hulls Cove, ME	4,831	Saint Joseph, MO	4,422
	Kalamazoo, MI	4,118	Sacramento, CA	4,138	N Canton, OH	5,303
	San Luis Obispo, CA	4,338	Myrtle Beach, SC	4,829	Albuquerque, NM	4,230
	Mackinaw City, MI	4,207	Boise, ID	4,457	Lake City, MN	4,956
	Dubuque, IA	5,345	Warehouse Point, CT	5,583	Corinth, MS	4,383
	Cody, WY	4,593	Merrifield, MN	5,502	Rawlins, WY	5,578
	Park City, KY	5,651	Saint Louis, MO	4,717	Santa Fe, NM	5,930
	Stockton, CA	5,849	Green Bay, WI	5,760	Meridian, MS	4,599
	Bridgeville, DE	5,038	Morrison, TN	4,814	Rochester, NY	4,997
	Springfield, IL	5,618	Evansville, IN	5,294	Lakeview, OR	5,174
	Freeport, TX	5,349	Yuma, AZ	5,851	Klamath Falls, OR	4,408
	Santa Fe, NM	4,623	Escanaba, MI	5,637	Alexandria, LA	4,584
	Rochester, NY	5,120	Dodge City, KS	4,532	Nashville, TN	4,293
	Evansville, IN	4,090	Harrisonburg, VA	4,992	Las Vegas, NV	4,883
	Atoka, OK	5,417	Spencer, IA	4,353	Jefferson City, MO	4,695
	Fresno, CA	4,669	Wilmington, NC	4,074	Baltimore, MD	4,880
	Gwinner, ND	4,080	Poplar Bluff, MO	4,291	Helena, MT	4,292
	Denver, CO	5,987	Bridgeville, DE	4,946	Baton Rouge, LA	5,246
	Wichita, KS	4,162	Tucson, AZ	4,758	Cisco, TX	4,843
	Jefferson City, MO	4,759	Roswell, NM	5,964	Robinson, IL	4,314
	Las Vegas, NV	5,217	Bismarck, ND	4,649	Needles, CA	4,889
	Fort Valley, GA	5,590	Greensboro, NC	4,146	San Luis Obispo, CA	5,980
	Blythe, CA	5,026	Auburn, MA	5,826	Aberdeen, SD	4,362
	Saint George, UT	4,426	Marquette, MI	4,050	Bartow, FL	5,510
	Escanaba, MI	5,247	Lamar, CO	4,972	San Francisco, CA	4,381
	Muskegon, MI	4,764	San Angelo, TX	5,919	Harrisonburg, VA	5,277
	Tucson, AZ	5,608	Mcallen, TX	5,134	Little Rock, AR	4,021
	Des Moines, IA	5,159	Tampa, FL	4,714	Vidalia, GA	5,899

Table E.9: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
C	Muncie, IN	3,225	Fort Valley, GA	2,907	Odessa, TX	2,932
	Bend, OR	3,211	Hubbard, OH	2,797	Bismarck, ND	2,857
	Columbus, MS	2,911	Cocoa, FL	3,386	North Platte, NE	3,002
	Great Bend, KS	2,959	Flagstaff, AZ	2,802	Chillicothe, MO	2,757
	Billings, MT	3,411	Westlake Village, CA	3,390	Calais, ME	3,011
	Montgomery, AL	2,583	San Francisco, CA	3,367	Portland, ME	3,082
	Boise, ID	2,740	Gallipolis, OH	2,759	Escanaba, MI	2,829
	Del Rio, TX	3,256	Atoka, OK	3,420	Tulsa, OK	3,028
	Newport, NY	3,127	Eureka, CA	2,984	Washington, DC	2,577
	Lake Village, AR	3,023	Nogales, AZ	2,577	Morrison, TN	2,941
	Aberdeen, SD	2,967	Bakersfield, CA	2,876	Columbia, SC	3,325
	Atlanta, GA	2,988	Victoria, TX	3,445	Boise, ID	2,994
	Calais, ME	2,812	Corpus Christi, TX	2,572	Cairo, IL	3,056
	Morrison, TN	3,275	Middletown, NY	2,884	Pittsburgh, PA	2,630
	Cuba, MO	3,235	Muncie, IN	2,978	Green Bay, WI	3,032
	Vidalia, GA	3,358	Phoenix, AZ	3,132	Bridgeville, DE	2,894
	Newport, OR	2,795	Brownsville, TX	2,722	Richmond, VA	2,627
	Gallipolis, OH	2,857	Winnemucca, NV	3,269	Scranton, PA	2,898
	Milwaukee, WI	2,632	Ely, NV	3,169	Oshkosh, WI	3,185
	Houlton, ME	2,861	Charleston, SC	2,832	Stockton, CA	2,662
	Eau Claire, WI	2,859	Socorro, NM	2,869	Tampa, FL	2,843
	Byron, IL	3,254	Dubuque, IA	3,330	Columbus, MS	3,403
	Urbana, OH	3,215	Muskegon, MI	3,380	Salt Lake City, UT	3,438
	Casper, WY	3,446	Barstow, CA	2,987	Montgomery, AL	3,158
	Crookston, MN	2,604	Bucyrus, OH	3,426	Blythe, CA	2,981
	Sumner, IA	2,570	Buffalo, NY	3,442	Bohemia, NY	2,569
	Louisville, KY	2,725	Little Rock, AR	2,885	Oakley, KS	3,043
	Spokane, WA	3,165	Wells, NV	3,405	Greensboro, NC	3,229
	Alexander Cy, AL	3,227	Lykens, OH	3,176	Rapid City, SD	3,087
	Concord, NH	3,196	Aberdeen, SD	2,752	Salina, UT	2,766
	Pasco, WA	2,774	Sturgis, MI	3,106	East Windsor, CT	2,799
	Grand Rapids, MI	2,849	Cuba, MO	2,837	Middletown, NY	2,553
	Twin Falls, ID	2,678	Des Moines, IA	3,262	Phoenix, AZ	2,550
	Muenster, TX	2,846	Alexandria, LA	2,941	Crossville, TN	3,079
	Philadelphia, PA	3,018	Dallas, TX	3,353	Gallipolis, OH	2,744
	Springdale, AR	3,125	Duluth, MN	3,378	Huntsville, AL	2,940
	Roswell, NM	3,076	Vidalia, GA	3,160	Saint Louis, MO	3,264
	Fort Myers, FL	3,233	Hays, KS	3,270	Charlotte, NC	3,311
	Carlsbad, NM	3,440	Paragould, AR	3,354	Dodge City, KS	3,288
	Walworth, WI	2,975	Washington, NC	3,239	Bucyrus, OH	3,026
	Rawlins, WY	2,743	Vaughn, NM	3,313	Pendleton, OR	3,310
	Wenatchee, WA	2,616	Philadelphia, PA	3,328	Lowell, AR	2,938
	Watertown, NY	2,752	Oshkosh, WI	3,353	Charleston, WV	2,558
	Cocoa, FL	3,321	Las Vegas, NV	3,345	Savannah, GA	3,172
	Tallahassee, FL	2,896	Florence, SC	3,060	Freeport, TX	3,153
	Modesto, CA	3,306	Jacksonville, FL	3,071	Newport, NY	3,076
	Watertown, SD	2,909	West Glacier, MT	2,608	Durango, CO	2,823
	Robinson, IL	3,377	Hammond, LA	2,662	Charleston, SC	3,174
	Merrifield, MN	2,741	Madison, WI	3,236	Fort Wayne, IN	3,185
	Vero Beach, FL	3,062	Houlton, ME	2,835	Wilmington, NC	2,574

Table E.10: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Kearney, NE	7,833	Carlsbad, NM	8,462	Freeport, TX	7,670
	Atoka, OK	9,774	Greenville, SC	7,716	Marquette, MI	8,981
	Freeport, TX	10,481	Michigan City, IN	12,187	Mobile, AL	10,198
	Fort Smith, AR	11,750	Hazlehurst, GA	7,821	Albert Lea, MN	10,529
	Oshkosh, WI	11,451	Bangor, ME	11,759	Fort Myers, FL	10,585
	Evansville, IN	8,069	Coos Bay, OR	12,153	Baltimore, MD	7,666
	Warehouse Point, CT	9,109	El Paso, TX	9,337	Westlake Village, CA	8,267
	Dodge City, KS	9,365	Dallas, TX	9,386	Merrifield, MN	9,342
	Rapid City, SD	11,850	Jacksonville, FL	11,586	Del Rio, TX	10,539
	Altoona, PA	10,566	Roswell, NM	12,497	Dallas, TX	10,811
	Billings, MT	9,015	Las Vegas, NV	7,920	Escanaba, MI	11,802
	Amarillo, TX	11,633	Muncie, IN	12,371	Ringwood, IL	11,309
	Washington, MO	11,459	Boston, MA	11,547	Michigan City, IN	11,801
	Tifton, GA	9,704	Lamar, CO	10,122	Needles, CA	12,113
	Augusta, GA	9,845	Baton Rouge, LA	8,354	Kearney, NE	11,930
	Pendleton, OR	11,629	Cody, WY	7,548	Seattle, WA	10,591
	Bismarck, ND	10,852	Phoenix, AZ	12,171	Gallipolis, OH	9,809
	Louisville, KY	9,789	Nashville, TN	8,476	Milwaukee, WI	8,253
	Baltimore, MD	8,265	Salinas, CA	12,057	Miami, FL	11,657
	Pueblo, CO	11,964	Miami, FL	9,013	Astoria, OR	10,274
B	Stockton, CA	5,102	Rawlins, WY	4,825	Denver, CO	5,862
	Raton, NM	4,852	Missoula, MT	4,685	Imlay City, MI	5,005
	Eugene, OR	5,744	Dodge City, KS	4,178	Rochester, IN	5,279
	Modesto, CA	4,592	Eau Claire, WI	4,017	Page, AZ	4,600
	Charleston, SC	5,906	Fall River, MA	5,027	Orlando, FL	4,112
	Muskegon, MI	5,827	New York, NY	4,719	Livingston, MT	4,184
	Middletown, NY	4,029	Lake City, MN	5,565	Concord, NH	4,602
	Rochester, IN	5,524	Meridian, MS	4,634	Modesto, CA	5,160
	Emmetsburg, IA	5,431	Tallahassee, FL	4,539	Birmingham, AL	5,826
	Westlake Village, CA	4,992	Mackinaw City, MI	4,738	Ely, NV	5,516
	Fort Scott, KS	5,187	Fort Scott, KS	5,039	Idaho Falls, ID	4,482
	Yuma, AZ	4,679	Wichita, KS	5,470	Lake Charles, LA	4,256
	San Francisco, CA	4,755	Sturgis, MI	5,055	Roanoke, VA	5,124
	Casper, WY	4,276	Wenatchee, WA	5,276	Atoka, OK	4,845
	Tulsa, OK	4,237	Auburn, MA	5,338	Springfield, IL	4,338
	Bohemia, NY	4,077	Hubbard, OH	4,216	Portland, ME	5,024
	Des Moines, IA	5,603	Youngstown, PA	4,671	Butte, MT	4,061
	Boise, ID	5,417	Corinth, MS	4,550	Anniston, AL	5,073
	Hayward, CA	4,787	Elmira, NY	4,393	Pasco, WA	5,722
	Miami, FL	4,862	Grants Pass, OR	4,229	Emmetsburg, IA	5,730
	Barstow, CA	5,328	Twin Falls, ID	5,690	Vaughn, NM	5,428
	Grand Rapids, MI	5,192	Concord, NH	5,708	Oakley, KS	4,052
	Idaho Falls, ID	4,179	Albuquerque, NM	5,385	Philadelphia, PA	5,000
	Fort Stockton, TX	5,239	N Canton, OH	5,330	Watertown, NY	4,265
	San Angelo, TX	5,963	Raton, NM	5,715	Lordsburg, NM	5,333
	Richmond, VA	5,032	Pueblo, CO	4,067	Austin, TX	5,648
	Paragould, AR	4,033	Rapid City, SD	5,660	Newport, NY	4,616
	San Diego, CA	5,557	Knoxville, TN	5,071	Coos Bay, OR	5,773
	Socorro, NM	5,728	Flagstaff, AZ	4,280	Salina, UT	5,827
	Austin, TX	4,651	Lowell, AR	4,624	Lykens, OH	5,876

Table E.11: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 4	d_i	Set 5	d_i	Set 6	d_i
C	Durango, CO	3,057	Bridgeville, DE	3,213	Pierre, SD	3,063
	Green Bay, WI	3,152	Kansas City, KS	3,045	Lowell, AR	3,087
	Mobile, AL	3,075	Santa Fe, NM	2,603	Harrisburg, PA	3,056
	Kansas City, KS	2,669	Sumner, IA	2,734	Oklahoma City, OK	2,626
	Gulfport, MS	3,379	Modesto, CA	2,631	Cuba, MO	3,098
	Wichita, KS	2,762	Columbus, MS	3,036	Fort Scott, KS	2,799
	Odessa, TX	2,699	Sheridan, WY	2,967	Sturgis, MI	2,949
	Green River, UT	2,901	Lincoln, NE	3,422	Texarkana, AR	3,378
	Astoria, OR	3,239	Peoria, IL	3,050	Mt Pleasant, IA	2,602
	Greenville, SC	2,593	Astoria, OR	2,911	Sioux Falls, SD	2,719
	Lincoln, NE	3,281	Gainesville, GA	2,638	Baton Rouge, LA	2,554
	Alexandria, LA	2,956	Baltimore, MD	3,139	Fresno, CA	2,730
	San Luis Obispo, CA	2,640	Spanish Fork, UT	2,676	Asheville, NC	3,287
	Mt Pleasant, IA	3,055	San Angelo, TX	3,210	Fargo, ND	3,179
	Binghamton, NY	3,126	Warehouse Point, CT	2,877	Grand Island, NE	3,440
	Little Rock, AR	2,750	Robinson, IL	2,747	Peoria, IL	3,069
	Springfield, MO	2,611	Asheville, NC	3,208	Flagstaff, AZ	2,872
	Saint Louis, MO	2,834	Walworth, WI	3,419	Poplar Bluff, MO	2,653
	Dothan, AL	2,784	Kearney, NE	2,957	Augusta, GA	3,409
	Vernon, TX	2,633	Gainesville, FL	2,809	Phoenix, AZ	2,714
	Pierre, SD	2,746	Marquette, MI	3,116	Dubuque, IA	2,585
	N Canton, OH	2,885	Hulls Cove, ME	3,050	Rensselaer, IN	2,619
	Sioux Falls, SD	2,550	Saint George, UT	3,046	Tucumcari, NM	2,641
	Cody, WY	3,141	Victoria, TX	2,925	Jackson, MS	3,404
	Buffalo, NY	3,357	Sioux Falls, SD	3,058	Boston, MA	2,605
	Bishop, CA	3,410	Dubuque, IA	2,640	Paragould, AR	3,281
	Great Bend, KS	2,981	Gulfport, MS	3,335	Fort Stockton, TX	2,942
	Lakeview, OR	3,077	Norfolk, VA	2,597	Lexington, KY	3,363
	Marathon, TX	2,952	Sacramento, CA	3,253	Russellville, AR	2,848
	Poplar Bluff, MO	3,352	Aberdeen, SD	3,060	Port Angeles, WA	2,725
	Page, AZ	3,329	Milwaukee, WI	2,888	Portland, OR	3,338
	Myrtle Beach, SC	2,550	Oklahoma City, OK	3,333	Bartow, FL	2,595
	Imlay City, MI	2,643	Imlay City, MI	2,942	East Windsor, CT	2,946
	Wilmington, NC	3,161	Salina, KS	3,237	Hays, KS	2,570
	Watertown, NY	2,675	Vernon, TX	2,738	Cleveland, OH	2,673
	Lykens, OH	2,666	Durango, CO	2,982	Grenada, MS	3,091
	Grenada, MS	3,223	Atlanta, GA	2,555	Morrison, TN	3,220
	Bridgeville, DE	3,308	Cairo, IL	3,421	Bohemia, NY	2,944
	San Antonio, TX	3,059	Kalamazoo, MI	3,303	Louisville, KY	2,960
	Hulls Cove, ME	3,218	Great Falls, MT	2,706	Elmira, NY	3,188
	Grand Forks, ND	2,890	Paragould, AR	2,777	Biggs, OR	2,756
	Atlanta, GA	2,583	Saint Louis, MO	2,901	Reno, NV	3,397
	Concord, NH	3,254	Mobile, AL	3,101	Raton, NM	3,369
	Springdale, UT	3,351	Socorro, NM	3,227	Corpus Christi, TX	2,622
	Gainesville, GA	2,933	Des Moines, IA	3,209	Helena, MT	3,101
	St Augustine, FL	3,213	Bishop, CA	3,060	Walworth, WI	3,395
	Fort Valley, GA	2,842	Portland, ME	3,423	Alexander Cy, AL	3,061
	Decorah, IA	2,569	Vidalia, GA	2,636	Des Moines, IA	2,817
	Vaughn, NM	2,692	Redding, CA	2,750	Plover, WI	2,804
	Chillicothe, MO	2,800	Saint Johns, MI	2,840	Minot, ND	3,367

Table E.12: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Pierre, SD	11,355	Vernon, TX	11,898	Biggs, OR	9,864
	Cairo, IL	8,109	Cody, WY	11,941	Austin, TX	11,978
	Elmira, NY	9,240	Byron, IL	7,737	Muenster, TX	11,951
	Detroit, MI	10,513	Charleston, WV	9,481	Washington, MO	11,124
	Lubbock, TX	12,387	Michigan City, IN	10,017	Westlake Village, CA	7,973
	Bonners Ferry, ID	9,292	Jefferson City, MO	8,919	Dothan, AL	9,796
	Mt Pleasant, IA	8,208	Needles, CA	7,989	Salina, KS	7,697
	Birmingham, AL	10,463	Springfield, IL	8,758	Great Bend, KS	12,394
	Reno, NV	9,750	Albany, NY	11,819	Everett, WA	9,450
	Port Angeles, WA	12,386	Amarillo, TX	8,441	Muskegon, MI	10,216
	Butte, MT	10,467	Livingston, MT	11,623	Byron, IL	11,231
	Charleston, WV	10,055	Saint Louis, MO	8,551	Rawlins, WY	10,977
	Rensselaer, IN	7,643	Des Moines, IA	9,723	Charleston, SC	12,479
	Chillicothe, MO	10,857	Gainesville, GA	9,744	Portland, OR	10,104
	Michigan City, IN	9,673	Texarkana, AR	11,381	St Augustine, FL	10,541
	Oshkosh, WI	7,625	Shelby, NC	8,083	Toledo, OH	7,562
	Craig, CO	8,667	Plover, WI	11,859	Kalamazoo, MI	9,999
	Snyder, TX	10,558	Evansville, IN	10,155	Sumner, IA	10,391
	Missoula, MT	8,993	Fort Wayne, IN	7,634	San Diego, CA	10,138
	Crossville, TN	11,210	Albert Lea, MN	9,803	Phoenix, AZ	9,257
B	Escanaba, MI	5,656	Spokane, WA	4,012	Miami, FL	4,731
	Durango, CO	4,638	Guymon, OK	5,850	Dodge City, KS	5,157
	Greensboro, NC	5,420	Grand Forks, ND	5,932	Imlay City, MI	5,268
	Watertown, SD	4,429	Bartow, FL	5,170	Fresno, CA	4,660
	Albuquerque, NM	5,484	Tampa, FL	4,584	Little Rock, AR	4,153
	St Augustine, FL	4,759	Kansas City, KS	5,020	Spencer, IA	4,327
	Nogales, AZ	5,280	Los Angeles, CA	5,640	Nederland, TX	5,624
	Tallahassee, FL	4,710	Marathon, TX	5,078	Paragould, AR	5,592
	Madison, IN	5,929	Helena, MT	5,606	Russellville, AR	4,176
	Imlay City, MI	4,551	Washington, NC	4,130	Green River, UT	4,026
	Burns, OR	5,029	Vidalia, GA	4,886	Hulls Cove, ME	5,501
	Sioux City, IA	4,536	Havre, MT	4,646	Rapid City, SD	5,913
	Chicago, IL	4,679	Tulsa, OK	4,386	Port Angeles, WA	4,779
	Binghamton, NY	4,574	Fort Myers, FL	5,396	Emmetsburg, IA	5,347
	Grenada, MS	5,061	Mackinaw City, MI	4,884	San Angelo, TX	5,831
	Knoxville, TN	4,159	Port Angeles, WA	4,017	Norfolk, VA	4,999
	Harrisonburg, VA	5,775	Aberdeen, SD	5,105	Cincinnati, OH	5,503
	Middletown, NY	4,421	Harrisonburg, VA	4,978	Sturgis, MI	5,283
	Kearney, NE	4,288	Daytona Beach, FL	5,282	Cheyenne, WY	4,909
	Savannah, GA	5,306	Dallas, TX	5,779	Concord, NH	4,472
	Billings, MT	4,058	Odessa, TX	4,063	Baltimore, MD	5,469
	Pittsburgh, PA	5,598	Peoria, IL	4,814	Modesto, CA	5,075
	Morrison, TN	4,921	Chillicothe, MO	5,220	Elmira, NY	4,434
	Laredo, TX	4,583	Hays, KS	4,718	Bluefield, WV	4,655
	Lake City, MN	4,177	Rochester, NY	4,109	Syracuse, NY	5,221
	Peoria, IL	4,990	Corinth, MS	5,124	San Luis Obispo, CA	5,169
	Spencer, IA	4,338	Elmira, NY	5,276	Fort Valley, GA	4,571
	Harrisburg, PA	5,098	Roanoke, VA	4,682	Calais, ME	4,186
	Casper, WY	5,758	Crookston, MN	4,987	Butte, MT	5,372
	Amarillo, TX	5,547	Wilmington, NC	4,609	Shelby, NC	5,027

Table E.13: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
C	Columbia, SC	2,930	Baltimore, MD	3,275	East Windsor, CT	2,683
	Carlsbad, NM	2,579	Nashville, TN	2,688	Orlando, FL	3,354
	La Crosse, WI	3,421	Cisco, TX	2,888	Park City, KY	2,992
	Bucyrus, OH	3,180	Cleveland, OH	3,207	Roswell, NM	2,643
	Grants Pass, OR	3,354	Muskegon, MI	3,058	Bartow, FL	2,985
	Salina, KS	2,870	Walworth, WI	2,817	Lexington, KY	2,738
	Byron, IL	3,022	Tifton, GA	3,393	San Francisco, CA	2,870
	Blythe, CA	2,820	Florence, SC	3,442	Crossville, TN	3,365
	Corinth, MS	2,685	Kalamazoo, MI	2,941	Pierre, SD	2,701
	Dubuque, IA	3,270	Roswell, NM	2,806	Savannah, GA	2,970
	Lexington, KY	3,125	Bucyrus, OH	3,136	Evansville, IN	3,013
	Bluefield, WV	2,836	Decorah, IA	2,568	Cairo, IL	3,333
	Dothan, AL	3,121	Philadelphia, PA	3,136	Wichita, KS	2,871
	Montgomery, AL	3,170	Saginaw, MI	2,582	Lakeview, OR	3,315
	Marathon, TX	2,806	Cedar Rapids, IA	3,298	Raleigh, NC	3,343
	Kit Carson, CO	3,075	Urbana, OH	2,886	Saint Joseph, MO	3,408
	Newport, OR	2,980	Bridgeville, DE	3,153	Greensboro, NC	3,282
	Marquette, MI	3,315	Page, AZ	2,618	West Palm Beach, FL	3,386
	Rochester, NY	3,321	Reno, NV	2,626	Cleveland, OH	2,706
	Great Bend, KS	2,622	Freeport, TX	3,063	Warehouse Point, CT	3,134
	Phoenix, AZ	2,643	Calais, ME	2,640	Wenatchee, WA	3,247
	Muncie, IN	2,725	Fort Valley, GA	2,798	Muncie, IN	2,657
	Eureka, CA	3,352	Rochester, IN	2,873	Williams, AZ	2,775
	Auburn, MA	2,698	Lake Village, AR	3,261	Escanaba, MI	3,390
	Bartow, FL	2,976	Salinas, CA	3,027	Binghamton, NY	2,852
	Twin Falls, ID	3,102	La Crosse, WI	3,147	Grenada, MS	2,602
	Orlando, FL	2,756	Yuma, AZ	3,098	Sioux Falls, SD	3,078
	Cody, WY	3,110	Portland, OR	2,846	Florence, SC	2,834
	Austin, TX	2,810	Lubbock, TX	2,831	Altoona, PA	3,433
	Freeport, TX	2,868	Del Rio, TX	3,120	Portland, ME	2,852
	Calais, ME	2,598	Brownsville, TX	2,611	Chattanooga, TN	3,013
	Delphos, OH	2,982	Fort Stockton, TX	2,827	Anniston, AL	2,883
	Houston, TX	3,115	Gallup, NM	3,055	Rensselaer, IN	2,645
	Aberdeen, SD	2,616	Merrifield, MN	3,171	Watertown, SD	2,824
	Los Angeles, CA	2,969	Hubbard, OH	3,258	Pittsburgh, PA	3,344
	Saint Johns, MI	3,409	Fort Scott, KS	2,637	La Crosse, WI	2,560
	Charleston, SC	3,114	Gwinner, ND	3,158	Gallipolis, OH	2,889
	Springfield, IL	2,982	Minot, ND	3,394	Lamar, CO	3,226
	Albert Lea, MN	2,698	Albuquerque, NM	2,631	Spokane, WA	2,686
	Boston, MA	2,620	Boston, MA	2,974	Idaho Falls, ID	2,877
	New Orleans, LA	2,653	Atoka, OK	3,057	Amarillo, TX	3,151
	Fargo, ND	2,815	Myrtle Beach, SC	3,216	Mt Pleasant, IA	2,661
	Vernon, TX	3,076	Cairo, IL	2,866	Nashville, TN	3,169
	Fresno, CA	3,233	Grand Junction, CO	3,392	Vaughn, NM	2,701
	Roswell, NM	3,054	Muenster, TX	3,106	Kit Carson, CO	2,832
	Robinson, IL	3,058	Orlando, FL	2,565	Columbus, OH	2,667
	Duluth, MN	2,567	Imlay City, MI	2,710	El Paso, TX	3,297
	Omaha, NE	2,956	Escanaba, MI	3,169	Fort Worth, TX	3,106
	Rapid City, SD	2,723	Cocoa, FL	3,099	Charleston, WV	3,125
	Augusta, GA	2,925	Fort Worth, TX	2,868	Knoxville, TN	2,919

Table E.14: Customer Data Sets — Average Demand = 5,000; 100 Locations.

