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Optimization Models for Locating Cross-docks under Capacity Uncertainty

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By

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ABSTRACT

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The objective of this thesis is to develop mathematical models for locating cross-docks in a supply chain. Cross-docking is a strategy which can help consolidate the goods in the supply chain and save costs by reducing the number of truck trips. In this thesis four optimization models were developed. First two optimization models termed Model A and Model B were deterministic models. The goal of model A was to choose exactly P locations to locate cross-docks so that the transportation and handling costs are minimized. The goal of model B is to locate as many cross-docks as needed so that total routing, handling, and facility location costs are minimized. Then we developed a chance constraint model and a recourse model which accounted for capacity uncertainties at cross-dock location. The chance constraint model accounts for day to day operational uncertainties whereas the recourse model accounts to drastic reductions in capacities due to disruptions. Extensive computational analysis was conducted on two networks with parameters consistent with real world freight operations. The results reveal that cross-docking provides significant savings when the demand sizes are small and there is more potential for consolidation. For larger demands where the potential for consolidation is less, cross-dock savings diminish. The results were found to be consistent across a variety of capacity uncertainty scenarios.

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CHAPTER 1. INTRODUCTION

1.1 Motivation

The freight transportation industry is the back bone of US economy. Transportation activities account for approximately 11 percent of the national GDP (USDOT and BTS, 2002). Trucking accounts for 83 percent of freight transportation in US alone (Wilson 2002). The transportation sector plays a vital role in developing United States economic strength. When products are shipped over large distances, the logistics operations (the planning, implementation, and coordination of the details of a business or other operation) play a vital role in determining the costs. For example, Bayer AG, a chemical company with annual sales equivalent to $25 billion, has a logistics budget of $5 billion; it involves 3,000 different distribution points with handling about 740,000 different shipments (Johnson and Wood 1990). In the supply chain industry, the location of facilities like warehouses plays a significant role in cost of transportation and storage. Facility location models are decision support tools which can guide supply chain managers and logistics operators on optimal location of facilities.

Facility location problems gained importance when Weber (1909) introduced the planar Euclidean single facility minisum problem. The objective of the problem is to locate the warehouse in the best possible location such that the distance is minimized between the warehouse and the customers. Weiszfeld (1937) gave an iterative method to solve the minisum Euclidean problem, called Weiszfeld's Procedure. Hakimi (1964) introduced a seminal paper on locating one or more points on a network with an objective to minimize the maximum distance or sum of all distances from existing customer locations already on the network. Owen and Daskin (1998) reviewed various strategic location problems where they emphasized that a good facility location decision is a critical element in the success of any supply chain. They explained median problems, center problems, covering problems and other dynamic location problem formulations in the context of a supply chain environment. (Kotian, 2005).

In large supply chains and logistics networks, facilities are normally located at intermediate points for distributing goods. These intermediate centers allow the consolidation of goods from manufacturers to retailers. The intermediate distribution centers are of two types. One is an inventory coordination point and the other is an inventory storage point. In this thesis we will be dealing with the inventory coordination points which follow cross-docking strategy whereas the inventory storage points follow traditional warehousing strategy (Kreng and Chen 2008). Cross- docking strategy has been acknowledged as having great potential to reduce transportation costs and delivery times without increasing inventory (Sung and Song 2003). Cross-docking is a special warehousing policy moving goods from inbound trucks (ITs) to outbound trucks (OTs) without storage or just temporary storage. In a typical logistics distribution network, products are sent to a warehousing facility for storing, retrieving, sorting and reconsolidating (Sunil and Meindl, 2002; van den Berg and Zijm, 1999; Zäpfel and Wasner, 2006). Products are subsequently sent out to retailers upon requests (Baker, 2008). Effective cross-docking practices can lead to decreased overall transportation costs through consolidation of goods. In the case of Wal-Mart, cross-docking is often regarded as a key driver of the retailer's superior logistics management (Hammer 2004).

The two major categories of shipments in trucking industry are LTL (Less than Truck Load which can only take loads less than 10000 pounds) and TL (Truck Load which can take loads greater than 10000 pounds) (Swan, 1996). From the observations made, the LTL container utilization was less than 50% (Thompson, 2004) that means each container is carrying fewer amounts of loads which increases the number of trips and increases the logistics costs. In order to reduce these costs, the companies are moving towards adopting the consolidation strategies such as cross-docking by which the container utilization can be increased to the desired extent. Motivated by the usefulness of the cross docks, we have developed a model which is helpful for delivering the products from the manufacturers to the retailers by locating cross-docks from a given nodes.