	Set 10	d_i		**Set 10**	d_i
A	Springdale, UT	11,609	**C**	Salinas, CA	3,310
	Gallipolis, OH	8,921		Milwaukee, WI	2,869
	Marathon, TX	8,819		Fargo, ND	2,983
	Tucumcari, NM	10,556		Brownsville, TX	3,176
	Wenatchee, WA	11,117		Carlsbad, NM	2,917
	Knoxville, TN	8,206		Concord, NH	3,134
	Clovis, NM	11,228		Santa Fe, NM	2,627
	Boise, ID	11,463		Eau Claire, WI	2,660
	Dothan, AL	9,424		Wichita, KS	3,020
	Kearney, NE	12,336		Spencer, IA	3,122
	El Paso, TX	8,707		Tallahassee, FL	3,140
	Detroit, MI	7,857		Baltimore, MD	2,614
	Freeport, TX	12,410		Springfield, MO	2,722
	Scranton, PA	7,797		Del Rio, TX	3,134
	Saginaw, MI	8,757		Cocoa, FL	3,106
	Harrisburg, PA	10,135		Idaho Falls, ID	3,089
	Altoona, PA	11,868		Tucson, AZ	3,320
	Jefferson City, MO	8,121		Newport, OR	3,378
	Bartow, FL	11,147		Fort Stockton, TX	2,558
	Savannah, GA	10,446		Oshkosh, WI	2,932
B	Victoria, TX	5,991		Poplar Bluff, MO	2,562
	San Francisco, CA	5,902		Buffalo, NY	2,656
	Bridgeville, DE	5,783		Walworth, WI	3,103
	Nogales, AZ	5,258		Byron, IL	3,100
	Saint Johns, MI	5,574		Craig, CO	2,881
	Ellensburg, WA	4,468		Fort Scott, KS	3,392
	Hulls Cove, ME	4,846		Lamar, CO	3,064
	Bend, OR	5,533		Reno, NV	3,402
	Philadelphia, PA	4,694		Guymon, OK	3,308
	Gulfport, MS	5,168		Davenport, IA	3,168
	North Platte, NE	5,785		Havre, MT	3,292
	Gainesville, GA	5,871		Phoenix, AZ	3,310
	Williston, ND	5,204		Sioux Falls, SD	2,643
	Port Angeles, WA	4,402		Lubbock, TX	2,647
	Montgomery, AL	4,303		Dodge City, KS	2,945
	Blythe, CA	5,748		Amarillo, TX	2,769
	Pasco, WA	5,363		Nashville, TN	3,143
	Imlay City, MI	4,649		Estes Park, CO	2,554
	San Antonio, TX	4,421		Louisville, KY	3,110
	International Falls, MN	4,371		Great Bend, KS	3,215
	Paragould, AR	5,748		Salina, KS	2,959
	Fort Wayne, IN	5,363		Sheridan, WY	2,762
	Billings, MT	5,662		Roswell, NM	2,892
	Orlando, FL	4,198		Wells, NV	2,635
	Mackinaw City, MI	5,443		Dallas, TX	2,821
	Sioux City, IA	4,839		Corpus Christi, TX	2,725
	Houston, TX	4,076		Columbia, SC	3,001
	N Canton, OH	4,137		Hayward, CA	2,560
	Urbana, OH	4,034		Grand Junction, CO	2,777
	Fort Smith, AR	4,024		Saint Joseph, MO	3,089

Appendix F

Customer Location and Demand Data — Average Demand of 20,000

Table F.1: Customer Data Sets — Average Demand = 20,000; 20 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Idaho Falls, ID	41,596	Plover, WI	33,582	Roswell, NM	49,119
	Nogales, AZ	35,540	Pueblo, CO	30,108	Sheridan, WY	45,212
	Plover, WI	47,702	Nogales, AZ	34,919	Knoxville, TN	49,880
	Tallahassee, FL	46,472	Houston, TX	47,077	Pasco, WA	40,247
B	Gallup, NM	23,381	Baton Rouge, LA	23,929	Eugene, OR	23,496
	Omaha, NE	23,823	Hubbard, OH	23,916	Chattanooga, TN	23,682
	Binghamton, NY	19,804	Westlake Village, CA	20,966	Lincoln, NE	22,099
	Oshkosh, WI	18,416	Des Moines, IA	22,165	Vernon, TX	19,127
	Westlake Village, CA	18,979	Amarillo, TX	16,551	North Platte, NE	23,839
	Laredo, TX	23,497	Crossville, TN	17,951	Grand Junction, CO	16,733
C	Pueblo, CO	12,887	Elmira, NY	12,272	Needles, CA	11,232
	Rochester, IN	13,614	Watertown, SD	11,392	Lykens, OH	10,838
	Charleston, SC	10,200	Minneapolis, MN	10,957	Snyder, TX	11,234
	Portland, ME	12,950	Minot, ND	12,257	Cairo, IL	11,017
	Charlotte, NC	11,671	Nashville, TN	11,278	St Augustine, FL	11,686
	Aberdeen, SD	11,157	Asheville, NC	11,996	Missoula, MT	12,566
	Salina, UT	12,417	Saint Johns, MI	11,916	Grand Island, NE	12,440
	Boston, MA	11,102	Youngstown, PA	12,167	Walworth, WI	11,008
	Greenville, SC	12,935	Rochester, IN	12,962	Carlsbad, NM	11,632
	Corinth, MS	12,968	Oklahoma City, OK	13,537	Marathon, TX	13,055
	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Bakersfield, CA	45,599	Greensboro, NC	49,136	Toledo, OH	47,214
	Lamar, CO	41,530	Byron, IL	47,044	Stockton, CA	34,911
	Alexander Cy, AL	49,077	Gulfport, MS	39,294	Binghamton, NY	39,910
	Plover, WI	46,411	Jefferson City, MO	37,381	Philadelphia, PA	44,296
B	Toledo, OH	23,442	Lake City, MN	19,634	Vaughn, NM	17,777
	Nogales, AZ	22,368	Calais, ME	23,368	Sheridan, WY	19,771
	Hays, KS	19,696	Needles, CA	19,413	Chattanooga, TN	18,204
	Birmingham, AL	19,161	Fort Valley, GA	17,376	Woodstock, IL	17,259
	Lakeview, OR	18,465	Fresno, CA	17,112	Watertown, NY	22,179
	Cedar Rapids, IA	21,819	Birmingham, AL	17,702	Eau Claire, WI	18,655
C	Great Bend, KS	11,792	Springfield, MO	10,812	Gwinner, ND	11,096
	Miami, FL	11,625	Florence, SC	11,774	Tucumcari, NM	10,377
	Pierre, SD	13,300	Orlando, FL	12,692	Little Rock, AR	13,558
	Green Bay, WI	13,526	Estes Park, CO	12,805	Billings, MT	12,214
	Tucson, AZ	12,013	Spanish Fork, UT	11,893	Marquette, MI	12,971
	Ely, NV	13,274	Lubbock, TX	11,727	Alexandria, LA	12,330
	Minneapolis, MN	10,679	Corpus Christi, TX	11,393	Salina, UT	12,247
	Bonners Ferry, ID	13,083	Livingston, MT	11,964	Greensboro, NC	11,295
	Fort Stockton, TX	12,335	Wilmington, NC	13,165	Hulls Cove, ME	12,443
	Myrtle Beach, SC	11,359	Hays, KS	12,551	Urbana, OH	10,429

Table F.2: Customer Data Sets — Average Demand = 20,000; 20 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Sioux City, IA	49,918	Raton, NM	44,182	Tucumcari, NM	31,575
	Newport, OR	42,732	Helena, MT	33,898	Hubbard, OH	39,583
	Indianapolis, IN	30,249	Gallup, NM	45,133	Harrisonburg, VA	30,880
	New York, NY	37,933	Bishop, CA	32,432	Albuquerque, NM	44,265
B	Charlotte, NC	23,311	Meridian, MS	16,847	Los Angeles, CA	17,127
	Crossville, TN	21,228	Davenport, IA	22,880	Minot, ND	22,573
	Minneapolis, MN	17,433	Cleveland, OH	20,612	Newport, NY	21,366
	Austin, TX	18,213	Alexander Cy, AL	17,297	Vidalia, GA	23,352
	Wichita, KS	22,967	Washington, DC	21,860	Fort Wayne, IN	23,703
	Oklahoma City, OK	19,538	Louisville, KY	20,634	Mt Pleasant, IA	23,631
C	Omaha, NE	12,897	Grants Pass, OR	10,534	Green River, UT	11,001
	Hayward, CA	12,883	Havre, MT	11,775	Alexander Cy, AL	12,741
	Hays, KS	13,351	Fort Wayne, IN	10,675	Robinson, IL	12,306
	Knoxville, TN	12,379	Baltimore, MD	13,137	Vernon, TX	11,893
	Lowell, AR	11,585	Williams, AZ	11,514	Sioux Falls, SD	12,364
	Pittsburgh, PA	11,807	Bangor, ME	12,886	Calais, ME	11,297
	Gainesville, GA	13,054	Pittsburgh, PA	13,391	Bridgeville, DE	11,439
	Paragould, AR	12,249	Watertown, SD	12,886	Brownsville, TX	10,324
	Oakley, KS	11,253	West Glacier, MT	12,094	Barstow, CA	10,201
	Pierre, SD	13,064	Roswell, NM	13,525	Port Angeles, WA	12,425
	Set 10	d_i				
A	Dubuque, IA	40,011				
	Klamath Falls, OR	48,612				
	Pasco, WA	43,707				
	Tulsa, OK	30,723				
B	Madison, IN	17,823				
	Newport, OR	17,601				
	Gwinner, ND	19,231				
	Boise, ID	21,782				
	Estes Park, CO	16,758				
	Shreveport, LA	17,890				
C	Memphis, TN	12,445				
	Charleston, SC	11,051				
	Miles City, MT	12,769				
	Milwaukee, WI	10,279				
	N Canton, OH	13,719				
	Idaho Falls, ID	10,799				
	El Paso, TX	11,019				
	Kearney, NE	10,707				
	Vaughn, NM	11,506				
	Chicago, IL	12,296				

Table F.3: Customer Data Sets — Average Demand = 20,000; 50 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Corinth, MS	43,340	West Palm Beach, FL	44,057	North Haven, CT	48,327
	Louisville, KY	34,072	Michigan City, IN	32,604	Milwaukee, WI	33,081
	Lincoln, NE	44,636	Syracuse, NY	34,080	Cincinnati, OH	30,692
	Savannah, GA	37,876	Newport, OR	49,877	New York, NY	38,524
	Saint George, UT	30,973	Park City, KY	37,013	Plover, WI	41,064
	Florence, SC	49,673	Emmetsburg, IA	44,719	Rensselaer, IN	49,415
	Des Moines, IA	49,440	Madison, IN	32,382	Salinas, CA	33,400
	Marquette, MI	46,964	Grand Rapids, MI	37,793	Kansas City, KS	33,841
	Memphis, TN	30,191	Chattanooga, TN	37,284	Las Vegas, NV	36,912
	New Orleans, LA	39,306	Louisville, KY	45,840	Roanoke, VA	46,676
B	Hubbard, OH	16,620	Snyder, TX	19,184	Chattanooga, TN	22,571
	Hays, KS	23,548	Coos Bay, OR	19,816	Crossville, TN	23,915
	Cody, WY	21,058	Hammond, LA	16,170	Rapid City, SD	16,293
	Plover, WI	21,397	Newport, NY	23,835	Shreveport, LA	22,533
	San Angelo, TX	22,739	San Angelo, TX	19,242	Evansville, IN	17,177
	Billings, MT	16,758	Great Falls, MT	22,395	Gallup, NM	19,537
	Fort Stockton, TX	19,013	Gainesville, FL	17,508	Washington, MO	18,699
	Park City, KY	18,423	New Orleans, LA	21,295	Coos Bay, OR	22,423
	Modesto, CA	22,404	Salinas, CA	21,116	Montgomery, AL	20,864
	Salt Lake City, UT	19,112	Grants Pass, OR	20,085	Watertown, SD	22,352
	Dodge City, KS	17,228	Baltimore, MD	21,116	Michigan City, IN	22,959
	Columbus, MS	17,501	Hulls Cove, ME	22,632	Morrison, TN	20,825
	Oshkosh, WI	17,222	Lincoln, NE	19,595	Page, AZ	16,994
	Charlotte, NC	20,075	Wenatchee, WA	16,985	Aberdeen, SD	21,503
	Bismarck, ND	17,146	Youngstown, PA	16,232	Gwinner, ND	22,712
C	Guymon, OK	13,056	Binghamton, NY	10,648	Lake Charles, LA	12,696
	Seattle, WA	12,936	Knoxville, TN	11,105	Fort Stockton, TX	11,346
	Minneapolis, MN	11,815	North Platte, NE	13,313	Alexander Cy, AL	13,458
	North Haven, CT	12,617	Imlay City, MI	10,229	Bartow, FL	13,170
	Burns, OR	13,302	Las Vegas, NV	11,435	Hammond, LA	12,358
	Myrtle Beach, SC	12,849	Concord, NH	13,613	Socorro, NM	10,888
	New York, NY	11,487	Little Rock, AR	12,567	Fall River, MA	10,368
	Vidalia, GA	12,813	Poplar Bluff, MO	11,008	Miami, FL	11,203
	West Glacier, MT	11,377	Spanish Fork, UT	12,705	Des Moines, IA	11,382
	Lake City, MN	11,748	Evansville, IN	12,071	Decorah, IA	11,258
	Mackinaw City, MI	13,249	Orlando, FL	12,113	Columbia, SC	11,396
	Pendleton, OR	12,815	Jacksonville, FL	11,061	Bishop, CA	12,916
	Craig, CO	11,152	Urbana, OH	13,392	Corinth, MS	10,633
	Texarkana, AR	10,293	Watertown, NY	12,197	Altoona, PA	10,430
	Lexington, KY	12,777	Escanaba, MI	12,485	Minot, ND	10,786
	Chicago, IL	12,662	Elmira, NY	12,771	Miles City, MT	11,319
	San Diego, CA	10,673	Washington, DC	11,974	Gainesville, FL	11,514
	Toledo, OH	11,723	Great Bend, KS	13,427	Seattle, WA	11,512
	Rawlins, WY	13,744	Gwinner, ND	13,714	Sioux Falls, SD	11,498
	Springfield, MO	12,356	Minneapolis, MN	10,287	Butte, MT	11,225
	N Canton, OH	12,609	Mackinaw City, MI	13,053	Portland, ME	10,698
	Fargo, ND	10,948	Fort Scott, KS	11,561	Jefferson City, MO	12,168
	Salina, UT	11,910	Watertown, SD	12,406	Amarillo, TX	10,960
	Miami, FL	13,215	Fort Smith, AR	10,405	Bluefield, WV	11,818
	Portland, OR	13,373	Tampa, FL	12,662	Charleston, WV	12,326

Table F.4: Customer Data Sets — Average Demand = 20,000; 50 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Springfield, MO	48,169	Fort Worth, TX	47,198	Muskegon, MI	34,787
	Baltimore, MD	39,107	San Antonio, TX	36,776	Peoria, IL	48,500
	Plover, WI	37,025	Chillicothe, MO	30,338	Watertown, NY	39,343
	Rochester, IN	41,948	Raton, NM	39,258	Grand Rapids, MI	49,386
	Mt Pleasant, IA	33,733	Bakersfield, CA	42,628	Washington, NC	47,885
	Muskegon, MI	34,213	Baton Rouge, LA	31,413	Daytona Beach, FL	31,419
	Los Angeles, CA	37,123	Redding, CA	43,814	Great Bend, KS	45,810
	Nashville, TN	36,083	Chattanooga, TN	31,403	Bucyrus, OH	32,125
	Barstow, CA	30,179	Fall River, MA	31,785	Lake City, MN	41,942
	East Windsor, CT	49,967	Marquette, MI	31,412	Missoula, MT	41,974
B	Springdale, AR	18,855	Carlsbad, NM	19,634	Brownsville, TX	23,809
	Brownwood, TX	16,768	Shelby, NC	21,002	Odessa, TX	22,670
	Eureka, CA	16,482	Lake Charles, LA	23,094	Baton Rouge, LA	23,727
	Hubbard, OH	18,829	Meridian, MS	19,674	Craig, CO	17,929
	Washington, NC	22,308	Fort Stockton, TX	20,226	Pittsburgh, PA	17,818
	Grand Island, NE	18,221	Warehouse Point, CT	20,042	Altoona, PA	20,508
	Nederland, TX	18,014	Idaho Falls, ID	19,793	Wilmington, NC	23,479
	Phoenix, AZ	19,904	Decorah, IA	21,301	New Orleans, LA	17,652
	Greensboro, NC	16,247	Guymon, OK	16,277	Gallup, NM	21,221
	Merrifield, MN	23,792	Davenport, IA	22,450	Everett, WA	23,273
	Pasco, WA	22,473	Saginaw, MI	23,603	Warehouse Point, CT	18,975
	Livingston, MT	16,425	Las Vegas, NV	21,762	Portland, ME	17,162
	Winnemucca, NV	23,582	Hulls Cove, ME	17,418	Lykens, OH	19,812
	Grand Junction, CO	19,253	Springfield, MO	18,143	Marquette, MI	18,766
	N Canton, OH	17,078	San Luis Obispo, CA	19,481	Vernon, TX	23,602
C	Albuquerque, NM	12,227	Wells, NV	13,742	Toledo, OH	10,509
	Tallahassee, FL	11,242	Oakley, KS	11,513	Ellensburg, WA	12,303
	Roanoke, VA	12,851	Green Bay, WI	12,961	Houlton, ME	12,188
	Cincinnati, OH	13,541	Saint Johns, MI	10,575	Denver, CO	13,099
	Washington, DC	11,806	North Platte, NE	13,401	Durango, CO	12,362
	Estes Park, CO	12,392	Huntsville, AL	10,622	Baltimore, MD	13,338
	Cocoa, FL	11,036	Sioux City, IA	13,460	Cuba, MO	10,497
	Freeport, TX	13,257	Williams, AZ	11,458	Rensselaer, IN	11,413
	Tucson, AZ	11,113	Milwaukee, WI	12,748	Eau Claire, WI	13,622
	Eugene, OR	10,280	El Paso, TX	10,524	Del Rio, TX	11,166
	Corpus Christi, TX	11,571	Billings, MT	11,524	Kansas City, KS	11,292
	Meridian, MS	12,173	Calais, ME	11,980	Robinson, IL	11,789
	Russellville, AR	12,900	Miami, FL	10,267	Madison, WI	12,511
	San Diego, CA	10,867	Walworth, WI	13,392	Duluth, MN	11,430
	Rapid City, SD	12,425	Rapid City, SD	12,063	Biggs, OR	13,795
	Woodstock, IL	11,693	Delphos, OH	13,468	Alexandria, LA	10,425
	Hazlehurst, GA	11,509	Minot, ND	12,015	Allentown, PA	12,458
	Madison, WI	10,895	Boise, ID	11,557	New York, NY	10,435
	Raton, NM	13,575	Eau Claire, WI	13,456	Green Bay, WI	13,573
	Norfolk, VA	12,767	Gainesville, FL	13,347	Meridian, MS	12,776
	Pittsburgh, PA	13,662	Jefferson City, MO	13,169	Port Angeles, WA	12,819
	Tulsa, OK	11,253	Watertown, NY	11,510	Columbia, SC	10,576
	Gallup, NM	10,814	Birmingham, AL	12,309	Modesto, CA	13,349
	Middletown, NY	12,374	Mackinaw City, MI	13,581	Atoka, OK	13,566
	Port Angeles, WA	12,657	Amarillo, TX	13,163	Victoria, TX	11,595

Table F.5: Customer Data Sets — Average Demand = 20,000; 50 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Columbia, SC	49,233	Salt Lake City, UT	49,674	Great Bend, KS	37,819
	Calais, ME	34,532	Everett, WA	33,142	New Orleans, LA	33,924
	Grand Island, NE	45,637	Portland, ME	42,849	Augusta, GA	37,916
	Salinas, CA	37,141	Watertown, SD	40,995	Lincoln, NE	32,198
	Birmingham, AL	42,202	Sioux City, IA	32,536	Charlotte, NC	42,809
	Madison, WI	35,854	Cocoa, FL	40,176	Salt Lake City, UT	44,598
	Washington, NC	40,088	Fresno, CA	35,878	Huntsville, AL	37,716
	Chattanooga, TN	35,085	St Augustine, FL	34,301	Chattanooga, TN	33,513
	Bismarck, ND	40,114	North Haven, CT	34,077	Redding, CA	47,498
	San Luis Obispo, CA	47,026	Vernon, TX	30,076	Toledo, OH	46,850
B	Huntsville, AL	22,291	Denver, CO	17,728	Ringwood, IL	16,111
	Salt Lake City, UT	23,983	San Francisco, CA	22,312	Bakersfield, CA	20,596
	Lordsburg, NM	16,814	Dallas, TX	20,996	Atlantic City, NJ	18,364
	Saint Johns, MI	20,369	Chicago, IL	17,299	Lakeview, OR	20,286
	Sheridan, WY	23,601	Seattle, WA	17,273	Tulsa, OK	22,131
	Urbana, OH	19,111	Winnemucca, NV	19,362	Indianapolis, IN	22,168
	Sacramento, CA	17,062	Rawlins, WY	17,134	Nederland, TX	19,679
	International Falls, MN	17,251	Biggs, OR	22,197	Hubbard, OH	20,420
	Carlsbad, NM	16,782	Louisville, KY	16,676	Rochester, NY	19,665
	Portland, OR	18,688	Bakersfield, CA	20,287	Kearney, NE	19,640
	Gainesville, FL	19,051	Charleston, SC	17,803	Corinth, MS	16,516
	Middletown, NY	16,228	Urbana, OH	17,107	Saint Johns, MI	16,312
	Vernon, TX	20,152	Saint Louis, MO	19,330	Jackson, MS	22,952
	Cedar Rapids, IA	18,814	Park City, KY	16,501	Syracuse, NY	17,692
	Portland, ME	20,002	Mobile, AL	16,138	Muncie, IN	16,633
C	Spencer, IA	10,749	Jacksonville, FL	11,080	Spokane, WA	13,218
	Needles, CA	11,366	Lincoln, NE	10,944	Reno, NV	11,221
	Robinson, IL	10,867	Spokane, WA	10,478	Pasco, WA	11,836
	Daytona Beach, FL	13,415	Fargo, ND	10,364	Birmingham, AL	10,471
	Gwinner, ND	12,197	Tucson, AZ	13,069	Carlsbad, NM	11,995
	Green Bay, WI	13,011	Richmond, VA	12,583	Scranton, PA	11,795
	Barstow, CA	11,701	Coos Bay, OR	12,028	Newport, NY	10,731
	Clovis, NM	11,086	Saint George, UT	10,837	Billings, MT	13,124
	Green River, UT	13,414	Allentown, PA	13,168	Nogales, AZ	11,510
	Detroit, MI	12,408	Charlotte, NC	12,638	Fort Worth, TX	11,633
	Decorah, IA	10,405	Des Moines, IA	12,071	Park City, KY	13,783
	Fort Valley, GA	13,408	Chattanooga, TN	10,866	Burns, OR	12,976
	Muncie, IN	13,144	Paragould, AR	10,332	Richmond, VA	11,648
	Wenatchee, WA	13,269	Kit Carson, CO	13,601	Binghamton, NY	13,185
	Lake Charles, LA	13,076	N Canton, OH	10,207	Winnemucca, NV	10,980
	Washington, MO	10,656	Columbia, SC	11,780	Columbia, SC	10,367
	Missoula, MT	11,730	West Palm Beach, FL	12,054	Emmetsburg, IA	11,528
	Gallipolis, OH	11,666	Modesto, CA	11,873	Kalamazoo, MI	11,921
	Cheyenne, WY	10,762	Socorro, NM	10,362	Byron, IL	12,497
	Mackinaw City, MI	13,387	Fort Smith, AR	11,534	Gallipolis, OH	13,063
	Estes Park, CO	12,837	Butte, MT	11,487	Michigan City, IN	12,452
	Buffalo, NY	12,131	Pasco, WA	13,143	Fort Smith, AR	13,022
	Albany, NY	10,891	Muskegon, MI	10,224	Mcallen, TX	12,826
	Vaughn, NM	11,782	Davenport, IA	11,594	Mackinaw City, MI	12,216
	Corinth, MS	11,096	Bonners Ferry, ID	11,058	Bangor, ME	10,680

Table F.6: Customer Data Sets — Average Demand = 20,000; 50 Locations.

	Set 10	d_i
A	Lincoln, NE	49,266
	Casper, WY	48,532
	Columbus, OH	46,816
	Clovis, NM	31,115
	Fort Wayne, IN	34,055
	Saint Louis, MO	48,863
	Shreveport, LA	35,264
	San Diego, CA	33,529
	Biggs, OR	32,901
	Livingston, MT	48,087
B	Warehouse Point, CT	18,292
	Saint George, UT	22,177
	Bismarck, ND	19,991
	Amarillo, TX	20,795
	Page, AZ	21,809
	Green River, UT	22,047
	Morrison, TN	21,522
	Missoula, MT	23,826
	N Canton, OH	17,860
	Cleveland, OH	21,170
	Fargo, ND	22,311
	Savannah, GA	17,748
	Del Rio, TX	18,882
	Estes Park, CO	16,582
	Davenport, IA	23,178
C	Flagstaff, AZ	11,672
	Shelby, NC	13,270
	Alexandria, LA	11,719
	Cocoa, FL	12,761
	Atoka, OK	12,440
	Rensselaer, IN	13,357
	Tulsa, OK	12,863
	Fort Valley, GA	11,338
	Nederland, TX	11,153
	Hulls Cove, ME	10,429
	Lake Village, AR	10,823
	Fall River, MA	13,555
	Bohemia, NY	10,553
	Nogales, AZ	13,097
	Baton Rouge, LA	13,595
	Freeport, TX	10,378
	Philadelphia, PA	13,568
	Bakersfield, CA	10,266
	Tucumcari, NM	13,399
	Grand Forks, ND	12,423
	St Augustine, FL	10,309
	Lakeview, OR	13,022
	Victoria, TX	11,163
	Augusta, GA	12,346
	Stockton, CA	13,270

Table F.7: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Modesto, CA	30,961	Middletown, NY	32,349	North Platte, NE	35,671
	Burns, OR	36,412	Eugene, OR	31,556	Aberdeen, SD	36,571
	Robinson, IL	49,818	Birmingham, AL	41,723	Binghamton, NY	34,246
	Wichita, KS	30,744	Dubuque, IA	34,979	Odessa, TX	38,197
	Tucson, AZ	43,570	Alexandria, LA	47,325	Spanish Fork, UT	43,208
	Cody, WY	49,084	San Angelo, TX	33,082	Eau Claire, WI	38,942
	Springfield, IL	41,013	Tampa, FL	45,883	Washington, DC	43,460
	Walworth, WI	38,288	New York, NY	33,059	Dodge City, KS	30,849
	Columbus, MS	49,893	Sturgis, MI	36,946	Little Rock, AR	36,148
	Atoka, OK	33,652	San Francisco, CA	44,235	Guymon, OK	49,551
	Billings, MT	45,736	Brownsville, TX	30,968	Baltimore, MD	31,630
	Carlsbad, NM	43,927	Nogales, AZ	40,670	Stockton, CA	40,323
	Montgomery, AL	33,306	Portland, ME	46,744	Tulsa, OK	49,468
	Green River, UT	46,705	West Glacier, MT	34,907	Livingston, MT	37,457
	Jacksonville, FL	38,623	Green Bay, WI	40,975	Newport, NY	34,110
	Harrisonburg, VA	34,378	Cuba, MO	43,461	Helena, MT	47,814
	Charlotte, NC	32,228	Westlake Village, CA	33,895	Bucyrus, OH	30,038
	Seattle, WA	35,362	Los Angeles, CA	48,809	Cody, WY	48,226
	Emmetsburg, IA	46,290	Hays, KS	39,540	Harrisonburg, VA	40,038
	Newport, NY	34,240	Paragould, AR	40,632	Crossville, TN	44,896
B	Fort Stockton, TX	21,031	Snyder, TX	21,083	Baton Rouge, LA	21,746
	Vidalia, GA	18,438	Pueblo, CO	23,896	Charleston, WV	21,594
	Escanaba, MI	17,616	Philadelphia, PA	17,952	Gulfport, MS	23,873
	Las Vegas, NV	23,499	Jacksonville, FL	16,605	Blythe, CA	22,623
	Bohemia, NY	16,617	Boise, ID	21,010	Columbus, MS	21,229
	Fresno, CA	17,081	Marquette, MI	19,515	Cairo, IL	16,804
	Lubbock, TX	17,510	Laredo, TX	17,220	Bohemia, NY	23,449
	Pasco, WA	18,234	Winnemucca, NV	16,247	Salt Lake City, UT	19,933
	Lamar, CO	17,262	Oshkosh, WI	16,008	Cleveland, OH	17,384
	Freeport, TX	19,755	Louisville, KY	21,262	Bridgeville, DE	19,178
	Concord, NH	16,038	Bluefield, WV	22,172	Montgomery, AL	17,282
	Gallipolis, OH	19,887	Tucson, AZ	21,835	Nashville, TN	21,453
	Merrifield, MN	20,161	Escanaba, MI	19,401	Bartow, FL	20,694
	Springdale, AR	16,402	Eureka, CA	21,822	Park City, KY	23,511
	Tifton, GA	22,454	Saint Louis, MO	19,227	Tifton, GA	16,424
	Dubuque, IA	22,677	Austin, TX	17,605	Rapid City, SD	18,542
	Del Rio, TX	17,651	Morrison, TN	16,738	Klamath Falls, OR	18,440
	Stockton, CA	16,208	Knoxville, TN	16,069	Boise, ID	16,298
	Calais, ME	17,842	Muskegon, MI	16,417	Marquette, MI	17,016
	Alexander Cy, AL	22,927	Buffalo, NY	18,624	Lakeview, OR	19,623
	Cisco, TX	18,317	Socorro, NM	22,501	Albuquerque, NM	17,987
	Urbana, OH	21,504	Atoka, OK	17,308	Escanaba, MI	20,699
	Wenatchee, WA	18,157	Yuma, AZ	23,489	Middletown, NY	20,605
	Muncie, IN	16,034	Cocoa, FL	23,805	Las Vegas, NV	16,183
	Jefferson City, MO	19,950	Rochester, NY	17,742	Pendleton, OR	16,473
	Houlton, ME	23,059	Bakersfield, CA	19,707	Rochester, NY	20,203
	Twin Falls, ID	16,477	Craig, CO	16,096	Freeport, TX	23,108
	Bend, OR	19,250	Poplar Bluff, MO	19,863	Dubuque, IA	16,200
	Denver, CO	18,847	Hulls Cove, ME	17,083	Corinth, MS	20,677
	Bridgeville, DE	23,542	Fall River, MA	23,806	Saint Louis, MO	19,644

Table F.8: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
C	Muskegon, MI	10,831	Gulfport, MS	13,632	Evansville, IN	11,598
	Sumner, IA	11,559	Barstow, CA	13,045	Richmond, VA	10,248
	Williston, ND	10,221	Sacramento, CA	10,284	Robinson, IL	11,695
	Fort Valley, GA	10,833	Roswell, NM	13,569	Santa Fe, NM	10,504
	Eau Claire, WI	12,672	Aberdeen, SD	11,898	Jefferson City, MO	10,738
	Paragould, AR	13,122	Houlton, ME	13,572	Atlanta, GA	10,514
	Cuba, MO	11,300	Warehouse Point, CT	13,536	Columbia, SC	13,329
	Cocoa, FL	12,637	Vidalia, GA	11,721	Redding, CA	11,125
	Evansville, IN	11,629	Victoria, TX	12,540	Charleston, SC	10,537
	Great Bend, KS	11,308	Myrtle Beach, SC	13,356	Kit Carson, CO	12,128
	Grand Rapids, MI	11,924	Lamar, CO	13,628	Lake City, MN	11,344
	Newport, OR	12,880	Corpus Christi, TX	11,772	Bismarck, ND	13,057
	Lake Village, AR	10,874	Everett, WA	11,104	Oshkosh, WI	10,956
	Milwaukee, WI	12,078	Hubbard, OH	12,034	Phoenix, AZ	11,198
	Lake Charles, LA	12,299	Spencer, IA	12,533	Green Bay, WI	12,135
	Vero Beach, FL	13,416	Phoenix, AZ	12,753	Cisco, TX	13,361
	Aberdeen, SD	10,348	Lake Charles, LA	13,780	Portland, ME	11,493
	San Luis Obispo, CA	12,466	Muncie, IN	12,328	Durango, CO	12,038
	Rochester, NY	12,289	Hammond, LA	11,969	Saint Joseph, MO	10,280
	Kalamazoo, MI	12,990	Washington, NC	10,324	Indianapolis, IN	11,197
	Meridian, MS	12,862	Florence, SC	11,128	Scranton, PA	12,718
	Marathon, TX	11,389	Fort Valley, GA	11,247	Vidalia, GA	10,871
	Watertown, SD	12,712	Lykens, OH	13,227	Calais, ME	12,985
	Hubbard, OH	13,293	Madison, WI	12,923	Alexandria, LA	13,759
	Muenster, TX	12,242	Dallas, TX	11,061	Coos Bay, OR	10,685
	Park City, KY	10,695	Merrifield, MN	10,289	San Francisco, CA	11,545
	Santa Fe, NM	13,044	Harrisonburg, VA	13,764	East Windsor, CT	12,218
	Fort Myers, FL	10,224	El Paso, TX	13,718	Shreveport, LA	12,291
	Saint George, UT	11,120	Houston, TX	11,377	Gallipolis, OH	11,112
	Boise, ID	11,266	Auburn, MA	11,396	Meridian, MS	12,580
	Gainesville, GA	13,422	Charleston, SC	11,239	Greensboro, NC	12,961
	Des Moines, IA	11,397	Bridgeville, DE	10,438	San Luis Obispo, CA	11,432
	Blythe, CA	11,294	Greensboro, NC	10,865	Pittsburgh, PA	12,226
	Morrison, TN	11,303	Evansville, IN	10,344	Needles, CA	11,118
	Casper, WY	10,750	Mcallen, TX	10,877	Oakley, KS	11,317
	Tallahassee, FL	11,881	Bucyrus, OH	10,863	Fort Wayne, IN	10,820
	Miami, FL	11,275	Las Vegas, NV	13,163	Woodstock, IL	11,961
	Atlanta, GA	12,923	Vaughn, NM	11,592	Salina, UT	13,390
	Mackinaw City, MI	10,921	Madison, IN	12,665	Rawlins, WY	10,617
	Crookston, MN	12,093	Des Moines, IA	11,476	Chillicothe, MO	12,294
	Spokane, WA	12,805	Wells, NV	12,283	Morrison, TN	12,212
	Gwinner, ND	13,019	Wilmington, NC	12,745	Tampa, FL	12,355
	Watertown, NY	12,421	Bismarck, ND	11,707	Huntsville, AL	11,939
	Roswell, NM	13,470	Duluth, MN	12,706	Auburn, MA	11,401
	Everett, WA	13,364	Gallipolis, OH	10,888	Lowell, AR	12,347
	Louisville, KY	11,605	Flagstaff, AZ	13,405	Charlotte, NC	11,129
	Columbia, SC	12,354	Little Rock, AR	12,653	Wilmington, NC	12,421
	Byron, IL	11,006	Hazlehurst, GA	10,698	Spokane, WA	11,413
	Philadelphia, PA	13,304	Ely, NV	10,243	N Canton, OH	10,689
	Rawlins, WY	12,743	Dodge City, KS	12,031	Savannah, GA	10,678

Table F.9: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Decorah, IA	30,949	Albuquerque, NM	34,319	Peoria, IL	49,758
	Alexandria, LA	32,336	Redding, CA	42,229	Sturgis, MI	32,799
	Pendleton, OR	43,930	Fall River, MA	42,226	Orlando, FL	38,621
	Dothan, AL	33,983	Paragould, AR	43,667	Fresno, CA	41,509
	Astoria, OR	48,997	Great Falls, MT	31,640	Fort Scott, KS	48,444
	Freeport, TX	38,429	Wenatchee, WA	34,651	Augusta, GA	39,345
	Buffalo, NY	32,153	Auburn, MA	40,247	Reno, NV	47,319
	Mt Pleasant, IA	32,818	Asheville, NC	30,193	Elmira, NY	31,410
	Kansas City, KS	38,453	Gainesville, FL	32,977	Dubuque, IA	42,105
	San Angelo, TX	34,353	Aberdeen, SD	47,530	Paragould, AR	45,566
	Tulsa, OK	42,231	Robinson, IL	42,381	Denver, CO	49,413
	Casper, WY	33,318	Michigan City, IN	38,168	Westlake Village, CA	30,008
	Little Rock, AR	44,259	Mackinaw City, MI	42,055	Astoria, OR	32,208
	Rapid City, SD	34,211	Lamar, CO	38,154	Livingston, MT	38,816
	Baltimore, MD	41,072	Miami, FL	44,826	Page, AZ	48,888
	Greenville, SC	36,440	Missoula, MT	32,497	Texarkana, AR	33,056
	Muskegon, MI	35,932	Sumner, IA	41,423	Raton, NM	32,128
	Middletown, NY	32,359	Coos Bay, OR	42,272	Philadelphia, PA	35,293
	Bohemia, NY	46,816	Twin Falls, ID	34,129	Asheville, NC	48,485
	Grand Rapids, MI	49,486	Spanish Fork, UT	39,829	Atoka, OK	34,535
B	San Francisco, CA	16,529	Portland, ME	20,781	Marquette, MI	17,661
	Pierre, SD	22,544	Elmira, NY	23,502	Fort Myers, FL	19,558
	Miami, FL	16,777	Raton, NM	22,628	Rochester, IN	19,653
	Bishop, CA	23,667	Oklahoma City, OK	23,461	Des Moines, IA	17,132
	Vernon, TX	19,413	Wichita, KS	19,398	Alexander Cy, AL	22,074
	Billings, MT	20,264	Bridgeville, DE	19,685	Lordsburg, NM	16,655
	Imlay City, MI	17,933	Durango, CO	22,817	Lykens, OH	18,507
	Odessa, TX	21,252	Sacramento, CA	20,241	East Windsor, CT	16,317
	Boise, ID	19,404	Saint Johns, MI	20,047	Poplar Bluff, MO	20,815
	Austin, TX	22,909	Baltimore, MD	20,825	Portland, ME	23,791
	N Canton, OH	19,277	Marquette, MI	22,691	Needles, CA	16,772
	Idaho Falls, ID	19,409	Salinas, CA	17,522	Bartow, FL	23,799
	Gulfport, MS	21,268	Vidalia, GA	22,996	Idaho Falls, ID	18,271
	Mobile, AL	23,199	Imlay City, MI	16,397	Lowell, AR	20,680
	San Antonio, TX	16,975	Hulls Cove, ME	21,692	Imlay City, MI	19,357
	Bismarck, ND	21,820	Sturgis, MI	22,403	Austin, TX	22,772
	Warehouse Point, CT	17,468	El Paso, TX	17,921	Albert Lea, MN	22,739
	Lykens, OH	17,491	Salina, KS	20,672	Springfield, IL	20,621
	Tifton, GA	20,868	San Angelo, TX	23,711	Ely, NV	21,379
	Fort Valley, GA	22,294	Lincoln, NE	23,518	Corpus Christi, TX	18,051
	Atoka, OK	22,906	Muncie, IN	20,529	Fargo, ND	18,742
	Cody, WY	21,379	Las Vegas, NV	17,568	Jackson, MS	19,178
	Rochester, IN	16,579	Peoria, IL	22,824	Flagstaff, AZ	20,260
	Springfield, MO	23,371	Pueblo, CO	21,432	Hays, KS	16,533
	Hayward, CA	23,118	Boston, MA	17,193	Anniston, AL	17,242
	Westlake Village, CA	19,236	Lake City, MN	21,341	Birmingham, AL	22,219
	Barstow, CA	20,179	Astoria, OR	20,362	Gallipolis, OH	17,722
	Saint Louis, MO	18,248	Rawlins, WY	18,185	Louisville, KY	23,323
	Fort Scott, KS	21,434	Hazlehurst, GA	20,136	Grenada, MS	22,252
	Green River, UT	22,562	Fort Scott, KS	21,570	Lexington, KY	22,994

Table F.10: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
C	Marathon, TX	12,327	Walworth, WI	13,349	Grand Island, NE	12,239
	Raton, NM	11,136	Youngstown, PA	13,165	Mt Pleasant, IA	11,434
	Kearney, NE	10,347	Cody, WY	10,366	Rensselaer, IN	13,214
	Pueblo, CO	12,676	Saint George, UT	10,429	Fort Stockton, TX	10,669
	Des Moines, IA	10,751	Lowell, AR	12,392	Tucumcari, NM	13,285
	Atlanta, GA	10,880	Modesto, CA	10,674	Bohemia, NY	11,316
	Chillicothe, MO	12,117	Des Moines, IA	10,888	Baton Rouge, LA	10,511
	Green Bay, WI	11,250	Santa Fe, NM	13,113	Modesto, CA	10,511
	Watertown, NY	11,821	Nashville, TN	13,478	Del Rio, TX	13,419
	Vaughn, NM	11,064	Phoenix, AZ	10,298	Plover, WI	13,146
	Fort Stockton, TX	12,162	Columbus, MS	12,937	Walworth, WI	10,659
	Myrtle Beach, SC	11,486	Rapid City, SD	11,789	Cuba, MO	13,391
	Grenada, MS	10,551	Dubuque, IA	11,970	Oakley, KS	12,078
	Grand Forks, ND	10,733	Hubbard, OH	13,675	Russellville, AR	13,489
	Gainesville, GA	12,364	Victoria, TX	13,206	Pasco, WA	12,060
	Great Bend, KS	11,378	Baton Rouge, LA	13,121	Dallas, TX	11,067
	St Augustine, FL	12,501	Kearney, NE	11,519	Coos Bay, OR	12,087
	Page, AZ	10,857	Corinth, MS	11,741	Cleveland, OH	12,403
	Springdale, UT	11,473	Saint Louis, MO	11,697	Baltimore, MD	12,096
	Fort Smith, AR	11,663	Socorro, NM	13,324	Merrifield, MN	12,722
	Paragould, AR	13,096	Jacksonville, FL	12,140	Port Angeles, WA	13,176
	Hulls Cove, ME	13,679	Tallahassee, FL	10,441	Sioux Falls, SD	11,950
	San Diego, CA	12,183	Roswell, NM	10,969	Emmetsburg, IA	13,598
	Yuma, AZ	12,183	Flagstaff, AZ	10,312	Harrisburg, PA	12,998
	Modesto, CA	11,205	Mobile, AL	10,424	Helena, MT	11,905
	Amarillo, TX	13,288	Vernon, TX	11,335	Pierre, SD	11,614
	Altoona, PA	12,768	Concord, NH	13,014	Freeport, TX	11,369
	Poplar Bluff, MO	12,397	Dallas, TX	13,140	Seattle, WA	10,257
	Wilmington, NC	11,177	Kalamazoo, MI	13,262	Kearney, NE	11,892
	Lakeview, OR	11,305	Sheridan, WY	12,928	Lake Charles, LA	12,015
	Emmetsburg, IA	13,548	New York, NY	12,487	Michigan City, IN	12,740
	Binghamton, NY	11,851	Milwaukee, WI	13,002	Morrison, TN	11,048
	Oshkosh, WI	13,793	Bangor, ME	10,413	Ringwood, IL	11,297
	Augusta, GA	12,224	N Canton, OH	12,594	Mobile, AL	13,501
	Stockton, CA	12,586	Grants Pass, OR	10,474	Roanoke, VA	13,222
	Louisville, KY	12,644	Carlsbad, NM	11,166	Boston, MA	10,200
	Socorro, NM	11,421	Norfolk, VA	13,098	Phoenix, AZ	11,389
	Richmond, VA	12,295	Bishop, CA	11,366	Escanaba, MI	12,670
	Bridgeville, DE	13,157	Gulfport, MS	13,253	Newport, NY	13,117
	Durango, CO	10,230	Eau Claire, WI	13,796	Vaughn, NM	12,320
	Lincoln, NE	10,739	Gainesville, GA	10,591	Portland, OR	11,415
	Evansville, IN	10,721	Dodge City, KS	11,781	Milwaukee, WI	13,124
	San Luis Obispo, CA	12,006	Warehouse Point, CT	12,496	Butte, MT	11,752
	Sioux Falls, SD	10,604	Atlanta, GA	12,278	Oklahoma City, OK	13,159
	Dodge City, KS	11,102	Cairo, IL	12,905	Salina, UT	13,499
	Charleston, SC	12,790	Sioux Falls, SD	12,848	Minot, ND	10,533
	Washington, MO	13,209	Kansas City, KS	12,608	Biggs, OR	10,529
	Wichita, KS	12,442	Meridian, MS	11,028	Concord, NH	11,401
	Eugene, OR	10,253	Greenville, SC	12,724	Watertown, NY	11,502
	Concord, NH	12,727	Knoxville, TN	11,947	Miami, FL	10,714

Table F.11: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Corinth, MS	39,548	Walworth, WI	46,732	Butte, MT	35,251
	Albuquerque, NM	46,854	Rochester, IN	41,424	Syracuse, NY	33,835
	Rensselaer, IN	35,737	Fort Worth, TX	37,944	Fort Valley, GA	43,549
	Springfield, IL	38,293	Saint Louis, MO	48,620	San Luis Obispo, CA	34,993
	Sioux City, IA	35,848	Peoria, IL	39,492	Spokane, WA	30,354
	Salina, KS	34,957	Guymon, OK	38,846	Spencer, IA	39,676
	Twin Falls, ID	49,462	Evansville, IN	30,374	Crossville, TN	39,349
	Fargo, ND	48,039	Helena, MT	44,481	Saint Joseph, MO	46,527
	Muncie, IN	36,639	Myrtle Beach, SC	49,679	Mt Pleasant, IA	49,456
	Dothan, AL	33,958	Philadelphia, PA	42,539	Elmira, NY	48,861
	Los Angeles, CA	46,226	Nashville, TN	32,911	East Windsor, CT	47,679
	Laredo, TX	39,819	Tifton, GA	37,275	Salina, KS	43,848
	Omaha, NE	30,708	Urbana, OH	44,939	Bartow, FL	44,894
	Delphos, OH	43,256	Fort Stockton, TX	42,305	Dothan, AL	43,110
	Vernon, TX	30,952	Decorah, IA	36,942	Fort Worth, TX	43,347
	Middletown, NY	38,757	Gallup, NM	43,537	Cheyenne, WY	31,917
	New Orleans, LA	34,514	Fort Scott, KS	33,783	Lakeview, OR	38,447
	Lexington, KY	40,547	Cedar Rapids, IA	31,000	Knoxville, TN	44,599
	Saint Johns, MI	35,938	Vernon, TX	32,071	Muskegon, MI	39,659
	Charleston, SC	40,113	Saginaw, MI	47,893	Amarillo, TX	45,566
B	Missoula, MT	19,318	Port Angeles, WA	19,115	Nashville, TN	16,228
	Elmira, NY	22,242	Freeport, TX	18,662	Pierre, SD	23,589
	Calais, ME	23,963	Michigan City, IN	21,451	Nederland, TX	22,426
	La Crosse, WI	21,771	Bartow, FL	20,233	San Francisco, CA	17,891
	Oshkosh, WI	19,906	Boston, MA	17,393	Little Rock, AR	20,859
	Carlsbad, NM	16,359	Page, AZ	18,658	Williams, AZ	20,102
	Austin, TX	23,862	Portland, OR	18,211	Raleigh, NC	22,884
	Eureka, CA	18,428	Orlando, FL	23,776	Imlay City, MI	23,599
	Grenada, MS	17,470	Roswell, NM	21,254	Muncie, IN	18,634
	Tallahassee, FL	19,955	Des Moines, IA	23,959	Idaho Falls, ID	18,522
	Madison, IN	16,835	Washington, NC	22,418	Dodge City, KS	17,141
	Snyder, TX	16,282	Merrifield, MN	23,021	Great Bend, KS	19,535
	Bucyrus, OH	19,706	Corinth, MS	23,730	Chattanooga, TN	20,308
	Pierre, SD	19,426	Kansas City, KS	21,629	Austin, TX	23,023
	Byron, IL	17,685	Elmira, NY	23,992	Cairo, IL	19,455
	Newport, OR	19,016	Rochester, NY	21,507	Sturgis, MI	23,333
	Robinson, IL	16,888	Amarillo, TX	20,373	Florence, SC	22,832
	Pittsburgh, PA	23,953	Grand Forks, ND	16,256	Rapid City, SD	22,109
	Lubbock, TX	20,105	Cisco, TX	19,930	Bluefield, WV	20,917
	Harrisonburg, VA	18,818	Imlay City, MI	21,043	La Crosse, WI	22,765
	Phoenix, AZ	19,362	Hubbard, OH	22,138	Altoona, PA	22,010
	Duluth, MN	19,719	Wilmington, NC	23,432	Cincinnati, OH	19,772
	Auburn, MA	22,946	Hays, KS	20,581	Evansville, IN	22,223
	Fresno, CA	17,096	Atoka, OK	20,845	Grenada, MS	21,689
	Morrison, TN	16,437	Charleston, WV	18,429	Biggs, OR	18,109
	Watertown, SD	23,656	Brownsville, TX	23,105	Port Angeles, WA	16,565
	Cairo, IL	19,868	Havre, MT	22,448	Pittsburgh, PA	19,949
	Marathon, TX	23,608	Baltimore, MD	21,555	Binghamton, NY	19,756
	Peoria, IL	20,642	Odessa, TX	21,510	Calais, ME	19,626
	Detroit, MI	21,412	Gainesville, GA	16,088	Greensboro, NC	16,865

Table F.12: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 7	d_i	Set 8	d_i	Set 9	d_i
C	Savannah, GA	13,512	Tulsa, OK	12,393	Baltimore, MD	13,181
	Birmingham, AL	10,893	Reno, NV	11,176	Hulls Cove, ME	11,506
	Marquette, MI	12,080	Cleveland, OH	11,131	Warehouse Point, CT	10,916
	Harrisburg, PA	13,414	Mackinaw City, MI	13,762	Sioux Falls, SD	10,210
	Montgomery, AL	13,537	Needles, CA	11,118	Everett, WA	11,658
	Spencer, IA	11,011	Lubbock, TX	10,888	Byron, IL	11,935
	Durango, CO	10,529	Los Angeles, CA	12,330	Charleston, WV	10,376
	Roswell, NM	10,435	Florence, SC	11,512	Norfolk, VA	11,488
	Greensboro, NC	13,508	Byron, IL	11,191	West Palm Beach, FL	11,429
	Dubuque, IA	13,489	Vidalia, GA	12,705	Columbus, OH	11,783
	Orlando, FL	13,236	Bridgeville, DE	13,006	Rensselaer, IN	12,722
	Craig, CO	12,254	Lake Village, AR	11,834	Sumner, IA	13,229
	Grants Pass, OR	10,776	Escanaba, MI	11,524	St Augustine, FL	12,988
	Bartow, FL	10,548	Minot, ND	13,135	Kit Carson, CO	13,193
	Chicago, IL	11,804	Muskegon, MI	12,792	Savannah, GA	13,110
	Imlay City, MI	13,330	Fort Myers, FL	13,615	Orlando, FL	10,218
	Aberdeen, SD	10,783	Aberdeen, SD	12,013	Toledo, OH	11,511
	Great Bend, KS	12,513	Shelby, NC	10,405	San Diego, CA	12,009
	Casper, WY	13,229	Crookston, MN	12,652	Green River, UT	12,487
	Butte, MT	11,997	Dallas, TX	11,261	Phoenix, AZ	12,665
	St Augustine, FL	12,960	Gwinner, ND	10,646	Rawlins, WY	11,190
	Cody, WY	11,815	Cairo, IL	10,305	Shelby, NC	10,754
	Rapid City, SD	10,776	Jefferson City, MO	12,610	Portland, ME	11,750
	Columbia, SC	11,182	Tampa, FL	11,683	Lamar, CO	11,833
	Houston, TX	11,606	Albany, NY	10,262	Wenatchee, WA	11,812
	Reno, NV	10,533	Kalamazoo, MI	11,887	San Angelo, TX	12,144
	Boston, MA	11,095	Bucyrus, OH	13,099	Vaughn, NM	11,766
	Burns, OR	12,604	Fort Valley, GA	10,983	Park City, KY	13,179
	Augusta, GA	11,027	Cocoa, FL	10,791	Gallipolis, OH	11,988
	Binghamton, NY	11,861	Marathon, TX	12,091	Emmetsburg, IA	11,277
	Blythe, CA	12,498	Grand Junction, CO	12,597	Russellville, AR	12,285
	Bonners Ferry, ID	13,744	Livingston, MT	12,999	El Paso, TX	12,851
	Albert Lea, MN	12,014	Daytona Beach, FL	13,358	Escanaba, MI	11,922
	Mt Pleasant, IA	11,071	Harrisonburg, VA	12,025	Kalamazoo, MI	10,811
	Charleston, WV	10,963	Texarkana, AR	11,210	Miami, FL	12,222
	Escanaba, MI	12,875	Del Rio, TX	11,314	Modesto, CA	10,342
	Nogales, AZ	12,104	Cody, WY	13,032	Roswell, NM	10,685
	Bluefield, WV	13,500	Plover, WI	12,491	Westlake Village, CA	13,732
	Billings, MT	10,359	Muenster, TX	12,254	Concord, NH	11,237
	Kearney, NE	10,343	Albuquerque, NM	12,206	Fresno, CA	11,362
	Knoxville, TN	11,071	Roanoke, VA	13,185	Portland, OR	10,462
	Michigan City, IN	12,788	La Crosse, WI	11,637	Paragould, AR	12,896
	Amarillo, TX	11,240	Albert Lea, MN	12,268	Lexington, KY	11,596
	Lake City, MN	13,372	Spokane, WA	11,446	Washington, MO	11,550
	Crossville, TN	11,632	Calais, ME	11,299	Muenster, TX	12,285
	Port Angeles, WA	12,218	Salinas, CA	10,763	Charleston, SC	10,630
	Chillicothe, MO	11,774	Springfield, IL	13,782	Watertown, SD	12,515
	Rochester, NY	11,271	Yuma, AZ	11,472	Cleveland, OH	10,871
	Freeport, TX	13,575	Fort Wayne, IN	13,568	Wichita, KS	11,707
	Kit Carson, CO	11,852	Chillicothe, MO	11,796	Anniston, AL	11,089

Table F.13: Customer Data Sets — Average Demand = 20,000; 100 Locations.