1.2 Contribution

Several researchers have developed models which model cross-dock facility location and various other aspects of cross-dock logistics operation. For example, Bachlaus et al. (2008) gave a multi-objective optimization problem which minimizes the costs and to maximizes the plant flexibility and volume flexibility to design a network which consists of suppliers, plants, distribution centers, cross docks, and customer. McWilliams et al. (2005) proposed a model to minimize the time span of transfer operation. However the developed models have been limited in capturing the impact of uncertainty in cross-dock operations. The uncertainty can be in the form of demand uncertainty (day to day variation in demand), travel costs uncertainty (accidents, disasters) or capacity uncertainty (workers fall sick, machinery break downs). The contributions of this thesis are highlighted below:

(i) Develop two optimization models for locating cross-docks in supply chain network with multiple commodities

(ii) Develop two optimization models which account for the impact of capacity uncertainty in cross-docking models.

(iii) Study the value of cross-docking by comparing the total system costs with and without cross-docking for a number of scenarios.

1.3 Numerical Example

I have provided a simple example to clearly illustrate the value of cross-docking and to further motivate the need for the work conducted in this thesis. Consider a small network which has two suppliers (origins), two destinations, one cross-dock (intermediate point), and one commodity. Figure 1 describes the structure of the network.

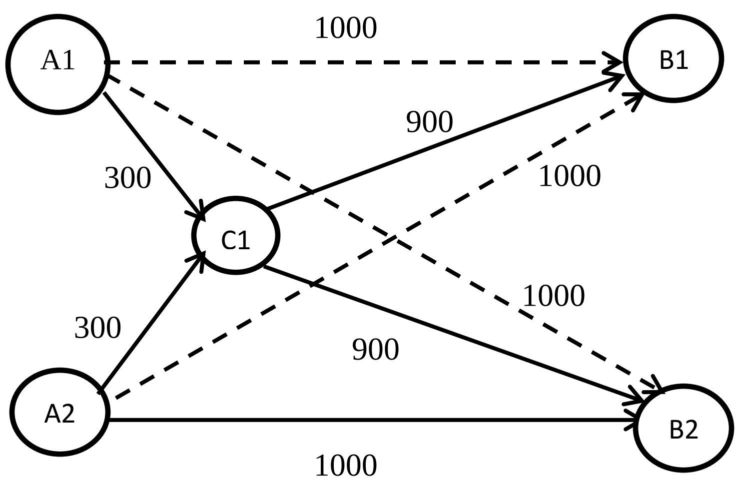

Figure 1: Example Network

The numbers on the arcs denote the distances between the nodes. The first supplier needs to transport goods from A1 to B1 and from A1 to B2. Let us consider the goods from A1 to B1: He has two options – he can send the goods directly from A1 to B1 which is a distance of 100 miles or he can send the goods to a cross-dock C1 and from C1 to B1 – which is a distance of 120 miles. Even though it is longer to send goods via a cross-dock, the supplier can get a reduced rate in the C1 to B1 leg due to consolidation opportunities. Let us consider the goods from A1 to B2. In the same way he can either send the goods directly from A1 to B2 or send it via a cross-dock from A1 to C1 and C1 to B2. The direct route has lesser cost but the cross-dock route can provide reduced rates due to consolidation opportunities.

Normally in freight transportation the freight rates are provided as cost per mile per truckload. In this example, I am assuming that the suppliers are transporting dry goods for which the standard industry rate is $ 1.4 per mile per truckload. In the food industry the unit for demand is a pallet. A truck can normally handle 28 pallets. For this example, I assume that there are 10 pallets of goods to be supplied between every supplier and destination. Let us consider the case where everybody ships their goods continuously without using the cross-dock. In this case the total cost of shipping goods directly is $ 5600.