	Set 10	d_i		**Set 10**	d_i
A	Philadelphia, PA	46,826	**C**	Gallipolis, OH	11,214
	Eau Claire, WI	40,887		Poplar Bluff, MO	11,975
	Havre, MT	46,417		Pasco, WA	12,444
	Oshkosh, WI	47,422		Nashville, TN	12,119
	Carlsbad, NM	34,406		Del Rio, TX	10,966
	Nogales, AZ	33,460		Boise, ID	12,578
	Orlando, FL	30,556		Hulls Cove, ME	12,398
	Saint Joseph, MO	33,799		Davenport, IA	11,016
	Bend, OR	42,982		Tallahassee, FL	11,102
	Springfield, MO	49,884		Estes Park, CO	13,379
	Billings, MT	30,742		International Falls, MN	13,787
	Walworth, WI	44,823		Grand Junction, CO	12,815
	Wichita, KS	48,552		Craig, CO	13,557
	Springdale, UT	37,027		Imlay City, MI	13,039
	Fort Smith, AR	35,281		Kearney, NE	12,106
	Harrisburg, PA	41,970		Sheridan, WY	11,199
	Idaho Falls, ID	33,902		San Francisco, CA	13,619
	Gulfport, MS	33,035		Milwaukee, WI	13,764
	Mackinaw City, MI	33,407		Jefferson City, MO	11,949
	N Canton, OH	41,515		Brownsville, TX	12,036
B	Louisville, KY	22,781		Fort Scott, KS	10,937
	Wenatchee, WA	21,668		Port Angeles, WA	10,969
	Lubbock, TX	22,855		Corpus Christi, TX	11,228
	Williston, ND	16,778		Amarillo, TX	11,641
	Urbana, OH	20,493		Bartow, FL	13,366
	Saginaw, MI	21,004		Bridgeville, DE	13,241
	Saint Johns, MI	20,495		Sioux Falls, SD	12,265
	Columbia, SC	20,428		Hayward, CA	10,234
	Buffalo, NY	18,843		Victoria, TX	12,279
	Sioux City, IA	16,040		Guymon, OK	11,393
	Blythe, CA	21,261		Salinas, CA	11,172
	Gainesville, GA	22,985		Altoona, PA	12,048
	Reno, NV	16,788		Baltimore, MD	12,818
	Montgomery, AL	22,707		Tucumcari, NM	13,113
	Dodge City, KS	19,589		Salina, KS	11,968
	Great Bend, KS	22,403		Concord, NH	13,323
	Marathon, TX	20,380		Santa Fe, NM	13,399
	Phoenix, AZ	23,511		Detroit, MI	11,116
	North Platte, NE	23,454		Clovis, NM	13,463
	Newport, OR	19,695		Cocoa, FL	10,536
	Tucson, AZ	23,190		Byron, IL	12,362
	Scranton, PA	20,245		San Antonio, TX	12,028
	Dothan, AL	19,189		Spencer, IA	10,966
	Knoxville, TN	20,661		Paragould, AR	12,430
	Fargo, ND	22,699		Dallas, TX	10,696
	Savannah, GA	23,168		Freeport, TX	13,165
	Fort Wayne, IN	22,600		Fort Stockton, TX	12,879
	Ellensburg, WA	16,557		Lamar, CO	10,491
	Wells, NV	20,537		Roswell, NM	11,822
	Houston, TX	17,515		El Paso, TX	10,379

Appendix G

Customer Location and Demand Data — Average Demand of 50,000

Table G.1: Customer Data Sets — Average Demand = 50,000; 20 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Tallahassee, FL	122,547	Amarillo, TX	118,994	Needles, CA	97,568
	Aberdeen, SD	101,537	Pueblo, CO	87,560	Pasco, WA	88,904
	Pueblo, CO	88,651	Minot, ND	124,436	Marathon, TX	106,275
	Idaho Falls, ID	105,837	Nashville, TN	100,093	Knoxville, TN	119,922
B	Westlake Village, CA	51,047	Saint Johns, MI	41,386	Roswell, NM	55,321
	Salina, UT	49,749	Houston, TX	53,732	St Augustine, FL	46,392
	Charleston, SC	54,166	Westlake Village, CA	56,938	Lincoln, NE	56,673
	Nogales, AZ	43,654	Youngstown, PA	46,797	Cairo, IL	56,782
	Omaha, NE	44,594	Elmira, NY	57,563	Carlsbad, NM	56,703
	Oshkosh, WI	51,260	Crossville, TN	54,961	Snyder, TX	56,336
C	Boston, MA	31,580	Hubbard, OH	27,759	Grand Junction, CO	28,230
	Laredo, TX	31,087	Watertown, SD	31,813	Vernon, TX	28,850
	Portland, ME	34,330	Asheville, NC	29,998	Grand Island, NE	33,219
	Charlotte, NC	32,067	Baton Rouge, LA	26,558	Lykens, OH	26,989
	Gallup, NM	26,163	Minneapolis, MN	29,989	Missoula, MT	30,125
	Greenville, SC	31,848	Nogales, AZ	32,722	North Platte, NE	25,653
	Rochester, IN	28,448	Des Moines, IA	29,077	Walworth, WI	26,155
	Plover, WI	30,068	Rochester, IN	27,039	Sheridan, WY	34,365
	Binghamton, NY	27,894	Plover, WI	32,412	Chattanooga, TN	25,598
	Corinth, MS	32,704	Oklahoma City, OK	33,045	Eugene, OR	31,352
	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Alexander Cy, AL	90,458	Needles, CA	83,890	Little Rock, AR	100,991
	Pierre, SD	98,098	Lubbock, TX	94,366	Gwinner, ND	96,959
	Myrtle Beach, SC	78,369	Gulfport, MS	78,647	Tucumcari, NM	91,106
	Hays, KS	123,008	Hays, KS	110,391	Urbana, OH	115,672
B	Fort Stockton, TX	58,318	Fresno, CA	53,623	Billings, MT	59,364
	Lakeview, OR	58,765	Florence, SC	54,913	Hulls Cove, ME	50,899
	Nogales, AZ	53,008	Fort Valley, GA	57,997	Watertown, NY	43,006
	Tucson, AZ	54,566	Livingston, MT	50,035	Toledo, OH	54,202
	Great Bend, KS	52,246	Springfield, MO	54,324	Woodstock, IL	40,066
	Lamar, CO	51,139	Estes Park, CO	55,385	Stockton, CA	41,080
C	Green Bay, WI	33,766	Jefferson City, MO	33,918	Marquette, MI	32,867
	Plover, WI	31,939	Byron, IL	27,099	Sheridan, WY	29,222
	Toledo, OH	26,970	Wilmington, NC	26,066	Alexandria, LA	27,199
	Ely, NV	28,933	Lake City, MN	26,390	Philadelphia, PA	30,171
	Minneapolis, MN	31,344	Calais, ME	28,442	Greensboro, NC	32,342
	Cedar Rapids, IA	28,143	Corpus Christi, TX	33,061	Binghamton, NY	29,385
	Bakersfield, CA	31,601	Spanish Fork, UT	33,333	Vaughn, NM	28,134
	Birmingham, AL	33,436	Orlando, FL	28,836	Salina, UT	33,553
	Bonners Ferry, ID	31,019	Greensboro, NC	30,923	Chattanooga, TN	30,165
	Miami, FL	32,191	Birmingham, AL	29,140	Eau Claire, WI	28,309

Table G.2: Customer Data Sets — Average Demand = 50,000; 20 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Oakley, KS	79,434	Pittsburgh, PA	100,636	Barstow, CA	94,032
	Minneapolis, MN	82,009	Louisville, KY	106,655	Harrisonburg, VA	103,649
	Sioux City, IA	76,842	Meridian, MS	121,981	Port Angeles, WA	99,450
	Charlotte, NC	79,806	Alexander Cy, AL	82,209	Bridgeville, DE	112,374
B	New York, NY	47,236	Helena, MT	44,961	Newport, NY	44,188
	Crossville, TN	51,471	Gallup, NM	51,493	Albuquerque, NM	53,633
	Lowell, AR	55,963	Havre, MT	55,185	Alexander Cy, AL	50,810
	Oklahoma City, OK	52,257	Fort Wayne, IN	55,689	Green River, UT	51,828
	Hayward, CA	54,726	Raton, NM	46,146	Tucumcari, NM	44,379
	Indianapolis, IN	41,779	Williams, AZ	43,809	Los Angeles, CA	55,685
C	Omaha, NE	34,240	Watertown, SD	33,088	Calais, ME	27,189
	Pittsburgh, PA	32,979	Roswell, NM	32,162	Mt Pleasant, IA	27,388
	Knoxville, TN	30,210	Cleveland, OH	29,922	Minot, ND	27,854
	Paragould, AR	30,937	Davenport, IA	27,973	Vernon, TX	29,530
	Austin, TX	30,847	Washington, DC	31,047	Vidalia, GA	28,728
	Gainesville, GA	34,007	Baltimore, MD	31,218	Fort Wayne, IN	29,989
	Newport, OR	30,673	Grants Pass, OR	26,728	Robinson, IL	29,543
	Wichita, KS	26,103	Bishop, CA	28,092	Hubbard, OH	34,330
	Hays, KS	28,458	Bangor, ME	29,381	Brownsville, TX	33,161
	Pierre, SD	31,136	West Glacier, MT	31,825	Sioux Falls, SD	33,085
	Set 10	d_i				
A	Miles City, MT	110,681				
	Dubuque, IA	102,454				
	Pasco, WA	115,408				
	Shreveport, LA	76,838				
B	Kearney, NE	48,093				
	Tulsa, OK	42,378				
	Chicago, IL	44,334				
	Memphis, TN	50,928				
	Estes Park, CO	43,338				
	Milwaukee, WI	52,460				
C	Klamath Falls, OR	32,811				
	Idaho Falls, ID	34,371				
	El Paso, TX	26,919				
	Newport, OR	27,721				
	Gwinner, ND	33,291				
	Charleston, SC	31,046				
	N Canton, OH	27,763				
	Vaughn, NM	30,190				
	Madison, IN	26,204				
	Boise, ID	29,314				

Table G.3: Customer Data Sets — Average Demand = 50,000; 50 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Des Moines, IA	81,862	Watertown, NY	76,733	Plover, WI	79,877
	Park City, KY	75,524	Newport, NY	114,019	Gwinner, ND	88,828
	Toledo, OH	88,103	Tampa, FL	84,885	Lake Charles, LA	88,937
	Oshkosh, WI	89,545	Minneapolis, MN	115,013	Charleston, WV	113,283
	Memphis, TN	76,380	New Orleans, LA	97,826	Fort Stockton, TX	111,829
	Lincoln, NE	121,252	North Platte, NE	110,267	Las Vegas, NV	78,838
	Guymon, OK	115,881	Salinas, CA	86,146	Bishop, CA	80,779
	Billings, MT	106,512	Coos Bay, OR	104,205	Shreveport, LA	95,858
	Springfield, MO	105,076	San Angelo, TX	105,983	Gainesville, FL	82,097
	San Diego, CA	89,649	Gainesville, FL	119,748	Gallup, NM	93,541
B	Burns, OR	44,464	Fort Smith, AR	51,590	Aberdeen, SD	41,997
	Pendleton, OR	58,548	Spanish Fork, UT	51,372	Miles City, MT	40,709
	Fargo, ND	48,375	Newport, OR	49,410	Morrison, TN	55,134
	Fort Stockton, TX	49,173	Grand Rapids, MI	56,755	North Haven, CT	53,618
	Minneapolis, MN	47,653	Binghamton, NY	47,938	Salinas, CA	48,061
	Cody, WY	40,768	Youngstown, PA	47,893	Decorah, IA	51,774
	Columbus, MS	56,520	Fort Scott, KS	40,814	Seattle, WA	53,619
	Florence, SC	58,680	Orlando, FL	47,232	Chattanooga, TN	51,168
	Saint George, UT	53,662	Jacksonville, FL	48,334	Rapid City, SD	45,197
	Portland, OR	46,796	Knoxville, TN	57,708	Michigan City, IN	50,248
	New York, NY	52,582	Gwinner, ND	47,103	Corinth, MS	51,042
	San Angelo, TX	49,144	Mackinaw City, MI	49,103	Roanoke, VA	45,887
	Lake City, MN	40,825	Watertown, SD	41,593	Sioux Falls, SD	59,294
	Charlotte, NC	50,944	Wenatchee, WA	49,841	Evansville, IN	48,940
	Savannah, GA	43,882	Madison, IN	54,724	Des Moines, IA	42,692
C	Myrtle Beach, SC	29,464	Washington, DC	30,091	Washington, MO	26,828
	Dodge City, KS	27,674	Syracuse, NY	32,465	Cincinnati, OH	26,402
	Rawlins, WY	26,103	Little Rock, AR	33,382	Socorro, NM	29,096
	N Canton, OH	31,625	Baltimore, MD	29,258	New York, NY	32,206
	Marquette, MI	26,644	Emmetsburg, IA	28,163	Bluefield, WV	26,920
	West Glacier, MT	27,710	Michigan City, IN	33,086	Crossville, TN	32,825
	Plover, WI	27,993	Great Bend, KS	32,137	Minot, ND	27,605
	Bismarck, ND	25,781	Evansville, IN	31,854	Altoona, PA	29,777
	Craig, CO	28,578	Hulls Cove, ME	34,213	Bartow, FL	29,161
	Seattle, WA	29,167	Elmira, NY	25,976	Butte, MT	33,724
	Texarkana, AR	28,098	Snyder, TX	34,127	Watertown, SD	29,489
	North Haven, CT	27,158	Chattanooga, TN	30,220	Page, AZ	30,458
	Salt Lake City, UT	28,425	West Palm Beach, FL	29,506	Fall River, MA	28,229
	Hays, KS	32,755	Lincoln, NE	33,182	Montgomery, AL	30,876
	Chicago, IL	29,063	Park City, KY	30,345	Miami, FL	25,555
	Modesto, CA	26,206	Poplar Bluff, MO	25,617	Hammond, LA	26,244
	Mackinaw City, MI	34,376	Hammond, LA	31,548	Portland, ME	27,975
	Corinth, MS	33,727	Imlay City, MI	30,939	Kansas City, KS	25,680
	Miami, FL	28,238	Escanaba, MI	33,525	Rensselaer, IN	31,264
	Lexington, KY	34,037	Louisville, KY	28,534	Columbia, SC	30,686
	Louisville, KY	33,069	Grants Pass, OR	31,173	Milwaukee, WI	34,168
	Vidalia, GA	27,019	Great Falls, MT	28,768	Amarillo, TX	30,147
	Salina, UT	27,103	Concord, NH	34,453	Coos Bay, OR	32,147
	New Orleans, LA	33,627	Las Vegas, NV	27,125	Jefferson City, MO	32,408
	Hubbard, OH	28,026	Urbana, OH	30,821	Alexander Cy, AL	31,280

Table G.4: Customer Data Sets — Average Demand = 50,000; 50 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Woodstock, IL	119,997	Las Vegas, NV	102,189	Portland, ME	76,217
	Tucson, AZ	98,073	Hulls Cove, ME	108,291	Columbia, SC	93,501
	Washington, DC	85,366	Amarillo, TX	89,006	Watertown, NY	84,568
	Plover, WI	92,644	Chattanooga, TN	86,965	Wilmington, NC	108,481
	N Canton, OH	118,381	Chillicothe, MO	97,808	Marquette, MI	104,739
	Russellville, AR	80,588	Redding, CA	83,879	Odessa, TX	100,548
	San Diego, CA	123,525	Green Bay, WI	89,646	Grand Rapids, MI	90,098
	Middletown, NY	95,622	Minot, ND	123,096	Victoria, TX	118,518
	Barstow, CA	115,048	San Antonio, TX	79,815	Lake City, MN	124,399
	Nashville, TN	89,110	Meridian, MS	78,717	Gallup, NM	82,104
B	East Windsor, CT	56,194	Shelby, NC	46,863	Peoria, IL	53,542
	Port Angeles, WA	46,963	Jefferson City, MO	48,474	Atoka, OK	56,247
	Springdale, AR	45,494	Eau Claire, WI	43,743	Houlton, ME	46,947
	Eugene, OR	44,324	Calais, ME	47,754	Meridian, MS	51,993
	Rochester, IN	56,878	Bakersfield, CA	58,057	Denver, CO	42,524
	Cocoa, FL	56,104	Sioux City, IA	54,995	Duluth, MN	54,108
	Phoenix, AZ	57,196	Carlsbad, NM	50,315	Everett, WA	54,081
	Cincinnati, OH	58,314	Rapid City, SD	51,882	Washington, NC	56,070
	Rapid City, SD	57,350	Saint Johns, MI	52,265	Toledo, OH	43,147
	Freeport, TX	53,163	San Luis Obispo, CA	53,937	Missoula, MT	54,795
	Gallup, NM	55,115	Milwaukee, WI	59,528	Allentown, PA	59,025
	Raton, NM	45,659	Springfield, MO	41,523	New Orleans, LA	40,664
	Muskegon, MI	41,119	Davenport, IA	44,299	Craig, CO	52,853
	Hazlehurst, GA	53,572	Williams, AZ	48,128	Baltimore, MD	54,111
	Winnemucca, NV	50,520	El Paso, TX	47,233	Cuba, MO	43,848
C	Mt Pleasant, IA	33,258	Raton, NM	26,154	Alexandria, LA	25,796
	Greensboro, NC	31,505	Birmingham, AL	30,659	Kansas City, KS	27,367
	Springfield, MO	33,559	Marquette, MI	31,324	Bucyrus, OH	27,106
	Grand Junction, CO	25,574	Mackinaw City, MI	26,384	Madison, WI	32,640
	Corpus Christi, TX	25,832	Huntsville, AL	27,400	Del Rio, TX	31,805
	Livingston, MT	29,667	Decorah, IA	28,458	Great Bend, KS	25,510
	Nederland, TX	28,922	Gainesville, FL	32,943	Port Angeles, WA	30,618
	Roanoke, VA	32,534	Oakley, KS	25,778	Green Bay, WI	30,585
	Norfolk, VA	30,470	Fort Stockton, TX	30,540	Lykens, OH	30,134
	Estes Park, CO	31,527	Walworth, WI	31,220	Modesto, CA	26,031
	Washington, NC	33,379	Fort Worth, TX	28,827	Baton Rouge, LA	27,813
	Tulsa, OK	30,411	Delphos, OH	27,489	Biggs, OR	33,163
	Albuquerque, NM	28,151	Boise, ID	26,852	Daytona Beach, FL	28,381
	Baltimore, MD	28,874	North Platte, NE	33,688	Pittsburgh, PA	26,553
	Pasco, WA	33,481	Warehouse Point, CT	26,840	Eau Claire, WI	28,544
	Tallahassee, FL	31,390	Guymon, OK	30,742	Rensselaer, IN	26,937
	Los Angeles, CA	25,513	Lake Charles, LA	26,001	Muskegon, MI	32,218
	Pittsburgh, PA	26,220	Billings, MT	33,995	Durango, CO	25,706
	Eureka, CA	32,465	Baton Rouge, LA	33,248	Brownsville, TX	25,955
	Merrifield, MN	34,465	Miami, FL	26,175	Vernon, TX	30,700
	Madison, WI	28,542	Saginaw, MI	30,711	New York, NY	29,578
	Grand Island, NE	25,784	Wells, NV	30,153	Altoona, PA	25,948
	Hubbard, OH	29,325	Watertown, NY	31,886	Warehouse Point, CT	31,142
	Brownwood, TX	31,839	Idaho Falls, ID	28,689	Robinson, IL	28,868
	Meridian, MS	29,037	Fall River, MA	27,262	Ellensburg, WA	31,972

Table G.5: Customer Data Sets — Average Demand = 50,000; 50 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Cedar Rapids, IA	86,860	Mobile, AL	78,094	Richmond, VA	79,483
	Sacramento, CA	116,122	Socorro, NM	77,274	Newport, NY	119,067
	Lordsburg, NM	92,941	Biggs, OR	124,253	Billings, MT	112,606
	Muncie, IN	80,767	Spokane, WA	90,137	Fort Smith, AR	110,650
	Clovis, NM	79,606	Bakersfield, CA	102,435	Tulsa, OK	105,129
	Robinson, IL	124,279	Charleston, SC	120,364	Chattanooga, TN	80,278
	Wenatchee, WA	99,875	Seattle, WA	104,781	Lincoln, NE	77,296
	Gainesville, FL	86,912	Saint George, UT	117,877	Great Bend, KS	89,778
	Saint Johns, MI	80,030	Salt Lake City, UT	81,367	Spokane, WA	124,401
	Gallipolis, OH	89,901	Richmond, VA	120,982	Birmingham, AL	101,460
B	Birmingham, AL	41,565	Chattanooga, TN	40,189	Mackinaw City, MI	49,926
	Sheridan, WY	59,643	Park City, KY	48,088	Pasco, WA	50,674
	Bismarck, ND	51,527	Watertown, SD	57,977	Emmetsburg, IA	54,913
	Carlsbad, NM	53,764	Cocoa, FL	49,226	Reno, NV	43,903
	Corinth, MS	57,964	Fargo, ND	48,463	Corinth, MS	41,154
	Gwinner, ND	40,515	Pasco, WA	57,867	Michigan City, IN	40,543
	Salt Lake City, UT	48,829	Charlotte, NC	55,851	Columbia, SC	57,940
	Detroit, MI	57,787	Rawlins, WY	53,201	Ringwood, IL	50,154
	Calais, ME	49,621	North Haven, CT	51,336	Gallipolis, OH	50,338
	Decorah, IA	51,945	Everett, WA	56,718	Carlsbad, NM	56,495
	San Luis Obispo, CA	54,527	Jacksonville, FL	44,829	Bangor, ME	59,231
	Portland, OR	53,478	Coos Bay, OR	52,629	Hubbard, OH	43,144
	Urbana, OH	47,965	Chicago, IL	52,233	Muncie, IN	43,170
	Grand Island, NE	47,159	Bonners Ferry, ID	41,409	Huntsville, AL	43,661
	Portland, ME	51,570	Sioux City, IA	47,200	Park City, KY	59,523
C	Columbia, SC	32,175	Vernon, TX	32,218	Charlotte, NC	32,579
	Needles, CA	29,776	Winnemucca, NV	29,864	Burns, OR	25,887
	Barstow, CA	29,386	Kit Carson, CO	31,497	Mcallen, TX	27,721
	Daytona Beach, FL	25,824	Allentown, PA	30,930	Nederland, TX	30,216
	Cheyenne, WY	30,601	Modesto, CA	26,830	Atlantic City, NJ	31,370
	Estes Park, CO	34,184	Columbia, SC	31,009	Saint Johns, MI	33,336
	Spencer, IA	26,822	N Canton, OH	28,464	Salt Lake City, UT	26,603
	Washington, MO	33,529	Denver, CO	28,740	Bakersfield, CA	34,405
	Chattanooga, TN	29,318	Des Moines, IA	29,718	Toledo, OH	25,644
	Green Bay, WI	26,453	Fort Smith, AR	33,015	Scranton, PA	30,792
	Fort Valley, GA	30,118	Davenport, IA	27,919	Redding, CA	34,074
	Lake Charles, LA	31,669	Lincoln, NE	30,155	Byron, IL	31,853
	Vaughn, NM	32,977	St Augustine, FL	27,991	Winnemucca, NV	28,682
	Albany, NY	27,949	Louisville, KY	33,259	Kalamazoo, MI	26,785
	Missoula, MT	31,670	Fresno, CA	30,105	Jackson, MS	28,188
	Madison, WI	29,493	Muskegon, MI	32,347	Lakeview, OR	33,834
	Green River, UT	26,540	Butte, MT	32,159	New Orleans, LA	31,586
	Buffalo, NY	28,026	West Palm Beach, FL	29,236	Augusta, GA	30,630
	Vernon, TX	26,001	Urbana, OH	32,567	Nogales, AZ	31,339
	Middletown, NY	33,846	Portland, ME	33,528	Indianapolis, IN	25,553
	Huntsville, AL	27,407	San Francisco, CA	31,708	Binghamton, NY	33,128
	International Falls, MN	30,679	Tucson, AZ	27,017	Kearney, NE	32,788
	Mackinaw City, MI	28,930	Saint Louis, MO	32,795	Rochester, NY	33,565
	Salinas, CA	28,242	Dallas, TX	32,730	Syracuse, NY	33,982
	Washington, NC	30,388	Paragould, AR	31,438	Fort Worth, TX	32,755

Table G.6: Customer Data Sets — Average Demand = 50,000; 50 Locations.

	Set 10	d_i
A	Rensselaer, IN	113,704
	Philadelphia, PA	99,061
	Shelby, NC	89,195
	Cleveland, OH	96,428
	Bohemia, NY	79,233
	Tucumcari, NM	115,691
	Bismarck, ND	106,030
	N Canton, OH	82,501
	Flagstaff, AZ	102,893
	Morrison, TN	119,817
B	Fort Wayne, IN	40,264
	Fargo, ND	41,091
	Clovis, NM	42,673
	Columbus, OH	40,357
	Casper, WY	55,008
	Freeport, TX	58,548
	Baton Rouge, LA	40,137
	St Augustine, FL	52,878
	Biggs, OR	54,038
	Bakersfield, CA	49,187
	San Diego, CA	48,586
	Alexandria, LA	46,465
	Shreveport, LA	56,255
	Fall River, MA	56,943
	Green River, UT	59,596
C	Atoka, OK	29,708
	Amarillo, TX	33,135
	Tulsa, OK	25,675
	Saint Louis, MO	28,433
	Lincoln, NE	26,949
	Lake Village, AR	30,655
	Fort Valley, GA	28,044
	Cocoa, FL	30,534
	Warehouse Point, CT	32,608
	Victoria, TX	32,571
	Lakeview, OR	31,158
	Savannah, GA	28,906
	Grand Forks, ND	25,530
	Nederland, TX	30,238
	Page, AZ	31,249
	Saint George, UT	28,020
	Nogales, AZ	26,501
	Estes Park, CO	30,565
	Livingston, MT	34,241
	Stockton, CA	29,617
	Augusta, GA	26,815
	Davenport, IA	27,417
	Missoula, MT	32,154
	Del Rio, TX	29,880
	Hulls Cove, ME	26,623

Table G.7: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
A	Kalamazoo, MI	105,020	Merrifield, MN	95,747	Crossville, TN	109,920
	Cuba, MO	79,171	Craig, CO	93,971	Harrisonburg, VA	82,140
	Aberdeen, SD	100,404	Gulfport, MS	99,949	Woodstock, IL	113,407
	Watertown, NY	107,005	Cuba, MO	111,179	Montgomery, AL	81,815
	Vidalia, GA	102,474	Charleston, SC	92,713	Baltimore, MD	120,266
	Byron, IL	103,461	Alexandria, LA	95,867	Scranton, PA	86,029
	Gwinner, ND	120,257	Bridgeville, DE	122,523	Saint Louis, MO	105,516
	Carlsbad, NM	115,321	Everett, WA	104,058	Atlanta, GA	81,441
	Hubbard, OH	87,670	Muncie, IN	112,016	Chillicothe, MO	95,448
	Tucson, AZ	79,541	Auburn, MA	112,795	Blythe, CA	109,434
	Calais, ME	115,983	Socorro, NM	117,934	Lowell, AR	106,768
	Watertown, SD	93,260	Snyder, TX	90,200	Tampa, FL	78,280
	Vero Beach, FL	94,581	Victoria, TX	118,173	Pendleton, OR	104,837
	Bridgeville, DE	90,412	Madison, IN	82,437	Boise, ID	111,336
	Rochester, NY	80,600	Des Moines, IA	80,422	San Francisco, CA	85,274
	Jacksonville, FL	83,837	Brownsville, TX	88,256	Needles, CA	87,331
	Williston, ND	119,446	Atoka, OK	124,346	Helena, MT	87,521
	Montgomery, AL	97,924	Vaughn, NM	108,300	Green Bay, WI	110,210
	Park City, KY	81,589	Rochester, NY	121,161	Vidalia, GA	81,479
	Mackinaw City, MI	97,930	West Glacier, MT	76,669	Morrison, TN	124,288
B	Fort Valley, GA	55,608	Warehouse Point, CT	41,555	Kit Carson, CO	45,663
	Muenster, TX	56,395	Bismarck, ND	58,681	Portland, ME	47,347
	Stockton, CA	42,367	Eugene, OR	41,772	Fort Wayne, IN	44,505
	Casper, WY	54,665	Dubuque, IA	51,489	Eau Claire, WI	48,970
	Miami, FL	57,621	Evansville, IN	52,564	San Luis Obispo, CA	42,098
	Great Bend, KS	41,555	Gallipolis, OH	52,043	Columbus, MS	50,726
	Gallipolis, OH	53,846	Hulls Cove, ME	55,588	Lakeview, OR	46,408
	Eau Claire, WI	48,079	San Francisco, CA	47,249	Charleston, SC	58,403
	Merrifield, MN	40,806	Oshkosh, WI	59,805	Corinth, MS	53,560
	Newport, NY	40,775	Middletown, NY	43,087	Stockton, CA	50,526
	Tifton, GA	57,892	Cocoa, FL	40,149	Cisco, TX	41,804
	Blythe, CA	53,648	Houston, TX	57,142	Bucyrus, OH	49,806
	Fort Myers, FL	52,191	Yuma, AZ	47,732	Park City, KY	52,110
	Fresno, CA	44,330	Houlton, ME	45,307	Bohemia, NY	51,037
	Modesto, CA	44,396	Bakersfield, CA	43,408	Bismarck, ND	59,446
	Meridian, MS	49,309	Boise, ID	58,813	Rawlins, WY	55,104
	Gainesville, GA	51,971	Bluefield, WV	41,210	Binghamton, NY	58,759
	Springdale, AR	42,275	Wilmington, NC	55,269	Salina, UT	54,405
	Marathon, TX	54,086	Austin, TX	55,201	Saint Joseph, MO	53,853
	Louisville, KY	50,627	Little Rock, AR	50,375	Dodge City, KS	49,569
	Seattle, WA	40,906	Green Bay, WI	57,486	Jefferson City, MO	57,299
	Lubbock, TX	45,706	Spencer, IA	45,674	Greensboro, NC	50,444
	Jefferson City, MO	50,437	Roswell, NM	54,432	Huntsville, AL	53,382
	Bend, OR	54,853	Escanaba, MI	41,801	Las Vegas, NV	46,552
	Urbana, OH	57,499	Birmingham, AL	40,414	N Canton, OH	53,042
	Charlotte, NC	41,750	Buffalo, NY	57,873	Middletown, NY	48,246
	Robinson, IL	47,152	Marquette, MI	54,579	Aberdeen, SD	47,921
	Cisco, TX	49,781	Winnemucca, NV	42,790	Gulfport, MS	57,026
	Des Moines, IA	42,265	Jacksonville, FL	49,296	Lake City, MN	54,100
	Rawlins, WY	40,523	Muskegon, MI	58,547	Evansville, IN	58,125

Table G.8: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 1	d_i	**Set 2**	d_i	**Set 3**	d_i
C	Saint George, UT	29,001	Dodge City, KS	28,733	Charlotte, NC	27,643
	Lamar, CO	34,170	Harrisonburg, VA	33,814	Calais, ME	29,663
	Denver, CO	28,182	Greensboro, NC	33,175	Richmond, VA	32,663
	Freeport, TX	27,404	San Angelo, TX	33,010	Freeport, TX	31,048
	Everett, WA	26,250	Las Vegas, NV	30,603	Pittsburgh, PA	31,142
	Tallahassee, FL	31,377	Morrison, TN	29,618	Spokane, WA	30,198
	Emmetsburg, IA	34,076	Madison, WI	30,103	East Windsor, CT	26,140
	Concord, NH	32,569	Laredo, TX	33,971	Phoenix, AZ	33,517
	Harrisonburg, VA	30,671	Fall River, MA	25,539	Guymon, OK	28,831
	Wichita, KS	33,613	Dallas, TX	32,542	Odessa, TX	26,515
	Escanaba, MI	27,987	Hazlehurst, GA	31,690	Cairo, IL	27,827
	Del Rio, TX	27,789	Lykens, OH	33,576	Tifton, GA	29,742
	Morrison, TN	29,553	Washington, NC	34,060	Robinson, IL	32,482
	Santa Fe, NM	30,178	Corpus Christi, TX	25,668	Columbia, SC	31,952
	Philadelphia, PA	32,779	Hubbard, OH	26,204	Bartow, FL	28,331
	Lake Charles, LA	33,319	Florence, SC	30,215	Cody, WY	31,657
	Grand Rapids, MI	32,367	Tucson, AZ	29,066	Cleveland, OH	34,247
	San Luis Obispo, CA	29,013	Paragould, AR	29,057	Meridian, MS	27,358
	Milwaukee, WI	32,085	Phoenix, AZ	27,835	Auburn, MA	26,318
	Atoka, OK	27,580	El Paso, TX	31,414	Rapid City, SD	28,034
	Muskegon, MI	30,000	Bucyrus, OH	29,289	Rochester, NY	34,041
	Columbus, MS	32,707	Flagstaff, AZ	27,419	Wilmington, NC	29,093
	Lake Village, AR	33,254	New York, NY	29,905	Washington, DC	30,521
	Springfield, IL	29,633	Tampa, FL	31,253	Salt Lake City, UT	33,529
	Evansville, IN	31,915	Duluth, MN	27,213	Dubuque, IA	33,039
	Cody, WY	27,634	Sacramento, CA	27,049	Nashville, TN	27,031
	Spokane, WA	32,064	Poplar Bluff, MO	32,523	Bridgeville, DE	26,061
	Columbia, SC	28,397	Los Angeles, CA	30,792	Escanaba, MI	28,616
	Muncie, IN	32,730	Myrtle Beach, SC	32,360	Albuquerque, NM	27,023
	Boise, ID	32,214	Hays, KS	25,575	Durango, CO	32,139
	Sumner, IA	30,857	Vidalia, GA	29,646	Alexandria, LA	28,178
	Newport, OR	29,271	Lake Charles, LA	27,918	Marquette, MI	28,968
	Burns, OR	26,279	Sturgis, MI	29,227	Coos Bay, OR	27,147
	Cocoa, FL	31,413	Wells, NV	32,464	Spanish Fork, UT	32,302
	Green River, UT	30,939	Louisville, KY	33,299	Tulsa, OK	30,544
	Pasco, WA	34,135	Eureka, CA	29,234	Indianapolis, IN	31,801
	Las Vegas, NV	32,825	Pueblo, CO	33,046	Gallipolis, OH	27,380
	Roswell, NM	30,512	Aberdeen, SD	31,292	Oshkosh, WI	30,410
	Alexander Cy, AL	31,855	Mcallen, TX	32,518	Little Rock, AR	27,465
	Atlanta, GA	27,317	Fort Valley, GA	31,330	Shreveport, LA	25,810
	Billings, MT	27,898	Westlake Village, CA	31,843	Newport, NY	30,040
	Bohemia, NY	26,839	Barstow, CA	32,952	Livingston, MT	31,585
	Crookston, MN	28,355	Hammond, LA	27,321	North Platte, NE	26,356
	Dubuque, IA	29,101	Philadelphia, PA	28,726	Santa Fe, NM	30,061
	Walworth, WI	31,943	Portland, ME	34,075	Charleston, WV	27,796
	Fort Stockton, TX	26,908	Lamar, CO	29,883	Redding, CA	31,261
	Houlton, ME	27,248	Saint Louis, MO	31,735	Klamath Falls, OR	32,398
	Paragould, AR	26,271	Knoxville, TN	26,495	Savannah, GA	26,597
	Wenatchee, WA	30,293	Nogales, AZ	31,368	Oakley, KS	25,773
	Twin Falls, ID	25,593	Ely, NV	25,998	Baton Rouge, LA	29,022

Table G.9: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
A	Little Rock, AR	102,178	Durango, CO	123,372	Lordsburg, NM	94,887
	Myrtle Beach, SC	97,394	Walworth, WI	92,116	Cuba, MO	101,668
	San Luis Obispo, CA	113,770	Dubuque, IA	78,955	Birmingham, AL	90,537
	Marathon, TX	94,731	Mackinaw City, MI	78,332	Hays, KS	124,709
	Gulfport, MS	116,121	Great Falls, MT	117,855	Merrifield, MN	122,463
	Des Moines, IA	79,874	Kansas City, KS	110,487	Jackson, MS	116,712
	Vernon, TX	110,944	Concord, NH	97,833	Pierre, SD	88,343
	Grand Forks, ND	84,856	Sioux Falls, SD	124,529	Flagstaff, AZ	79,260
	Baltimore, MD	81,167	Boston, MA	103,060	Peoria, IL	80,266
	Billings, MT	102,610	Phoenix, AZ	109,650	Lykens, OH	103,290
	Mt Pleasant, IA	93,092	Imlay City, MI	76,503	Freeport, TX	121,689
	Muskegon, MI	113,761	El Paso, TX	103,125	Biggs, OR	117,861
	Fort Stockton, TX	106,293	Twin Falls, ID	99,805	Boston, MA	122,078
	Idaho Falls, ID	113,646	Nashville, TN	99,312	Page, AZ	80,454
	Concord, NH	122,374	Meridian, MS	107,607	Oakley, KS	100,923
	Grenada, MS	90,000	Paragould, AR	120,276	Escanaba, MI	78,320
	Grand Rapids, MI	102,854	Elmira, NY	84,935	Poplar Bluff, MO	95,560
	Modesto, CA	86,151	Fall River, MA	105,564	Dallas, TX	104,038
	Raton, NM	98,636	Jacksonville, FL	100,683	Grand Island, NE	117,906
	Socorro, NM	114,683	Mobile, AL	115,722	Tucumcari, NM	107,865
B	Hulls Cove, ME	55,611	Oklahoma City, OK	55,567	Texarkana, AR	51,306
	Bridgeville, DE	54,981	Fort Scott, KS	46,093	Del Rio, TX	55,038
	Greenville, SC	46,671	Rawlins, WY	46,054	Elmira, NY	45,220
	Emmetsburg, IA	46,577	Michigan City, IN	41,986	Seattle, WA	55,013
	Pendleton, OR	58,920	Corinth, MS	53,586	Milwaukee, WI	45,662
	Lakeview, OR	54,763	Aberdeen, SD	47,308	Asheville, NC	50,749
	Warehouse Point, CT	45,260	Knoxville, TN	58,591	Ely, NV	45,470
	Boise, ID	44,883	Norfolk, VA	43,894	Baltimore, MD	47,547
	Casper, WY	58,588	Hulls Cove, ME	55,089	Imlay City, MI	45,598
	Bohemia, NY	53,583	Tallahassee, FL	52,762	Kearney, NE	43,645
	Tulsa, OK	59,302	Saint Louis, MO	59,649	Emmetsburg, IA	42,436
	Lincoln, NE	42,244	Hubbard, OH	49,093	Salina, UT	50,087
	Bishop, CA	48,908	Albuquerque, NM	48,008	Denver, CO	49,299
	Oshkosh, WI	49,675	Cody, WY	56,315	Fort Myers, FL	45,751
	Fort Smith, AR	43,257	Hazlehurst, GA	48,596	Bohemia, NY	49,855
	Binghamton, NY	54,107	Portland, ME	48,397	Albert Lea, MN	47,693
	Rochester, IN	45,372	Marquette, MI	56,067	Bartow, FL	40,869
	Watertown, NY	45,616	Lamar, CO	52,851	Reno, NV	41,685
	Saint Louis, MO	43,864	Robinson, IL	48,728	Rochester, IN	59,109
	Decorah, IA	54,016	Rapid City, SD	42,961	Marquette, MI	52,139
	Washington, MO	49,438	Eau Claire, WI	44,210	Fresno, CA	56,595
	Stockton, CA	59,091	Wenatchee, WA	55,931	Lake Charles, LA	55,705
	Wichita, KS	57,164	Des Moines, IA	54,834	Portland, OR	41,913
	Pierre, SD	48,439	Grants Pass, OR	47,972	Baton Rouge, LA	58,395
	Cody, WY	44,416	Socorro, NM	59,190	Plover, WI	59,240
	Gainesville, GA	53,821	Flagstaff, AZ	45,616	Ringwood, IL	53,856
	Bismarck, ND	59,607	Pueblo, CO	56,822	Sioux Falls, SD	58,787
	St Augustine, FL	58,020	Baltimore, MD	46,284	Harrisburg, PA	48,749
	Louisville, KY	55,987	N Canton, OH	57,063	Newport, NY	50,149
	Chillicothe, MO	47,204	Sacramento, CA	51,757	Russellville, AR	57,996

Table G.10: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 4	d_i	**Set 5**	d_i	**Set 6**	d_i
C	Odessa, TX	34,267	Raton, NM	30,061	Lexington, KY	33,181
	Dodge City, KS	33,089	Spanish Fork, UT	32,720	Portland, ME	29,093
	Tifton, GA	26,841	Lowell, AR	33,228	Morrison, TN	28,436
	Miami, FL	33,560	Astoria, OR	30,881	Rensselaer, IN	31,596
	Pueblo, CO	28,520	Warehouse Point, CT	33,952	Pasco, WA	26,147
	Green Bay, WI	31,491	Sturgis, MI	33,073	Livingston, MT	31,181
	San Francisco, CA	34,157	Cairo, IL	33,555	Cleveland, OH	32,317
	Fort Valley, GA	26,665	Coos Bay, OR	28,058	Louisville, KY	31,994
	Sioux Falls, SD	29,920	Bangor, ME	31,414	Idaho Falls, ID	33,718
	Page, AZ	34,231	Vernon, TX	32,477	Raton, NM	28,442
	Eugene, OR	31,124	Youngstown, PA	26,886	Butte, MT	34,069
	Astoria, OR	27,405	Gainesville, FL	29,014	Walworth, WI	29,200
	Mobile, AL	27,061	Las Vegas, NV	30,843	Vaughn, NM	25,998
	Vaughn, NM	27,151	Bishop, CA	28,397	Miami, FL	26,568
	Augusta, GA	30,575	Salina, KS	28,822	Watertown, NY	30,491
	Great Bend, KS	30,841	Auburn, MA	31,861	Fargo, ND	34,467
	Dothan, AL	27,318	Saint George, UT	34,191	Grenada, MS	26,985
	Westlake Village, CA	27,120	Dodge City, KS	30,182	Springfield, IL	26,348
	San Angelo, TX	29,107	Wichita, KS	29,699	Westlake Village, CA	31,149
	Richmond, VA	34,307	Baton Rouge, LA	27,694	Corpus Christi, TX	27,540
	Imlay City, MI	31,679	Muncie, IN	26,296	Augusta, GA	28,051
	Barstow, CA	31,100	New York, NY	30,282	Oklahoma City, OK	26,967
	Freeport, TX	28,149	Kalamazoo, MI	30,848	Minot, ND	33,391
	Atoka, OK	33,417	Milwaukee, WI	32,584	East Windsor, CT	26,298
	Kansas City, KS	29,779	Peoria, IL	31,765	Coos Bay, OR	25,962
	Alexandria, LA	28,595	Lake City, MN	33,632	Sturgis, MI	32,330
	San Diego, CA	32,061	Asheville, NC	33,527	Helena, MT	29,077
	Poplar Bluff, MO	28,838	Missoula, MT	29,472	Concord, NH	32,918
	N Canton, OH	31,339	Sumner, IA	32,079	Austin, TX	31,904
	Hayward, CA	29,242	Redding, CA	30,663	Philadelphia, PA	31,315
	Kearney, NE	29,155	Kearney, NE	27,238	Astoria, OR	28,331
	Wilmington, NC	29,467	Dallas, TX	32,139	Atoka, OK	30,054
	Rapid City, SD	29,954	Santa Fe, NM	26,318	Fort Scott, KS	29,046
	Buffalo, NY	26,554	Roswell, NM	27,592	Alexander Cy, AL	26,878
	Fort Scott, KS	28,387	Columbus, MS	28,475	Mobile, AL	34,202
	Durango, CO	26,430	Atlanta, GA	28,247	Paragould, AR	26,475
	Springfield, MO	30,470	Victoria, TX	26,564	Michigan City, IN	31,720
	Evansville, IN	30,342	Gainesville, GA	32,623	Orlando, FL	32,124
	Springdale, UT	33,948	San Angelo, TX	34,419	Lowell, AR	27,469
	Paragould, AR	30,248	Lincoln, NE	25,717	Phoenix, AZ	33,418
	Yuma, AZ	29,162	Modesto, CA	25,615	Fort Stockton, TX	33,331
	San Antonio, TX	31,426	Vidalia, GA	32,461	Port Angeles, WA	33,013
	Green River, UT	27,276	Carlsbad, NM	26,458	Dubuque, IA	30,869
	Austin, TX	27,194	Bridgeville, DE	31,278	Anniston, AL	34,296
	Altoona, PA	31,395	Salinas, CA	33,311	Roanoke, VA	31,917
	Atlanta, GA	32,885	Greenville, SC	28,023	Gallipolis, OH	29,308
	Lykens, OH	29,755	Sheridan, WY	29,261	Modesto, CA	31,028
	Middletown, NY	29,346	Miami, FL	28,686	Mt Pleasant, IA	26,094
	Amarillo, TX	28,947	Gulfport, MS	28,283	Needles, CA	26,401
	Charleston, SC	27,030	Saint Johns, MI	30,225	Des Moines, IA	32,411

Table G.11: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
A	Oshkosh, WI	79,978	Shelby, NC	115,646	Rawlins, WY	84,869
	Twin Falls, ID	76,364	Rochester, NY	114,192	Charleston, WV	116,297
	Chillicothe, MO	87,096	Peoria, IL	89,235	Phoenix, AZ	109,525
	Spencer, IA	83,444	Gwinner, ND	89,234	Fort Valley, GA	104,133
	Amarillo, TX	119,065	Daytona Beach, FL	82,049	Hulls Cove, ME	104,579
	New Orleans, LA	94,990	Springfield, IL	113,530	Muncie, IN	80,094
	Salina, KS	109,222	Cedar Rapids, IA	89,495	Binghamton, NY	114,928
	Auburn, MA	124,014	Muskegon, MI	94,799	Mt Pleasant, IA	116,201
	Cody, WY	97,164	Des Moines, IA	85,437	Concord, NH	120,870
	Lubbock, TX	109,407	Philadelphia, PA	90,292	Crossville, TN	123,023
	Mt Pleasant, IA	91,733	Fort Wayne, IN	118,871	Gallipolis, OH	116,362
	Duluth, MN	123,969	Muenster, TX	84,874	Bluefield, WV	100,898
	Harrisonburg, VA	105,412	Lake Village, AR	111,378	West Palm Beach, FL	78,482
	Laredo, TX	108,835	Cocoa, FL	103,055	Saint Joseph, MO	86,535
	Houston, TX	77,741	Tulsa, OK	109,031	Green River, UT	76,310
	Fargo, ND	114,152	Rochester, IN	102,213	Bartow, FL	107,029
	Grants Pass, OR	92,288	Plover, WI	93,158	Austin, TX	95,194
	Bluefield, WV	119,086	Odessa, TX	119,581	Idaho Falls, ID	109,130
	Billings, MT	97,834	Wilmington, NC	112,300	East Windsor, CT	124,235
	Rochester, NY	84,859	Portland, OR	109,675	St Augustine, FL	120,872
B	Snyder, TX	57,247	Fort Stockton, TX	58,873	Fresno, CA	47,229
	Austin, TX	45,160	Michigan City, IN	50,104	Spencer, IA	45,373
	Freeport, TX	42,674	Myrtle Beach, SC	54,192	Russellville, AR	55,615
	Marathon, TX	44,478	Chillicothe, MO	57,594	Knoxville, TN	58,608
	Los Angeles, CA	47,597	Kansas City, KS	52,504	Kalamazoo, MI	46,544
	Delphos, OH	55,507	Lubbock, TX	47,267	Columbus, OH	58,969
	Bonners Ferry, ID	54,094	Decorah, IA	58,128	Sumner, IA	58,055
	Birmingham, AL	44,135	Spokane, WA	53,770	Muskegon, MI	41,145
	Cairo, IL	40,921	Bartow, FL	56,020	Portland, OR	52,866
	Phoenix, AZ	51,922	Escanaba, MI	49,236	Biggs, OR	43,585
	Montgomery, AL	53,373	Helena, MT	49,147	San Luis Obispo, CA	58,136
	Roswell, NM	59,127	Kalamazoo, MI	41,478	San Angelo, TX	56,446
	St Augustine, FL	46,734	Los Angeles, CA	41,940	Calais, ME	59,489
	Rensselaer, IN	56,931	Grand Forks, ND	59,892	Raleigh, NC	45,853
	Carlsbad, NM	42,845	Cisco, TX	54,417	Charleston, SC	51,988
	Saint Johns, MI	48,036	Brownsville, TX	54,768	Rapid City, SD	41,762
	Michigan City, IN	49,262	Evansville, IN	53,985	Everett, WA	48,528
	Bartow, FL	48,812	Gallup, NM	45,964	San Francisco, CA	58,194
	Newport, OR	47,031	Calais, ME	55,512	Emmetsburg, IA	44,813
	Lake City, MN	54,556	Nashville, TN	41,130	Lamar, CO	54,410
	Elmira, NY	58,052	Atoka, OK	46,903	Dothan, AL	41,430
	Aberdeen, SD	46,997	Albuquerque, NM	58,224	Lexington, KY	51,683
	Watertown, SD	46,436	Tampa, FL	40,985	Fort Worth, TX	42,032
	Lexington, KY	54,443	Saginaw, MI	46,675	Muenster, TX	48,979
	Blythe, CA	45,046	Guymon, OK	43,422	Dodge City, KS	47,201
	Craig, CO	43,615	Bridgeville, DE	52,907	Cincinnati, OH	50,090
	Grenada, MS	46,234	Amarillo, TX	45,707	Florence, SC	56,857
	Madison, IN	47,131	Walworth, WI	57,366	Little Rock, AR	55,484
	Columbia, SC	41,250	Mackinaw City, MI	51,605	Altoona, PA	46,341
	La Crosse, WI	44,157	Yuma, AZ	53,297	Anniston, AL	56,817

Table G.12: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 7	d_i	**Set 8**	d_i	**Set 9**	d_i
C	Corinth, MS	29,394	Fort Valley, GA	28,988	Pittsburgh, PA	32,833
	Morrison, TN	33,647	Page, AZ	31,467	Sturgis, MI	25,793
	Albuquerque, NM	29,851	Fort Scott, KS	30,266	Wenatchee, WA	25,834
	Pittsburgh, PA	29,774	Grand Junction, CO	29,881	Cairo, IL	26,701
	Nogales, AZ	32,588	Roswell, NM	30,776	Amarillo, TX	26,468
	Middletown, NY	31,714	Baltimore, MD	31,463	Sioux Falls, SD	33,445
	Harrisburg, PA	25,714	Florence, SC	32,194	Chattanooga, TN	32,285
	Imlay City, MI	26,669	Albany, NY	26,167	Shelby, NC	31,418
	Port Angeles, WA	30,492	Vernon, TX	30,062	Portland, ME	29,060
	Charleston, WV	25,651	Dallas, TX	29,116	Baltimore, MD	30,087
	Calais, ME	29,277	Fort Worth, TX	27,503	Grenada, MS	33,427
	Rapid City, SD	32,515	Freeport, TX	33,364	Syracuse, NY	31,733
	Detroit, MI	29,007	Havre, MT	29,434	Lakeview, OR	29,538
	Kearney, NE	29,191	Bucyrus, OH	33,531	Modesto, CA	27,652
	Robinson, IL	31,241	Elmira, NY	30,118	Warehouse Point, CT	28,603
	Durango, CO	26,589	Reno, NV	31,317	Roswell, NM	33,239
	Escanaba, MI	28,324	Tifton, GA	25,631	Paragould, AR	26,365
	Vernon, TX	25,823	Hubbard, OH	27,457	Port Angeles, WA	27,817
	Dothan, AL	32,793	La Crosse, WI	34,412	Miami, FL	33,288
	Reno, NV	33,620	Port Angeles, WA	27,187	El Paso, TX	31,368
	Savannah, GA	30,907	Crookston, MN	26,391	Rensselaer, IN	28,912
	Boston, MA	31,794	Fort Myers, FL	31,718	Cheyenne, WY	33,319
	Byron, IL	26,699	Minot, ND	25,639	Butte, MT	26,321
	Pierre, SD	28,202	Hays, KS	33,322	La Crosse, WI	33,132
	Tallahassee, FL	27,701	Texarkana, AR	33,715	Evansville, IN	30,479
	Missoula, MT	32,301	Albert Lea, MN	33,847	Escanaba, MI	31,953
	Dubuque, IA	34,168	Merrifield, MN	29,241	San Diego, CA	30,046
	Greensboro, NC	27,996	Needles, CA	33,604	Wichita, KS	29,591
	Charleston, SC	33,666	Boston, MA	26,226	Cleveland, OH	33,360
	Augusta, GA	25,517	Del Rio, TX	25,823	Vaughn, NM	33,147
	Albert Lea, MN	32,547	Corinth, MS	25,717	Williams, AZ	34,462
	Burns, OR	29,389	Roanoke, VA	28,408	Pierre, SD	33,578
	Kit Carson, CO	26,295	Vidalia, GA	31,866	Byron, IL	33,967
	Butte, MT	29,351	Aberdeen, SD	30,205	Greensboro, NC	30,997
	Sioux City, IA	31,929	Gainesville, GA	28,812	Toledo, OH	34,155
	Eureka, CA	31,478	Livingston, MT	29,011	Norfolk, VA	31,451
	Springfield, IL	29,862	Urbana, OH	30,347	Spokane, WA	33,776
	Knoxville, TN	34,135	Saint Louis, MO	26,365	Park City, KY	29,008
	Great Bend, KS	33,300	Jefferson City, MO	30,551	Watertown, SD	28,016
	Bucyrus, OH	32,079	Harrisonburg, VA	29,917	Kit Carson, CO	32,017
	Fresno, CA	28,138	Byron, IL	32,461	Washington, MO	29,835
	Chicago, IL	32,973	Marathon, TX	29,227	Nederland, TX	27,628
	Peoria, IL	26,906	Cairo, IL	31,387	Westlake Village, CA	32,627
	Muncie, IN	33,883	Orlando, FL	29,989	Orlando, FL	33,294
	Casper, WY	31,499	Washington, NC	33,852	Elmira, NY	31,256
	Binghamton, NY	34,134	Cody, WY	32,904	Nashville, TN	34,337
	Crossville, TN	32,294	Salinas, CA	33,299	Salina, KS	30,604
	Omaha, NE	28,568	Imlay City, MI	25,681	Imlay City, MI	28,645
	Marquette, MI	27,323	Charleston, WV	31,480	Great Bend, KS	31,627
	Orlando, FL	26,372	Cleveland, OH	34,193	Savannah, GA	30,151

Table G.13: Customer Data Sets — Average Demand = 50,000; 100 Locations.

	Set 10	d_i		**Set 10**	d_i
A	Newport, OR	112,012	**C**	Reno, NV	30,181
	Concord, NH	123,689		Port Angeles, WA	26,577
	Poplar Bluff, MO	105,868		Brownsville, TX	28,722
	Hayward, CA	88,048		Fort Wayne, IN	25,937
	Boise, ID	80,375		Billings, MT	27,290
	Baltimore, MD	124,450		Oshkosh, WI	29,250
	Sioux Falls, SD	80,282		Dothan, AL	25,872
	Davenport, IA	111,552		Victoria, TX	26,563
	Kearney, NE	107,681		Bridgeville, DE	27,406
	Springfield, MO	92,756		Scranton, PA	28,081
	Milwaukee, WI	119,086		Urbana, OH	28,104
	Craig, CO	96,604		Gulfport, MS	33,289
	Gallipolis, OH	112,126		Imlay City, MI	30,707
	Buffalo, NY	102,358		Guymon, OK	30,403
	Santa Fe, NM	121,513		Lamar, CO	33,911
	Amarillo, TX	82,441		Detroit, MI	30,336
	Great Bend, KS	119,194		Wenatchee, WA	26,378
	Knoxville, TN	106,693		San Antonio, TX	27,715
	Wichita, KS	94,966		Houston, TX	30,576
	Williston, ND	122,267		Cocoa, FL	28,833
B	Philadelphia, PA	46,503		Wells, NV	30,112
	Phoenix, AZ	55,143		Carlsbad, NM	34,183
	Saginaw, MI	41,335		Orlando, FL	30,241
	Lubbock, TX	56,873		Dallas, TX	29,115
	Saint Johns, MI	46,413		Hulls Cove, ME	31,380
	Freeport, TX	49,722		Bend, OR	33,022
	Byron, IL	59,874		International Falls, MN	28,045
	Springdale, UT	46,009		Louisville, KY	29,296
	Salinas, CA	59,969		Idaho Falls, ID	26,129
	North Platte, NE	55,620		Dodge City, KS	32,574
	Nashville, TN	43,361		Sheridan, WY	31,883
	Columbia, SC	52,856		Eau Claire, WI	34,131
	Pasco, WA	42,687		Montgomery, AL	27,675
	Saint Joseph, MO	55,661		Jefferson City, MO	31,610
	Spencer, IA	50,021		Del Rio, TX	28,267
	Harrisburg, PA	42,380		Gainesville, GA	26,152
	Fort Scott, KS	43,823		Blythe, CA	29,279
	Walworth, WI	55,006		Paragould, AR	29,349
	Estes Park, CO	55,510		San Francisco, CA	33,686
	Clovis, NM	48,538		Savannah, GA	28,041
	Tallahassee, FL	40,961		N Canton, OH	27,032
	Nogales, AZ	50,952		Salina, KS	34,347
	Tucson, AZ	43,459		Fort Smith, AR	28,788
	Bartow, FL	40,398		Mackinaw City, MI	26,259
	Tucumcari, NM	59,691		Fort Stockton, TX	28,375
	Roswell, NM	48,508		Corpus Christi, TX	31,367
	El Paso, TX	59,712		Ellensburg, WA	26,658
	Marathon, TX	55,140		Grand Junction, CO	32,755
	Fargo, ND	54,173		Altoona, PA	27,420
	Havre, MT	51,926		Sioux City, IA	33,360

Appendix H

Manufacturer Location and Supply Data Sets

Table H.1: Manufacturer Data Sets — 5 Locations.

Set 1	**Product**	**Set 2**	**Product**	**Set 3**	**Product**
Shreveport, LA	1	Corpus Christi, TX	1	Mcallen, TX	1
Pierre, SD	2	Westlake Village, CA	2	Milwaukee, WI	2
Kalamazoo, MI	3	Crookston, MN	3	Bangor, ME	3
Fresno, CA	4	Fort Myers, FL	4	Rensselaer, IN	4
Cairo, IL	5	Port Angeles, WA	5	Paragould, AR	5
Set 4	**Product**	**Set 5**	**Product**	**Set 6**	**Product**
Marquette, MI	1	Rochester, IN	1	Minot, ND	1
Gainesville, GA	2	Omaha, NE	2	Toledo, OH	2
Tucumcari, NM	3	Del Rio, TX	3	Louisville, KY	3
Pueblo, CO	4	Grand Junction, CO	4	Miles City, MT	4
Ringwood, IL	5	Guymon, OK	5	Vaughn, NM	5
Set 7	**Product**	**Set 8**	**Product**	**Set 9**	**Product**
Detroit, MI	1	Watertown, SD	1	Billings, MT	1
San Francisco, CA	2	Bohemia, NY	2	Miami, FL	2
Wells, NV	3	Saint Louis, MO	3	Des Moines, IA	3
Williams, AZ	4	La Crosse, WI	4	Fresno, CA	4
Saint Joseph, MO	5	Hazlehurst, GA	5	San Angelo, TX	5
Set 10	**Product**				
Redding, CA	1				
Mcallen, TX	2				
Columbus, OH	3				
Baltimore, MD	4				
Middletown, NY	5				

Table H.2: Manufacturer Data Sets — 10 Locations.

Set 1	**Product**	**%age**	**Set 2**	**Product**	**%age**
Chillicothe, MO	1	20%	Charleston, SC	1	20%
Elmira, NY	1	80%	Fort Stockton, TX	1	80%
Cisco, TX	2	20%	Ringwood, IL	2	20%
Los Angeles, CA	2	80%	Sturgis, MI	2	80%
Indianapolis, IN	3	20%	Tifton, GA	3	20%
Gallup, NM	3	80%	Calais, ME	3	80%
Sheridan, WY	4	20%	Hays, KS	4	20%
West Palm Beach, FL	4	80%	West Glacier, MT	4	80%
Biggs, OR	5	20%	Wenatchee, WA	5	20%
Huntsville, AL	5	80%	Washington, MO	5	80%
Set 3	**Product**	**%age**	**Set 4**	**Product**	**%age**
Lowell, AR	1	20%	Jefferson City, MO	1	20%
Jacksonville, FL	1	80%	Altoona, PA	1	80%
Texarkana, AR	2	20%	Needles, CA	2	20%
Houlton, ME	2	80%	Saint Louis, MO	2	80%
Chicago, IL	3	20%	Rochester, NY	3	20%
Alexander Cy, AL	3	80%	Saginaw, MI	3	80%
Des Moines, IA	4	20%	Page, AZ	4	20%
Charleston, WV	4	80%	Pueblo, CO	4	80%
Little Rock, AR	5	20%	New York, NY	5	20%
Lordsburg, NM	5	80%	Santa Fe, NM	5	80%
Set 5	**Product**	**%age**	**Set 6**	**Product**	**%age**
Great Bend, KS	1	20%	Huntsville, AL	1	20%
Plover, WI	1	80%	Madison, WI	1	80%
Tucumcari, NM	2	20%	Saginaw, MI	2	20%
Texarkana, AR	2	80%	Guymon, OK	2	80%
Portland, OR	3	20%	Auburn, MA	3	20%
Los Angeles, CA	3	80%	Jacksonville, FL	3	80%
Sturgis, MI	4	20%	Grants Pass, OR	4	20%
Bohemia, NY	4	80%	Toledo, OH	4	80%
Lake Village, AR	5	20%	Williams, AZ	5	20%
Livingston, MT	5	80%	Springdale, AR	5	80%
Set 7	**Product**	**%age**	**Set 8**	**Product**	**%age**
Fresno, CA	1	20%	Modesto, CA	1	20%
Lubbock, TX	1	80%	Gallup, NM	1	80%
Davenport, IA	2	20%	Auburn, MA	2	20%
Delphos, OH	2	80%	Hubbard, OH	2	80%
Vidalia, GA	3	20%	Concord, NH	3	20%
Wenatchee, WA	3	80%	Portland, OR	3	80%
Los Angeles, CA	4	20%	Great Falls, MT	4	20%
Portland, ME	4	80%	Freeport, TX	4	80%
Salina, UT	5	20%	Russellville, AR	5	20%
Pierre, SD	5	80%	Green River, UT	5	80%

Table H.3: Manufacturer Data Sets — 10 Locations.

Set 9	**Product**	**%age**	**Set 10**	**Product**	**%age**
Gallipolis, OH	1	20%	Gulfport, MS	1	20%
Mobile, AL	1	80%	Gwinner, ND	1	80%
Albany, NY	2	20%	Lowell, AR	2	20%
Minot, ND	2	80%	Williston, ND	2	80%
Augusta, GA	3	20%	Grand Rapids, MI	3	20%
Hammond, LA	3	80%	Little Rock, AR	3	80%
Madison, IN	4	20%	Oakley, KS	4	20%
Miles City, MT	4	80%	Albany, NY	4	80%
Westlake Village, CA	5	20%	Louisville, KY	5	20%
Gainesville, GA	5	80%	Yuma, AZ	5	80%

Table H.4: Manufacturer Data Sets — 20 Locations.

Set 1	**Product**	**%age**	**Set 2**	**Product**	**%age**
Freeport, TX	1	10%	Ringwood, IL	1	10%
Auburn, MA	1	20%	Mobile, AL	1	20%
Raton, NM	1	20%	Warehouse Point, CT	1	20%
Mt Pleasant, IA	1	50%	Vaughn, NM	1	50%
Rochester, NY	2	10%	Watertown, NY	2	10%
Atlanta, GA	2	20%	Gainesville, GA	2	20%
Pierre, SD	2	20%	Calais, ME	2	20%
Hazlehurst, GA	2	50%	Winnemucca, NV	2	50%
Jefferson City, MO	3	10%	Bucyrus, OH	3	10%
Alexander Cy, AL	3	20%	Coos Bay, OR	3	20%
Columbus, OH	3	20%	Corpus Christi, TX	3	20%
Gulfport, MS	3	50%	Columbus, OH	3	50%
Escanaba, MI	4	10%	Bohemia, NY	4	10%
Grand Island, NE	4	20%	Cocoa, FL	4	20%
Gallipolis, OH	4	20%	Cody, WY	4	20%
Albany, NY	4	50%	Oklahoma City, OK	4	50%
Saint Louis, MO	5	10%	Woodstock, IL	5	10%
Little Rock, AR	5	20%	Hayward, CA	5	20%
Decorah, IA	5	20%	Portland, OR	5	20%
Milwaukee, WI	5	50%	Ely, NV	5	50%

Table H.5: Manufacturer Data Sets — 20 Locations.

Set 3	**Product**	**%age**	**Set 4**	**Product**	**%age**
Mt Pleasant, IA	1	10%	Las Vegas, NV	1	10%
Bonners Ferry, ID	1	20%	Cairo, IL	1	20%
Roswell, NM	1	20%	Del Rio, TX	1	20%
Richmond, VA	1	50%	Dodge City, KS	1	50%
Fall River, MA	2	10%	Miles City, MT	2	10%
Denver, CO	2	20%	Birmingham, AL	2	20%
Cairo, IL	2	20%	Alexandria, LA	2	20%
Huntsville, AL	2	50%	Washington, DC	2	50%
Hulls Cove, ME	3	10%	Meridian, MS	3	10%
St Augustine, FL	3	20%	Michigan City, IN	3	20%
Middletown, NY	3	20%	New York, NY	3	20%
Tucumcari, NM	3	50%	Green Bay, WI	3	50%
Saint Joseph, MO	4	10%	Hazlehurst, GA	4	10%
Lamar, CO	4	20%	Fort Scott, KS	4	20%
Bridgeville, DE	4	20%	Oshkosh, WI	4	20%
New York, NY	4	50%	Tallahassee, FL	4	50%
Atoka, OK	5	10%	Cincinnati, OH	5	10%
Corinth, MS	5	20%	Fort Smith, AR	5	20%
Saint George, UT	5	20%	Stockton, CA	5	20%
Salina, KS	5	50%	Shreveport, LA	5	50%
Set 5	**Product**	**%age**	**Set 6**	**Product**	**%age**
Gainesville, GA	1	10%	St Augustine, FL	1	10%
Lake Charles, LA	1	20%	Charlotte, NC	1	20%
Pasco, WA	1	20%	Houston, TX	1	20%
Grand Rapids, MI	1	50%	Alexandria, LA	1	50%
Cedar Rapids, IA	2	10%	Escanaba, MI	2	10%
Louisville, KY	2	20%	Philadelphia, PA	2	20%
Escanaba, MI	2	20%	Casper, WY	2	20%
Mackinaw City, MI	2	50%	Spencer, IA	2	50%
Williams, AZ	3	10%	Kansas City, KS	3	10%
Salinas, CA	3	20%	Saint Joseph, MO	3	20%
West Glacier, MT	3	20%	Oshkosh, WI	3	20%
Cuba, MO	3	50%	Lake Village, AR	3	50%
Grand Forks, ND	4	10%	Sioux City, IA	4	10%
Concord, NH	4	20%	Blythe, CA	4	20%
Columbia, SC	4	20%	Gainesville, GA	4	20%
Shreveport, LA	4	50%	Redding, CA	4	50%
Santa Fe, NM	5	10%	Salt Lake City, UT	5	10%
Morrison, TN	5	20%	Muncie, IN	5	20%
Lubbock, TX	5	20%	Urbana, OH	5	20%
Anniston, AL	5	50%	Tifton, GA	5	50%

Table H.6: Manufacturer Data Sets — 20 Locations.

Set 7	**Product**	**%age**	**Set 8**	**Product**	**%age**
Warehouse Point, CT	1	10%	Redding, CA	1	10%
Phoenix, AZ	1	20%	Gwinner, ND	1	20%
La Crosse, WI	1	20%	Binghamton, NY	1	20%
Evansville, IN	1	50%	Greenville, SC	1	50%
Dodge City, KS	2	10%	Kansas City, KS	2	10%
Lamar, CO	2	20%	Huntsville, AL	2	20%
Laredo, TX	2	20%	Merrifield, MN	2	20%
St Augustine, FL	2	50%	Muncie, IN	2	50%
Miami, FL	3	10%	Middletown, NY	3	10%
Springfield, IL	3	20%	Bridgeville, DE	3	20%
Butte, MT	3	20%	Muskegon, MI	3	20%
Pueblo, CO	3	50%	Alexander Cy, AL	3	50%
Des Moines, IA	4	10%	Memphis, TN	4	10%
Tifton, GA	4	20%	Tallahassee, FL	4	20%
Memphis, TN	4	20%	Vidalia, GA	4	20%
Watertown, NY	4	50%	Phoenix, AZ	4	50%
Coos Bay, OR	5	10%	Pendleton, OR	5	10%
Fort Smith, AR	5	20%	Lincoln, NE	5	20%
Grand Island, NE	5	20%	Guymon, OK	5	20%
Imlay City, MI	5	50%	Orlando, FL	5	50%
Set 9	**Product**	**%age**	**Set 10**	**Product**	**%age**
Woodstock, IL	1	10%	Rochester, IN	1	10%
Craig, CO	1	20%	Bohemia, NY	1	20%
Hammond, LA	1	20%	Harrisonburg, VA	1	20%
Fort Myers, FL	1	50%	Needles, CA	1	50%
Hulls Cove, ME	2	10%	Middletown, NY	2	10%
Tucson, AZ	2	20%	Westlake Village, CA	2	20%
Green River, UT	2	20%	Charlotte, NC	2	20%
Roswell, NM	2	50%	Boston, MA	2	50%
Idaho Falls, ID	3	10%	Omaha, NE	3	10%
Missoula, MT	3	20%	Lamar, CO	3	20%
Grand Island, NE	3	20%	Escanaba, MI	3	20%
Robinson, IL	3	50%	Pierre, SD	3	50%
Helena, MT	4	10%	Little Rock, AR	4	10%
Cairo, IL	4	20%	Atlanta, GA	4	20%
Cuba, MO	4	20%	Sturgis, MI	4	20%
El Paso, TX	4	50%	Nederland, TX	4	50%
Knoxville, TN	5	10%	Bismarck, ND	5	10%
Fort Valley, GA	5	20%	Russellville, AR	5	20%
Biggs, OR	5	20%	Wells, NV	5	20%
Pittsburgh, PA	5	50%	Gallipolis, OH	5	50%

Appendix I

Product Family Values

Table I.1: Product Family Values.

	Value	Value	Value
Product Family 1	14	70	73
Product Family 2	16	42	122
Product Family 3	4	44	96
Product Family 4	9	30	107
Product Family 5	7	64	102
Average	**10**	**50**	**100**

Appendix J

Summarized Research Results

The following information represents the summarized results for the ten data sets for each test parameter combination. The test parameter combination is abbreviated by three letters — the first letter represents the value for the # Customers vs. the # Manufacturers Ratio parameter, the second letter represents the value for the Average Customer Demand parameter, and the third letter represents the value for the Product Value vs. Unit Transportation $ Ratio parameter. Results are shown for both heuristics as well as the location model with a fixed inventory policy.

Table J.1: Summarized H1 Results for the Inventory-Location Model.

H1 Results	**Labor Cost**	**Land Cost**	**Transportation Cost**	**Inventory Cost**	**OH Cost**	**Total Cost**
MMM	$1,195,370	$27,782	$3,766,321	$201,953	$528,295	$5,719,720
MLM	$300,589	$8,288	$1,097,520	$72,280	$254,757	$1,733,433
MHM	$2,989,106	$58,047	$8,952,754	$414,492	$914,465	$13,328,864
MML	$1,116,559	$10,672	$451,724	$495,814	$256,576	$2,331,346
MMH	$1,258,535	$64,948	$16,729,929	$44,356	$1,571,778	$19,669,545
MHH	$3,351,697	$139,181	$39,961,523	$88,739	$2,815,281	$46,356,421
HML	$2,242,993	$14,172	$861,607	$964,091	$261,581	$4,344,443
HHL	$5,822,680	$53,761	$1,937,702	$1,693,598	$684,964	$10,192,706
HMM	$2,382,504	$44,579	$7,198,327	$366,038	$723,097	$10,714,545
LMH	$456,580	$5,982	$187,238	$210,042	$249,250	$1,109,092

Table J.2: Summarized H2 Results for the Inventory-Location Model.

H2 Results	Labor Cost	Land Cost	Transportation Cost	Inventory Cost	OH Cost	Total Cost
MMM	$1,194,963	$25,483	$3,768,816	$201,461	$524,974	$5,715,697
MLM	$293,063	$6,317	$1,108,559	$73,207	$250,772	$1,731,918
MHM	$2,993,716	$60,295	$8,863,585	$401,212	$991,346	$13,310,154
MML	$1,116,559	$10,655	$451,769	$495,814	$256,551	$2,331,349
MMH	$1,261,169	$63,580	$16,726,268	$44,360	$1,570,457	$19,665,834
MHH	$3,396,945	$136,528	$39,786,690	$81,724	$2,944,040	$46,345,927
HML	$2,242,993	$14,172	$861,607	$964,091	$261,581	$4,344,443
HHL	$5,827,787	$59,604	$1,935,839	$1,609,201	$766,639	$10,199,070
HMM	$2,376,168	$41,783	$7,181,784	$366,333	$742,837	$10,708,905
LMH	$456,580	$5,982	$187,238	$210,042	$249,250	$1,109,092

Table J.3: Summarized Results for the Fixed Inventory-Location Model.

	Labor Cost	Land Cost	Transportation Cost	Inventory Cost	OH Cost	Total Cost
MMM	$1,191,370	$28,304	$3,769,184	$203,583	$528,879	$5,721,319
MLM	$293,063	$6,317	$1,108,559	$73,207	$250,772	$1,731,918
MHM	$2,970,025	$58,771	$8,965,651	$429,073	$914,723	$13,338,243
MML	$1,116,559	$10,655	$451,769	$495,814	$256,551	$2,331,349
MMH	$1,268,740	$67,280	$16,642,838	$44,312	$1,652,734	$19,675,904
MHH	$3,342,748	$143,890	$39,814,248	$89,480	$2,971,549	$46,361,915
HML	$2,242,993	$14,172	$861,607	$964,091	$261,581	$4,344,443
HHL	$5,540,821	$25,364	$2,131,111	$2,505,801	$277,153	$10,480,249
HMM	$2,379,560	$44,175	$7,173,988	$371,209	$746,578	$10,715,509
LMH	$456,580	$5,982	$187,238	$210,042	$249,250	$1,109,092

Appendix K

Detailed Test Results - Example

The data in this Appendix is shown to give a complete example of the output of the inventory-location model output. This data includes the exact DC locations opened, a detailed cost breakdown, customer service performance metrics, order quantities, and re-order points for all open DCs.

Table K.1: Detailed Test Results Example - HHL Test Set 9.

Cost Summary Table:				
DC Location:	**WELLS, NV**	**GALLIPOLIS, OH**	**ATOKA, OK**	**Total:**
DC Node:	151	311	163	
Quantity:	956,445	2,383,674	1,812,614	**5,152,733**
Percent Demand:	0.19	0.46	0.35	**1.00**
Labor Cost:	$1,176,983	$2,826,814	$1,963,097	**$5,966,894**
NL Land Cost:	$6,956	$48,893	$13,145	**$68,994**
Total Transp Cost:	$424,870	$1,059,119	$703,948	**$2,187,937**
Inbound Transp Cost:	$286,555	$757,725	$418,136	**$1,462,415**
Outbound Transp Cost:	$138,316	$301,394	$285,812	**$725,522**
Total Inventory Cost:	$2,033,305	$2,370,916	$2,347,252	**$6,751,473**
Inv Holding & Order Cost:	$43,438	$70,477	$60,519	**$174,435**
Pipeline Inv Cost:	$272,289	$582,861	$569,155	**$1,424,305**
Inv Backorder Cost:	$1,717,578	$1,717,578	$1,717,578	**$5,152,733**
Total OH Cost:	$254,630	$315,207	$258,494	**$828,330**
Fixed OH Cost:	$200,000	$200,000	$200,000	**$600,000**
Labor-related OH Cost:	$44,315	$42,706	$39,001	**$126,022**
Land-related OH Cost:	$10,315	$72,501	$19,493	**$102,309**
Total Cost:	**$3,896,745**	**$6,620,949**	**$5,285,935**	**$15,803,629**
Avg Cust Distance (miles):	601	478	616	
Max Cust Distance (miles):	805	1,081	1,236	
P1 ME Order Quantity:	1,096	1,752	1,695	
P2 ME Order Quantity:	848	1,356	1,311	
P3 ME Order Quantity:	956	1,527	1,479	
P4 ME Order Quantity:	906	1,446	1,401	
P5 ME Order Quantity:	928	1,482	1,434	
P1 Re-order Point:	3,224	13,721	7,490	
P2 Re-order Point:	7,131	9,849	8,963	
P3 Re-order Point:	4,791	7,909	6,015	
P4 Re-order Point:	3,224	17,585	10,434	
P5 Re-order Point:	4,791	11,786	4,536	

Appendix L

Test Parameter Combination Results

The following information represents the detailed data sets for each of the ten data sets for each test parameter combination. The test parameter combination is abbreviated by three letters — the first letter represents the value for the # Customers vs. the # Manufacturers Ratio parameter, the second letter represents the value for the Average Customer Demand parameter, and the third letter represents the value for the Product Value vs. Unit Transportation $ Ratio parameter. Results are shown for both heuristics as well as the location model with a fixed inventory policy.

L.1 MMM Test Results

The following results represent the results for the MMM test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a medium Product Value vs. Unit Transportation $ Ratio.

Table L.1: MMM Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	6	6	6	6	6
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,208,271	$1,250,950	$1,152,737	$1,166,476	$1,197,809
Land Cost	$32,849	$32,388	$29,115	$30,937	$27,727
Transportation Cost	$4,004,786	$3,862,443	$3,615,735	$3,387,753	$3,901,868
Inventory Cost	$186,247	$197,771	$210,717	$200,183	$204,163
OH Cost	$536,608	$538,558	$526,685	$531,775	$529,111
Total Cost	$5,968,761	$5,882,109	$5,534,989	$5,317,124	$5,860,678
Avg Cust Distance	648	671	693	687	640
Max Cust Distance	1,335	1,552	1,989	1,688	1,512

Table L.2: MMM Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	6	7	7	6	7
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,190,178	$1,233,848	$1,097,142	$1,228,740	$1,227,547
Land Cost	$30,157	$31,671	$13,378	$26,804	$22,789
Transportation Cost	$3,374,329	$4,097,343	$4,074,831	$3,489,973	$3,854,146
Inventory Cost	$206,296	$208,194	$210,543	$186,958	$208,455
OH Cost	$528,327	$536,276	$504,860	$530,131	$520,618
Total Cost	$5,329,288	$6,107,332	$5,900,754	$5,462,607	$5,833,556
Avg Cust Distance	656	662	674	685	733
Max Cust Distance	1,890	1,461	1,537	1,303	1,533

Table L.3: MMM Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,226,405	$1,250,950	$1,179,203	$1,192,256	$1,124,839
Land Cost	$30,411	$32,261	$25,106	$29,717	$13,296
Transportation Cost	$4,002,013	$3,862,643	$3,592,446	$3,359,649	$3,978,598
Inventory Cost	$183,243	$197,771	$207,355	$198,211	$210,717
OH Cost	$533,140	$538,369	$522,348	$532,062	$504,737
Total Cost	$5,975,212	$5,881,993	$5,526,458	$5,311,894	$5,832,187
Avg Cust Distance	632	671	692	683	618
Max Cust Distance	1,436	1,552	1,989	1,666	1,772

Table L.4: MMM Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,188,698	$1,233,848	$1,097,142	$1,228,740	$1,227,547
Land Cost	$29,718	$31,543	$13,347	$26,710	$22,722
Transportation Cost	$3,375,972	$4,097,643	$4,074,881	$3,490,073	$3,854,246
Inventory Cost	$206,792	$208,194	$210,543	$186,958	$204,830
OH Cost	$527,675	$536,085	$504,814	$529,991	$520,519
Total Cost	$5,328,854	$6,107,312	$5,900,727	$5,462,471	$5,829,864
Avg Cust Distance	646	662	674	685	733
Max Cust Distance	1,890	1,461	1,537	1,303	1,533

Table L.5: MMM Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,208,271	$1,216,140	$1,155,128	$1,192,256	$1,197,809
Land Cost	$32,714	$32,339	$29,525	$29,717	$27,625
Transportation Cost	$4,004,986	$3,891,979	$3,613,010	$3,359,649	$3,902,018
Inventory Cost	$186,247	$206,540	$211,636	$198,211	$204,163
OH Cost	$536,409	$536,535	$527,293	$532,062	$528,959
Total Cost	$5,968,627	$5,883,533	$5,536,592	$5,311,894	$5,860,574

Table L.6: MMM Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	2	2	2	2	2
Labor Cost	$1,204,595	$1,233,848	$1,097,142	$1,180,966	$1,227,547
Land Cost	$31,193	$31,543	$13,347	$32,311	$22,722
Transportation Cost	$3,354,856	$4,097,643	$4,074,881	$3,538,571	$3,854,246
Inventory Cost	$209,729	$208,194	$210,543	$195,737	$204,830
OH Cost	$530,301	$536,085	$504,814	$535,811	$520,519
Total Cost	$5,330,674	$6,107,312	$5,900,727	$5,483,397	$5,829,864

L.2 MLM Test Results

The following results represent the results for the MLM test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, low value for Average Customer Demand parameter, and a medium Product Value vs. Unit Transportation $ Ratio.

Table L.7: MLM Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	4	4	4	4	4
Number of DCs Opened	1	1	1	1	1
Labor Cost	$289,366	$318,972	$296,494	$282,813	$287,442
Land Cost	$5,197	$9,208	$14,600	$5,135	$5,180
Transportation Cost	$1,231,035	$1,087,241	$1,027,405	$977,869	$1,131,897
Inventory Cost	$76,523	$68,794	$69,028	$69,786	$73,067
OH Cost	$248,414	$258,603	$263,575	$248,322	$248,389
Total Cost	$1,850,535	$1,742,819	$1,671,102	$1,583,926	$1,745,974
Avg Cust Distance	897	878	868	944	884
Max Cust Distance	1,820	2,029	2,261	1,972	1,818

Table L.8: MLM Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	4	4	4	4	4
Number of DCs Opened	1	1	1	1	1
Labor Cost	$317,804	$317,773	$308,157	$300,902	$286,165
Land Cost	$9,219	$9,219	$5,234	$14,731	$5,154
Transportation Cost	$942,820	$1,160,302	$1,283,248	$1,044,491	$1,088,888
Inventory Cost	$67,743	$69,245	$84,321	$70,068	$74,225
OH Cost	$258,618	$258,619	$250,906	$263,769	$248,350
Total Cost	$1,596,204	$1,815,159	$1,931,866	$1,693,961	$1,702,781
Avg Cust Distance	927	951	1,043	903	932
Max Cust Distance	1,890	1,780	1,759	2,113	1,806

Table L.9: MLM Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$289,366	$318,972	$288,909	$282,813	$287,442
Land Cost	$5,149	$9,077	$9,024	$5,083	$5,130
Transportation Cost	$1,231,135	$1,087,491	$1,038,266	$977,969	$1,132,047
Inventory Cost	$76,523	$68,794	$69,461	$69,786	$73,067
OH Cost	$248,342	$258,409	$254,235	$248,244	$248,314
Total Cost	$1,850,535	$1,742,819	$1,671,102	$1,583,926	$1,745,974
Avg Cust Distance	897	878	868	944	884
Max Cust Distance	1,820	2,029	2,261	1,972	1,818

Table L.10: MLM Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$287,816	$287,788	$308,157	$293,204	$286,165
Land Cost	$5,142	$5,147	$5,184	$9,132	$5,104
Transportation Cost	$980,205	$1,202,035	$1,283,398	$1,064,054	$1,088,988
Inventory Cost	$71,748	$72,783	$84,321	$71,357	$74,225
OH Cost	$248,333	$248,339	$250,833	$254,394	$248,276
Total Cost	$1,596,204	$1,815,159	$1,931,866	$1,693,961	$1,702,781
Avg Cust Distance	927	951	1,043	903	932
Max Cust Distance	1,890	1,780	1,759	2,113	1,806

Table L.11: MLM Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$289,366	$318,972	$288,909	$282,813	$287,442
Land Cost	$5,149	$9,077	$9,024	$5,083	$5,130
Transportation Cost	$1,231,135	$1,087,491	$1,038,266	$977,969	$1,132,047
Inventory Cost	$76,523	$68,794	$69,461	$69,786	$73,067
OH Cost	$248,342	$258,409	$254,235	$248,244	$248,314
Total Cost	$1,850,535	$1,742,819	$1,671,102	$1,583,926	$1,745,974

Table L.12: MLM Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$287,816	$287,788	$308,157	$293,204	$286,165
Land Cost	$5,142	$5,147	$5,184	$9,132	$5,104
Transportation Cost	$980,205	$1,202,035	$1,283,398	$1,064,054	$1,088,988
Inventory Cost	$71,748	$72,783	$84,321	$71,357	$74,225
OH Cost	$248,333	$248,339	$250,833	$254,394	$248,276
Total Cost	$1,596,204	$1,815,159	$1,931,866	$1,693,961	$1,702,781

L.3 MHM Test Results

The following results represent the results for the MHM test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, high value for Average Customer Demand parameter, and a medium Product Value vs. Unit Transportation $ Ratio.

Table L.13: MHM Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	11	10	10	10	10
Number of DCs Opened	3	3	4	3	4
Labor Cost	$2,931,803	$3,012,666	$2,857,996	$3,080,294	$2,879,246
Land Cost	$44,923	$61,327	$67,278	$50,157	$57,573
Transportation Cost	$9,319,089	$9,744,514	$8,255,675	$8,449,764	$8,961,853
Inventory Cost	$390,726	$479,708	$363,979	$429,044	$406,388
OH Cost	$798,876	$819,934	$1,072,099	$804,638	$1,056,391
Total Cost	$13,485,417	$14,118,149	$12,617,027	$12,813,896	$13,361,451
Avg Cust Distance	544	586	495	594	485
Max Cust Distance	1,037	1,552	1,700	1,390	1,511

Table L.14: MHM Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	9	9	9	8	8
Number of DCs Opened	2	3	4	4	4
Labor Cost	$2,861,148	$3,021,636	$3,227,176	$3,002,103	$3,016,990
Land Cost	$50,124	$53,102	$61,976	$74,154	$59,861
Transportation Cost	$8,175,315	$9,506,555	$9,946,517	$8,399,991	$8,768,272
Inventory Cost	$479,139	$423,672	$370,796	$398,474	$402,996
OH Cost	$557,935	$813,393	$1,074,767	$1,081,076	$1,065,536
Total Cost	$12,123,661	$13,818,357	$14,681,231	$12,955,799	$13,313,655
Avg Cust Distance	656	574	432	512	534
Max Cust Distance	1,890	1,235	1,114	1,303	1,291

Table L.15: MHM Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	3	4	4	4	5
Labor Cost	\$2,982,716	\$3,059,558	\$2,859,055	\$3,040,551	\$2,910,702
Land Cost	\$40,093	\$71,379	\$67,433	\$65,753	\$66,058
Transportation Cost	\$9,276,409	\$9,473,987	\$8,289,774	\$8,120,600	\$8,725,894
Inventory Cost	\$382,726	\$436,189	\$367,772	\$397,569	\$356,062
OH Cost	\$793,322	\$1,079,203	\$1,072,329	\$1,070,666	\$1,316,944
Total Cost	\$13,475,265	\$14,120,317	\$12,656,363	\$12,695,139	\$13,375,660
Avg Cust Distance	532	490	503	513	396
Max Cust Distance	1,037	1,451	1,700	1,390	1,146

Table L.16: MHM Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	2	3	4	4	4
Labor Cost	\$2,857,401	\$3,021,636	\$3,227,176	\$3,008,444	\$2,969,922
Land Cost	\$49,457	\$53,026	\$61,896	\$74,022	\$53,835
Transportation Cost	\$8,179,401	\$9,506,655	\$9,946,667	\$8,450,339	\$8,666,122
Inventory Cost	\$480,376	\$423,672	\$370,796	\$402,981	\$393,976
OH Cost	\$556,947	\$813,281	\$1,074,648	\$1,080,880	\$1,055,236
Total Cost	\$12,123,582	\$13,818,269	\$14,681,183	\$13,016,667	\$13,139,091
Avg Cust Distance	646	574	432	521	526
Max Cust Distance	1,890	1,235	1,114	1,303	1,361

Table L.17: MHM Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	3	3	3	4	5
Labor Cost	$2,931,803	$3,040,955	$2,758,657	$3,073,375	$2,879,246
Land Cost	$44,859	$74,152	$56,051	$65,953	$57,496
Transportation Cost	$9,319,139	$9,708,509	$8,566,901	$8,219,528	$8,961,953
Inventory Cost	$390,726	$476,177	$469,029	$402,942	$406,388
OH Cost	$798,781	$840,025	$808,017	$1,070,963	$1,056,278
Total Cost	$13,485,308	$14,139,818	$12,658,655	$12,832,761	$13,361,362

Table L.18: MHM Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	2	3	4	4	4
Labor Cost	$2,859,390	$3,019,878	$3,110,227	$3,009,725	$3,016,990
Land Cost	$49,758	$53,336	$53,480	$72,847	$59,776
Transportation Cost	$8,176,440	$9,507,832	$10,041,438	$8,386,298	$8,768,472
Inventory Cost	$479,613	$424,616	$433,851	$404,395	$402,996
OH Cost	$557,392	$813,740	$1,055,783	$1,080,844	$1,065,411
Total Cost	$12,122,592	$13,819,401	$14,694,779	$12,954,108	$13,313,645

L.4 MML Test Results

The following results represent the results for the MML test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a low Product Value vs. Unit Transportation $ Ratio.

Table L.19: MML Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	3	3	3	3	3
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,135,165	$1,128,855	$1,126,085	$1,104,016	$1,105,228
Land Cost	$8,524	$15,983	$15,803	$8,383	$8,385
Transportation Cost	$468,391	$466,269	$421,405	$413,923	$447,213
Inventory Cost	$467,184	$500,394	$466,439	$498,752	$483,351
OH Cost	$253,347	$264,554	$264,287	$253,138	$253,141
Total Cost	$2,332,612	$2,376,056	$2,294,019	$2,278,212	$2,297,319
Avg Cust Distance	897	906	868	944	884
Max Cust Distance	1,820	2,261	2,261	1,972	1,818

Table L.20: MML Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	3	3	3	3	3
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,105,228	$1,127,649	$1,063,959	$1,117,088	$1,152,317
Land Cost	$8,375	$8,565	$8,296	$15,837	$8,570
Transportation Cost	$447,213	$498,103	$488,993	$422,437	$443,291
Inventory Cost	$483,351	$541,562	$550,538	$471,646	$494,927
OH Cost	$253,126	$253,408	$253,009	$264,338	$253,416
Total Cost	$2,297,293	$2,429,287	$2,364,795	$2,291,346	$2,352,520
Avg Cust Distance	884	951	1,034	903	932
Max Cust Distance	1,818	1,780	1,989	2,113	1,806

Table L.21: MML Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,135,165	$1,128,855	$1,126,085	$1,104,016	$1,105,228
Land Cost	$8,513	$15,950	$15,770	$8,372	$8,375
Transportation Cost	$468,391	$466,469	$421,555	$413,923	$447,213
Inventory Cost	$467,184	$500,394	$466,439	$498,752	$483,351
OH Cost	$253,331	$264,505	$264,238	$253,121	$253,126
Total Cost	$2,332,583	$2,376,173	$2,294,086	$2,278,184	$2,297,293
Avg Cust Distance	897	906	868	944	884
Max Cust Distance	1,820	2,261	2,261	1,972	1,818

Table L.22: MML Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,105,228	$1,127,649	$1,063,959	$1,117,088	$1,152,317
Land Cost	$8,375	$8,554	$8,284	$15,800	$8,560
Transportation Cost	$447,213	$498,153	$488,993	$422,487	$443,291
Inventory Cost	$483,351	$541,562	$550,538	$471,646	$494,927
OH Cost	$253,126	$253,392	$252,992	$264,282	$253,400
Total Cost	$2,297,293	$2,429,311	$2,364,766	$2,291,303	$2,352,494
Avg Cust Distance	884	951	1,034	903	932
Max Cust Distance	1,818	1,780	1,989	2,113	1,806

Table L.23: MML Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,135,165	$1,128,855	$1,126,085	$1,104,016	$1,105,228
Land Cost	$8,513	$15,950	$15,770	$8,372	$8,375
Transportation Cost	$468,391	$466,469	$421,555	$413,923	$447,213
Inventory Cost	$467,184	$500,394	$466,439	$498,752	$483,351
OH Cost	$253,331	$264,505	$264,238	$253,121	$253,126
Total Cost	$2,332,583	$2,376,173	$2,294,086	$2,278,184	$2,297,293

Table L.24: MML Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	1	1	1	1	1
Labor Cost	$1,105,228	$1,127,649	$1,063,959	$1,117,088	$1,152,317
Land Cost	$8,375	$8,554	$8,284	$15,800	$8,560
Transportation Cost	$447,213	$498,153	$488,993	$422,487	$443,291
Inventory Cost	$483,351	$541,562	$550,538	$471,646	$494,927
OH Cost	$253,126	$253,392	$252,992	$264,282	$253,400
Total Cost	$2,297,293	$2,429,311	$2,364,766	$2,291,303	$2,352,494

L.5 MMH Test Results

The following results represent the results for the MMH test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a high Product Value vs. Unit Transportation $ Ratio.

Table L.25: MMH Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	12	11	13	11	10
Number of DCs Opened	6	6	5	5	7
Labor Cost	$1,298,733	$1,221,055	$1,280,719	$1,211,977	$1,220,607
Land Cost	$66,047	$76,207	$54,501	$58,180	$72,547
Transportation Cost	$17,809,351	$17,617,999	$16,154,098	$14,937,047	$16,837,808
Inventory Cost	$42,301	$45,247	$46,455	$43,646	$43,018
OH Cost	$1,578,941	$1,578,064	$1,312,576	$1,310,966	$1,822,265
Total Cost	$20,795,374	$20,538,573	$18,848,348	$17,561,816	$19,996,244
Avg Cust Distance	355	406	432	447	333
Max Cust Distance	885	988	2,029	1,352	614

Table L.26: MMH Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	11	12	11	12	9
Number of DCs Opened	5	6	7	5	8
Labor Cost	$1,280,617	$1,293,495	$1,272,922	$1,208,210	$1,297,012
Land Cost	$64,003	$74,589	$68,698	$54,382	$60,323
Transportation Cost	$15,281,842	$18,517,974	$17,582,559	$15,944,813	$16,615,798
Inventory Cost	$45,203	$43,389	$43,016	$42,977	$48,303
OH Cost	$1,316,724	$1,596,131	$1,843,420	$1,302,751	$2,055,939
Total Cost	$17,988,389	$21,525,579	$20,810,615	$18,553,133	$20,077,376
Avg Cust Distance	467	355	321	433	361
Max Cust Distance	1,453	721	780	1,240	1,291

Table L.27: MMH Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	6	6	5	5	7
Labor Cost	$1,298,733	$1,247,397	$1,280,719	$1,211,977	$1,220,607
Land Cost	$65,635	$66,128	$54,154	$57,811	$72,083
Transportation Cost	$17,809,901	$17,577,786	$16,154,348	$14,937,547	$16,838,158
Inventory Cost	$42,301	$45,288	$46,455	$43,646	$43,018
OH Cost	$1,578,330	$1,570,187	$1,312,062	$1,310,419	$1,821,578
Total Cost	$20,794,900	$20,506,786	$18,847,736	$17,561,401	$19,995,444
Avg Cust Distance	355	401	432	447	335
Max Cust Distance	885	1,498	2,029	1,352	847

Table L.28: MMH Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	5	5	5	5
Number of DCs Opened	5	6	7	5	8
Labor Cost	$1,280,617	$1,293,495	$1,272,922	$1,208,210	$1,297,012
Land Cost	$63,608	$74,117	$68,256	$54,035	$59,976
Transportation Cost	$15,282,492	$18,518,274	$17,582,859	$15,945,213	$16,616,098
Inventory Cost	$45,203	$43,389	$43,016	$42,977	$48,303
OH Cost	$1,316,139	$1,595,433	$1,842,764	$1,302,237	$2,055,425
Total Cost	$17,988,059	$21,524,709	$20,809,818	$18,552,672	$20,076,815
Avg Cust Distance	467	358	321	433	361
Max Cust Distance	1,453	1,219	780	1,240	1,291

Table L.29: MMH Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	7	6	6	5	7
Labor Cost	$1,331,676	$1,247,397	$1,300,743	$1,211,977	$1,220,607
Land Cost	$70,489	$66,128	$75,551	$57,811	$72,083
Transportation Cost	$17,521,799	$17,577,786	$15,884,444	$14,937,547	$16,838,158
Inventory Cost	$42,431	$45,288	$45,965	$43,646	$43,018
OH Cost	$1,842,184	$1,570,187	$1,599,172	$1,310,419	$1,821,578
Total Cost	$20,808,580	$20,506,786	$18,905,874	$17,561,401	$19,995,444

Table L.30: MMH Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	5	6	8	5	8
Labor Cost	$1,280,617	$1,293,495	$1,295,667	$1,208,210	$1,297,012
Land Cost	$63,608	$74,117	$79,005	$54,035	$59,976
Transportation Cost	$15,282,492	$18,518,274	$17,306,565	$15,945,213	$16,616,098
Inventory Cost	$45,203	$43,389	$42,898	$42,977	$48,303
OH Cost	$1,316,139	$1,595,433	$2,114,563	$1,302,237	$2,055,425
Total Cost	$17,988,059	$21,524,709	$20,838,697	$18,552,672	$20,076,815

L.6 HMM Test Results

The following results represent the results for the HMM test parameter combination. This is a high # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a medium Product Value vs. Unit Transportation $ Ratio.

Table L.31: HMM Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	10	9	7	7	8
Number of DCs Opened	2	3	3	3	2
Labor Cost	$2,385,948	$2,318,643	$2,351,266	$2,351,837	$2,388,383
Land Cost	$44,325	$46,328	$52,718	$44,245	$41,888
Transportation Cost	$7,020,142	$9,182,889	$6,536,924	$6,242,661	$6,573,761
Inventory Cost	$394,294	$362,230	$337,683	$368,850	$405,939
OH Cost	$553,626	$797,108	$809,070	$795,628	$548,013
Total Cost	$10,398,335	$12,707,198	$10,087,660	$9,803,220	$9,957,984
Avg Cust Distance	718	554	569	655	665
Max Cust Distance	1,528	1,528	1,598	1,467	1,761

Table L.32: HMM Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	8	10	8	10	9
Number of DCs Opened	3	3	2	3	3
Labor Cost	$2,416,001	$2,463,868	$2,381,808	$2,401,084	$2,366,200
Land Cost	$46,181	$29,664	$43,557	$46,782	$50,103
Transportation Cost	$6,509,575	$7,361,045	$6,149,990	$8,121,367	$8,284,915
Inventory Cost	$374,859	$344,898	$370,527	$355,429	$345,667
OH Cost	$798,500	$778,590	$548,636	$798,756	$803,048
Total Cost	$10,145,116	$10,978,066	$9,494,517	$11,723,418	$11,849,932
Avg Cust Distance	618	546	685	566	553
Max Cust Distance	1,467	1,531	1,890	1,510	1,240

Table L.33: HMM Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	2	3	3	3	3
Labor Cost	$2,385,948	$2,284,822	$2,352,846	$2,351,837	$2,345,814
Land Cost	$44,237	$33,882	$52,594	$44,162	$42,196
Transportation Cost	$7,020,242	$9,212,373	$6,536,878	$6,242,811	$6,363,731
Inventory Cost	$394,294	$375,520	$336,453	$368,850	$415,680
OH Cost	$553,495	$777,580	$808,887	$795,505	$789,178
Total Cost	$10,398,216	$12,684,176	$10,087,658	$9,803,164	$9,956,599
Avg Cust Distance	740	568	566	657	646
Max Cust Distance	1,609	1,609	1,295	1,467	1,761

Table L.34: HMM Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	3	3	3	3	3
Labor Cost	$2,415,166	$2,463,868	$2,383,449	$2,419,741	$2,358,194
Land Cost	$46,001	$29,621	$43,650	$38,000	$43,487
Transportation Cost	$6,510,832	$7,361,095	$6,148,242	$8,129,384	$8,292,256
Inventory Cost	$374,926	$344,898	$371,234	$337,618	$343,854
OH Cost	$798,232	$778,526	$548,774	$785,783	$792,407
Total Cost	$10,145,157	$10,978,008	$9,495,350	$11,710,526	$11,830,198
Avg Cust Distance	618	546	515	555	557
Max Cust Distance	1,467	1,531	1,890	1,349	1,240

Table L.35: HMM Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	2	3	3	3	3
Labor Cost	$2,385,948	$2,318,643	$2,340,229	$2,351,837	$2,345,814
Land Cost	$44,237	$46,241	$52,519	$44,162	$42,196
Transportation Cost	$7,020,242	$9,183,039	$6,547,362	$6,242,811	$6,363,731
Inventory Cost	$394,294	$362,230	$350,645	$368,850	$415,680
OH Cost	$553,495	$796,979	$808,043	$795,505	$789,178
Total Cost	$10,398,216	$12,707,131	$10,098,798	$9,803,164	$9,956,599

Table L.36: HMM Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	3	3	2	3	3
Labor Cost	$2,413,566	$2,463,868	$2,383,449	$2,400,019	$2,392,227
Land Cost	$46,095	$29,621	$43,650	$46,688	$46,337
Transportation Cost	$6,512,138	$7,361,095	$6,148,242	$8,120,551	$8,240,670
Inventory Cost	$374,993	$344,898	$371,234	$357,774	$371,490
OH Cost	$798,372	$778,526	$548,774	$798,617	$798,292
Total Cost	$10,145,164	$10,978,008	$9,495,350	$11,723,649	$11,849,016

L.7 LMH Test Results

The following results represent the results for the LMH test parameter combination. This is a low # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a high Product Value vs. Unit Transportation $ Ratio.

Table L.37: LMH Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$476,025	$424,433	$465,852	$486,699	$463,129
Land Cost	$5,505	$5,711	$6,030	$5,590	$10,230
Transportation Cost	$187,646	$194,964	$204,966	$184,732	$172,203
Inventory Cost	$224,727	$186,468	$226,978	$220,090	$191,308
OH Cost	$248,871	$247,470	$247,943	$248,997	$256,024
Total Cost	$1,142,773	$1,059,045	$1,151,769	$1,146,108	$1,092,894
Avg Cust Distance	954	856	897	919	888
Max Cust Distance	1,606	1,536	1,909	1,661	1,945

Table L.38: LMH Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$451,184	$461,254	$450,117	$445,430	$441,680
Land Cost	$5,343	$5,423	$5,353	$5,314	$5,316
Transportation Cost	$186,291	$173,147	$191,414	$186,339	$190,676
Inventory Cost	$224,318	$184,360	$219,727	$208,193	$214,249
OH Cost	$248,630	$248,748	$248,645	$248,588	$248,590
Total Cost	$1,115,765	$1,072,931	$1,115,256	$1,093,864	$1,100,510
Avg Cust Distance	917	703	1,015	985	876
Max Cust Distance	1,806	1,890	1,865	1,890	1,890

Table L.39: LMH Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$476,025	$424,433	$465,852	$486,699	$463,129
Land Cost	$5,505	$5,711	$6,030	$5,590	$10,230
Transportation Cost	$187,646	$194,964	$204,966	$184,732	$172,203
Inventory Cost	$224,727	$186,468	$226,978	$220,090	$191,308
OH Cost	$248,871	$247,470	$247,943	$248,997	$256,024
Total Cost	$1,142,773	$1,059,045	$1,151,769	$1,146,108	$1,092,894
Avg Cust Distance	954	856	897	919	888
Max Cust Distance	1,606	1,536	1,909	1,661	1,945

Table L.40: LMH Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$451,184	$461,254	$450,117	$445,430	$441,680
Land Cost	$5,343	$5,423	$5,353	$5,314	$5,316
Transportation Cost	$186,291	$173,147	$191,414	$186,339	$190,676
Inventory Cost	$224,318	$184,360	$219,727	$208,193	$214,249
OH Cost	$248,630	$248,748	$248,645	$248,588	$248,590
Total Cost	$1,115,765	$1,072,931	$1,115,256	$1,093,864	$1,100,510
Avg Cust Distance	917	703	1,015	985	876
Max Cust Distance	1,806	1,890	1,865	1,890	1,890

Table L.41: LMH Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$476,025	$424,433	$465,852	$486,699	$463,129
Land Cost	$5,505	$5,711	$6,030	$5,590	$10,230
Transportation Cost	$187,646	$194,964	$204,966	$184,732	$172,203
Inventory Cost	$224,727	$186,468	$226,978	$220,090	$191,308
OH Cost	$248,871	$247,470	$247,943	$248,997	$256,024
Total Cost	$1,142,773	$1,059,045	$1,151,769	$1,146,108	$1,092,894

Table L.42: LMH Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$451,184	$461,254	$450,117	$445,430	$441,680
Land Cost	$5,343	$5,423	$5,353	$5,314	$5,316
Transportation Cost	$186,291	$173,147	$191,414	$186,339	$190,676
Inventory Cost	$224,318	$184,360	$219,727	$208,193	$214,249
OH Cost	$248,630	$248,748	$248,645	$248,588	$248,590
Total Cost	$1,115,765	$1,072,931	$1,115,256	$1,093,864	$1,100,510

L.8 MHH Test Results

The following results represent the results for the MHH test parameter combination. This is a medium # Customers vs. the # Manufacturers Ratio, high value for Average Customer Demand parameter, and a high Product Value vs. Unit Transportation $ Ratio.

Table L.43: MHH Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	8	6	9	8	7
Number of DCs Opened	11	12	10	10	10
Labor Cost	$3,459,421	$3,345,293	$3,273,798	$3,536,699	$3,159,444
Land Cost	$141,196	$162,803	$137,155	$129,499	$132,687
Transportation Cost	$41,279,069	$42,521,798	$37,262,947	$37,351,759	$39,809,024
Inventory Cost	$88,252	$90,601	$86,366	$92,052	$86,678
OH Cost	$2,970,823	$3,204,694	$2,692,753	$2,689,780	$2,903,605
Total Cost	$47,938,761	$49,325,189	$43,453,019	$43,799,788	$46,091,439
Avg Cust Distance	219	236	249	284	232
Max Cust Distance	984	1,176	2,029	811	847

Table L.44: MHH Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	9	6	7	7	9
Number of DCs Opened	9	12	11	10	9
Labor Cost	$3,312,755	$3,241,391	$3,549,078	$3,385,412	$3,253,675
Land Cost	$128,728	$159,157	$142,230	$133,371	$124,989
Transportation Cost	$35,072,623	$42,248,789	$45,538,899	$38,649,298	$39,881,028
Inventory Cost	$93,231	$87,325	$90,162	$88,146	$84,572
OH Cost	$2,426,668	$3,215,234	$2,961,224	$2,678,477	$2,409,552
Total Cost	$41,034,004	$48,951,897	$52,281,593	$44,934,703	$45,753,817
Avg Cust Distance	312	215	262	279	296
Max Cust Distance	1,352	805	820	1,016	1,123

Table L.45: MHH Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	3	3	3	3	3
Number of DCs Opened	13	12	11	10	11
Labor Cost	$3,426,545	$3,392,921	$3,242,004	$3,536,699	$3,328,170
Land Cost	$153,965	$154,268	$124,051	$129,203	$115,053
Transportation Cost	$40,766,535	$42,462,626	$37,077,280	$37,351,959	$39,657,669
Inventory Cost	$88,285	$86,534	$79,728	$78,058	$81,679
OH Cost	$3,503,336	$3,203,260	$2,918,856	$2,689,341	$2,900,619
Total Cost	$47,938,665	$49,299,610	$43,441,918	$43,785,259	$46,083,189
Avg Cust Distance	222	238	292	284	231
Max Cust Distance	896	1,176	1,451	811	847

Table L.46: MHH Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	3	3	3	3	3
Number of DCs Opened	10	12	11	10	10
Labor Cost	$3,333,682	$3,279,964	$3,549,078	$3,459,169	$3,421,220
Land Cost	$139,113	$152,970	$141,925	$119,016	$135,714
Transportation Cost	$34,782,431	$42,215,241	$45,539,349	$38,564,532	$39,449,277
Inventory Cost	$78,472	$84,148	$81,823	$79,383	$79,135
OH Cost	$2,689,552	$3,206,986	$2,960,772	$2,677,897	$2,689,783
Total Cost	$41,023,251	$48,939,309	$52,272,948	$44,899,997	$45,775,127
Avg Cust Distance	290	222	262	259	257
Max Cust Distance	1,352	805	820	1,016	1,123

Table L.47: MHH Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	14	12	11	10	11
Labor Cost	$3,387,394	$3,345,293	$3,242,196	$3,536,699	$3,159,444
Land Cost	$164,709	$162,409	$141,635	$129,203	$132,374
Transportation Cost	$40,560,000	$42,522,198	$37,038,561	$37,351,959	$39,809,474
Inventory Cost	$93,624	$90,601	$87,484	$92,052	$86,678
OH Cost	$3,760,169	$3,204,109	$2,944,980	$2,689,341	$2,903,141
Total Cost	$47,965,896	$49,324,610	$43,454,856	$43,799,253	$46,091,112

Table L.48: MHH Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	10	12	11	10	10
Labor Cost	$3,333,682	$3,241,391	$3,549,078	$3,211,080	$3,421,220
Land Cost	$139,113	$158,775	$141,925	$133,042	$135,714
Transportation Cost	$34,782,431	$42,249,139	$45,539,349	$38,840,092	$39,449,277
Inventory Cost	$94,366	$87,325	$90,162	$88,598	$83,912
OH Cost	$2,689,552	$3,214,668	$2,960,772	$2,658,977	$2,689,783
Total Cost	$41,039,144	$48,951,299	$52,281,287	$44,931,789	$45,779,905

L.9 HML Test Results

The following results represent the results for the HML test parameter combination. This is a high # Customers vs. the # Manufacturers Ratio, medium value for Average Customer Demand parameter, and a low Product Value vs. Unit Transportation $ Ratio.

Table L.49: HML Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,225,230	$2,129,471	$2,228,853	$2,221,757	$2,264,660
Land Cost	$11,895	$12,908	$22,254	$11,839	$11,921
Transportation Cost	$828,567	$1,064,269	$788,077	$770,505	$770,070
Inventory Cost	$981,627	$1,079,726	$956,194	$937,554	$1,010,811
OH Cost	$258,345	$258,141	$273,853	$258,263	$258,384
Total Cost	$4,305,664	$4,544,515	$4,269,232	$4,199,918	$4,315,847
Avg Cust Distance	934	1,013	904	891	909
Max Cust Distance	1,890	2,055	2,261	2,005	2,005

Table L.50: HML Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,259,082	$2,233,109	$2,301,861	$2,291,313	$2,274,596
Land Cost	$11,972	$12,003	$22,587	$12,168	$12,173
Transportation Cost	$819,766	$903,432	$758,543	$928,268	$984,570
Inventory Cost	$947,386	$917,238	$869,417	$984,392	$956,561
OH Cost	$258,459	$258,506	$274,347	$258,751	$258,758
Total Cost	$4,296,665	$4,324,287	$4,226,754	$4,474,892	$4,486,656
Avg Cust Distance	897	884	845	932	892
Max Cust Distance	2,005	1,972	2,162	1,890	1,890

Table L.51: HML Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,225,230	$2,129,471	$2,228,853	$2,221,757	$2,264,660
Land Cost	$11,895	$12,908	$22,254	$11,839	$11,921
Transportation Cost	$828,567	$1,064,269	$788,077	$770,505	$770,070
Inventory Cost	$981,627	$1,079,726	$956,194	$937,554	$1,010,811
OH Cost	$258,345	$258,141	$273,853	$258,263	$258,384
Total Cost	$4,305,664	$4,544,515	$4,269,232	$4,199,918	$4,315,847
Avg Cust Distance	934	1,013	904	891	909
Max Cust Distance	1,890	2,055	2,261	2,005	2,005

Table L.52: HML Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,259,082	$2,233,109	$2,301,861	$2,291,313	$2,274,596
Land Cost	$11,972	$12,003	$22,587	$12,168	$12,173
Transportation Cost	$819,766	$903,432	$758,543	$928,268	$984,570
Inventory Cost	$947,386	$917,238	$869,417	$984,392	$956,561
OH Cost	$258,459	$258,506	$274,347	$258,751	$258,758
Total Cost	$4,296,665	$4,324,287	$4,226,754	$4,474,892	$4,486,656
Avg Cust Distance	897	884	845	932	892
Max Cust Distance	2,005	1,972	2,162	1,890	1,890

Table L.53: HML Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,225,230	$2,129,471	$2,228,853	$2,221,757	$2,264,660
Land Cost	$11,895	$12,908	$22,254	$11,839	$11,921
Transportation Cost	$828,567	$1,064,269	$788,077	$770,505	$770,070
Inventory Cost	$981,627	$1,079,726	$956,194	$937,554	$1,010,811
OH Cost	$258,345	$258,141	$273,853	$258,263	$258,384
Total Cost	$4,305,664	$4,544,515	$4,269,232	$4,199,918	$4,315,847

Table L.54: HML Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$2,259,082	$2,233,109	$2,301,861	$2,291,313	$2,274,596
Land Cost	$11,972	$12,003	$22,587	$12,168	$12,173
Transportation Cost	$819,766	$903,432	$758,543	$928,268	$984,570
Inventory Cost	$947,386	$917,238	$869,417	$984,392	$956,561
OH Cost	$258,459	$258,506	$274,347	$258,751	$258,758
Total Cost	$4,296,665	$4,324,287	$4,226,754	$4,474,892	$4,486,656

L.10 HHL Test Results

The following results represent the results for the HHL test parameter combination. This is a high # Customers vs. the # Manufacturers Ratio, high value for Average Customer Demand parameter, and a low Product Value vs. Unit Transportation $ Ratio.

Table L.55: HHL Summarized Results - H1 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	6	5	6	5	6
Number of DCs Opened	2	3	2	3	2
Labor Cost	$5,685,551	$5,819,214	$5,764,944	$5,796,007	$5,874,189
Land Cost	$41,358	$65,126	$41,497	$59,540	$43,986
Transportation Cost	$1,861,731	$2,346,891	$1,867,939	$1,825,460	$1,699,707
Inventory Cost	$1,885,559	$1,565,134	$1,670,548	$1,575,812	$1,965,936
OH Cost	$546,497	$822,789	$546,703	$814,506	$548,638
Total Cost	$10,020,696	$10,619,153	$9,891,632	$10,071,324	$10,132,455
Avg Cust Distance	640	554	599	540	727
Max Cust Distance	1,609	1,228	1,591	1,398	1,761

Table L.56: HHL Summarized Results - H1 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	5	6	6	5	5
Number of DCs Opened	3	2	2	3	3
Labor Cost	$5,861,277	$5,709,288	$5,864,422	$5,988,359	$5,863,551
Land Cost	$62,453	$25,348	$65,024	$70,264	$63,019
Transportation Cost	$1,792,005	$1,981,531	$1,655,399	$2,193,477	$2,152,880
Inventory Cost	$1,509,736	$1,936,795	$1,706,393	$1,567,524	$1,552,545
OH Cost	$819,264	$522,609	$578,761	$830,213	$819,665
Total Cost	$10,044,736	$10,175,571	$9,869,997	$10,649,838	$10,451,658
Avg Cust Distance	536	679	669	558	539
Max Cust Distance	1,269	1,772	2,033	1,081	1,120

Table L.57: HHL Summarized Results - H2 (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	2	3	3	3	3
Labor Cost	\$5,685,551	\$5,813,521	\$5,809,477	\$5,783,894	\$5,892,911
Land Cost	\$41,341	\$64,682	\$67,537	\$58,492	\$55,169
Transportation Cost	\$1,861,731	\$2,345,314	\$1,811,336	\$1,827,729	\$1,728,150
Inventory Cost	\$1,885,559	\$1,572,014	\$1,408,623	\$1,585,548	\$1,649,247
OH Cost	\$546,471	\$822,131	\$827,583	\$812,952	\$809,097
Total Cost	\$10,020,653	\$10,617,662	\$9,924,555	\$10,068,616	\$10,134,573
Avg Cust Distance	640	555	499	537	547
Max Cust Distance	1,609	1,228	1,101	1,398	1,447

Table L.58: HHL Summarized Results - H2 (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	2	2	2	2	2
Number of DCs Opened	3	3	2	3	3
Labor Cost	\$5,834,751	\$5,795,461	\$5,839,515	\$5,966,894	\$5,855,900
Land Cost	\$60,952	\$58,095	\$58,295	\$68,994	\$62,478
Transportation Cost	\$1,805,323	\$1,957,927	\$1,674,892	\$2,187,937	\$2,158,054
Inventory Cost	\$1,526,481	\$1,561,185	\$1,748,333	\$1,598,740	\$1,556,277
OH Cost	\$817,039	\$814,069	\$569,857	\$828,330	\$818,863
Total Cost	\$10,044,546	\$10,186,736	\$9,890,893	\$10,650,896	\$10,451,572
Avg Cust Distance	544	549	632	565	535
Max Cust Distance	1,398	1,285	1,890	1,236	1,236

Table L.59: HHL Summarized Results - Location Model with Fixed Inv. Policy (1-5).

Run Iteration	**1**	**2**	**3**	**4**	**5**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$5,334,481	$5,484,074	$5,649,934	$5,483,155	$5,514,827
Land Cost	$21,764	$22,644	$38,419	$22,083	$22,076
Transportation Cost	$2,083,243	$2,545,791	$1,838,073	$2,031,471	$1,948,529
Inventory Cost	$2,624,909	$2,600,320	$2,334,147	$2,552,824	$2,652,198
OH Cost	$271,274	$272,578	$297,823	$271,747	$271,737
Total Cost	$10,335,670	$10,925,406	$10,158,395	$10,361,280	$10,409,368

Table L.60: HHL Summarized Results - Location Model with Fixed Inv. Policy (6-10).

Run Iteration	**6**	**7**	**8**	**9**	**10**
# Iterations Completed	1	1	1	1	1
Number of DCs Opened	1	1	1	1	1
Labor Cost	$5,719,723	$5,377,990	$5,747,858	$5,580,511	$5,515,653
Land Cost	$20,588	$22,195	$38,671	$22,504	$22,692
Transportation Cost	$1,903,700	$2,324,405	$1,770,623	$2,368,860	$2,496,411
Inventory Cost	$2,269,877	$2,496,627	$2,168,664	$2,813,371	$2,545,076
OH Cost	$271,237	$271,914	$298,196	$272,371	$272,650
Total Cost	$10,185,126	$10,493,131	$10,024,013	$11,057,617	$10,852,482

Appendix M

Wilcoxon Signed-Rank Test — All Data

Table M.1: Ranking of Pairs — All Data.

Test Parameter Combination	Test Set	H1	H2	All Data: Signed Rank	>1 DC Data: Signed Rank
HHL	1	$10,020,696	$10,020,696	29	9
HML	1	$4,305,664	$4,305,664	29	0
HML	2	$4,544,515	$4,544,515	29	0
HML	3	$4,269,232	$4,269,232	29	0
HML	4	$4,199,918	$4,199,918	29	0
HML	5	$4,315,847	$4,315,847	29	0
HML	6	$4,296,665	$4,296,665	29	0
HML	7	$4,324,287	$4,324,287	29	0
HML	8	$4,226,754	$4,226,754	29	0
HML	9	$4,474,892	$4,474,892	29	0
HML	10	$4,486,656	$4,486,656	29	0
HMM	1	$10,398,335	$10,398,335	29	9
HMM	3	$10,087,660	$10,087,660	29	9
HMM	4	$9,803,220	$9,803,220	29	9
HMM	6	$10,145,116	$10,145,116	29	9
HMM	7	$10,978,066	$10,978,066	29	9
HMM	8	$9,494,517	$9,494,517	29	9
LMH	1	$1,142,773	$1,142,773	29	0
LMH	2	$1,059,045	$1,059,045	29	0
LMH	3	$1,151,769	$1,151,769	29	0
LMH	4	$1,146,108	$1,146,108	29	0
LMH	5	$1,092,894	$1,092,894	29	0
LMH	6	$1,115,765	$1,115,765	29	0
LMH	7	$1,072,931	$1,072,931	29	0
LMH	8	$1,115,256	$1,115,256	29	0
LMH	9	$1,093,864	$1,093,864	29	0
LMH	10	$1,100,510	$1,100,510	29	0
MHH	1	$47,938,761	$47,938,761	29	9
MHM	6	$12,123,661	$12,123,661	29	9
MHM	7	$13,818,357	$13,818,357	29	9
MHM	8	$14,681,231	$14,681,231	29	9

Test Parameter Combination	Test Set	H1	H2	All Data: Signed Rank	> 1 DC Data: Signed Rank
MLM	1	$1,850,535	$1,850,535	29	0
MLM	2	$1,742,819	$1,742,819	29	0
MLM	3	$1,671,102	$1,671,102	29	0
MLM	4	$1,583,926	$1,583,926	29	0
MLM	5	$1,745,974	$1,745,974	29	0
MLM	6	$1,596,204	$1,596,204	29	0
MLM	7	$1,815,159	$1,815,159	29	0
MLM	8	$1,931,866	$1,931,866	29	0
MLM	9	$1,693,961	$1,693,961	29	0
MLM	10	$1,702,781	$1,702,781	29	0
MMH	4	$17,561,816	$17,561,816	29	9
MMH	6	$17,988,389	$17,988,389	29	9
MML	1	$2,332,612	$2,332,612	29	0
MML	2	$2,376,056	$2,376,056	29	0
MML	3	$2,294,019	$2,294,019	29	0
MML	4	$2,278,212	$2,278,212	29	0
MML	5	$2,297,319	$2,297,319	29	0
MML	6	$2,297,293	$2,297,293	29	0
MML	7	$2,429,287	$2,429,287	29	0
MML	8	$2,364,795	$2,364,795	29	0
MML	9	$2,291,346	$2,291,346	29	0
MML	10	$2,352,520	$2,352,520	29	0
MMM	2	$5,882,109	$5,882,109	29	9
MMM	7	$6,107,332	$6,107,332	29	9
MMM	8	$5,900,754	$5,900,754	29	9
MMM	9	$5,462,607	$5,462,607	29	9
HHL	10	$10,451,658	$10,451,572	58	18
HHL	6	$10,044,736	$10,044,546	59	19
MMM	6	$5,329,288	$5,328,854	60	20
MMH	9	$18,553,133	$18,552,672	61	21
MMH	1	$20,795,374	$20,794,900	62	22
MMH	10	$20,077,376	$20,076,815	63	23
MMH	3	$18,848,348	$18,847,736	64	24
MMH	8	$20,810,615	$20,809,818	65	25
MMH	5	$19,996,244	$19,995,444	66	26
MMH	7	$21,525,579	$21,524,709	67	27

Test Parameter Combination	Test Set	H1	H2	All Data: Signed Rank	> 1 DC Data: Signed Rank
HHL	9	$10,649,838	$10,650,896	-68	-28
HMM	5	$9,957,984	$9,956,599	69	29
HHL	2	$10,619,153	$10,617,662	70	30
HHL	5	$10,132,455	$10,134,573	-71	-31
MHM	2	$14,118,149	$14,120,317	-72	-32
HHL	4	$10,071,324	$10,068,616	73	33
MMM	10	$5,833,556	$5,829,864	74	34
MMM	4	$5,317,124	$5,311,894	75	35
MMM	1	$5,968,761	$5,975,212	-76	-36
MHH	5	$46,091,439	$46,083,189	77	37
MHH	8	$52,281,593	$52,272,948	78	38
MHM	1	$13,485,417	$13,475,265	79	39
MHH	6	$41,034,004	$41,023,251	80	40
MHH	3	$43,453,019	$43,441,918	81	41
HHL	7	$10,175,571	$10,186,736	-82	-42
MHH	7	$48,951,897	$48,939,309	83	43
HMM	9	$11,723,418	$11,710,526	84	44
MHM	5	$13,361,451	$13,375,660	-85	-45
MHH	4	$43,799,788	$43,785,259	86	46
HMM	10	$11,849,932	$11,830,198	87	47
HHL	8	$9,869,997	$9,890,893	-88	-48
MHH	10	$45,753,817	$45,775,127	-89	-49
HMM	2	$12,707,198	$12,684,176	90	50
MHH	2	$49,325,189	$49,299,610	91	51
MMM	5	$5,860,678	$5,832,187	92	52
MMH	2	$20,538,573	$20,506,786	93	53
HHL	3	$9,891,632	$9,924,555	-94	-54
MHH	9	$44,934,703	$44,899,997	95	55
MHM	3	$12,617,027	$12,656,363	-96	-56
MHM	9	$12,955,799	$13,016,667	-97	-57
MHM	4	$12,813,896	$12,695,139	98	58
MMM	3	$5,534,989	$5,408,320	99	59
MHM	10	$13,313,655	$13,139,091	100	60
				4132	1199

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Vita

Tammy Jo Hodgdon was born in Presque Isle Maine on March 15th in 1977. She began her academic career as an Industrial Engineering major at New Mexico State University, but soon transferred to Virginia Tech to finish her undergraduate degree. Despite the cooler and windy climate, the success of the football team and the ISE department credentials at Virginia Tech were enough to convince her to stay and pursue a Masters of Science. During her Senior year of her undergraduate studies, Tammy was awarded a fellowship for a Dual-Degree program between Virginia Tech and Ecole des Mines de Nantes (EMN) in Nantes, France. This program split the course and research load between these two universities and was the first of its type at Virginia Tech.

During her first year of graduate school, Tammy focused her research interests and planned to study international facility location and outsourcing. This research topic evolved throughout her time at Virginia Tech and eventually matured into to what is seen in this research. The completion of this thesis marks the end of a long but very educational journey through graduate school. Tammy is now employed by Northrop Grumman Electronic Systems in Baltimore, MD where she works in the IE department. She enjoys this role and seeks to find new industrial uses for implementing analytical tools for automating and providing needed data to help determine manufacturing and machine performance.