Now let us consider the case when the suppliers use the cross-docks. At the cross-dock there is an additional cost as pallets will have to be transferred from one truck to another which is normally of the order of $ 2 - $ 5 per pallet. In this example, I am assuming a handling cost of $ 3 per pallet. I also assume that the cross-dock has a capacity of 30 units. Note that due to consolidation happening at cross-docks, shippers normally get reduced freight rates from cross-docks to destinations. This is because carriers are able to effectively manage their fleet given consolidated goods and are able to provide reduced rates to the shippers. In this case I will assume that there is a discount factor of 0.8 in the cross-dock to the destination leg. Note that the discount factor of 0.8 is a conservative estimate and normally consolidation can provide even more discounts. So when the cross-docks are used, the truck routes are: (i) A1-C1-B1, (ii) A1-C1-B2, (iii) A1-B1, and (iv) A2-B1. The total routing and handling cost is $ 4708. Thus because of cross-docking the around $ 892 of savings are obtained. Note that these savings can increase with higher discount factors and more consolidation opportunities. However in certain cases, cross-docking may not yield any savings and maybe more inefficient than direct shipping. Therefore there is a need to develop a model which can evaluate the benefits of using a cross-dock.

Next I will demonstrate the need for considering uncertainty in the cross-dock model. In this thesis, we are primarily focusing on capacity uncertainty of cross-docks. Let us assume that the cross-dock operates in two states: (i) regular operating conditions at which it has a capacity of 30, and (ii) disrupted operating conditions at which the capacity is halved to 15. Let us assume that the cross-dock operates regularly 80 % of the time (thus has a probability of 0.8) and in disrupted state 20% of the time (thus has a probability of 0.2). In the regular operating conditions the total cost of routing and handling the goods is $ 4336 and in disrupted conditions the total cost of routing and handling the goods is $ 5600. The expected cost (long range operating costs) of the solution is $ 4596. In a lot of cases, this uncertainty in capacity is not accounted for. We need to recognize and characterize this uncertainty, and develop separate routing and operating strategies for each uncertain scenario. However the common practice is to develop one routing and handling strategy for the expected condition. For example, in this case the expected capacity of the cross-dock is 27. I solved for the optimal routing strategy under this deterministic scenario with an expected capacity of 27. I evaluated the routing strategy calculated for the deterministic case under regular and disrupted operating conditions. I got the expected routing and handling cost to be $ 4838. Thus the strategy of characterizing the uncertainty and developing separate routing strategies for each uncertain state resulted in savings of $ 4838 - $ 4596 = $ 242. Note that characterizing the uncertainty and developing separate models for each uncertain state is significantly more work than just developing one model for the deterministic case. However the savings generated for this simple example demonstrate it might be worth wile to develop models which account for this uncertainty. Of course this savings can increase or decrease and can vary significantly depending on the nature of the uncertainty. One of the main contributions of this thesis is to develop models which account for this uncertainty in developing solutions.

The remainder of this thesis is organized as follows. The literature review is provided in chapter 2. In chapter 3, I develop two optimization models for locating cross-docks where all inputs are known with certainty. In chapter 4, I developed two optimization models to account for capacity uncertainty in cross-docks. In chapter 5, I conducted detailed numerical analysis to study the value of cross-docking under uncertainty under numerous scenarios. Chapter 6 provides the summary, conclusion, and the directions for future research.

CHAPTER 2. LITERATURE REVIEW

The literature review of this thesis provides an overview of two relevant literature streams: facility location problems and cross-dock operation modeling.

2.1 Facility Location Problem

Facility location problems are concerned with locating facilities in order to serve demand from the customers. Depending on how much is produced and the capacity restrictions, the facility location problems fall into two categories: (i) the problems with capacity constraints are capacitated facility location problem (CFLP), (ii) the problems without capacity constraints are uncapacitated facility location problem (UFLP), and (iii) p-median problems The primary input parameters to the UFLP are the potential locations of facilities, locations of customers which need to be serviced by the facility, the cost of transporting goods from facility locations, cost of opening a facility and customer locations. The objective of UFLP is to open a subset of facilities and connect each customer location to an open facility so that total cost (comprising of transportation costs and facility opening cost) is minimized. (Mahdian 2004). Based on the assumptions made, several variants of the UFLP have been studied. For example, one class of UFLP models the variations in costs with commodity volumes at facilities using cost functions. Depending on the cost functions, these UFLP research studies are further classified into those with concave cost function, convex cost function and S-shaped cost function (Lu 2010). Another class of problems focus on whether a customer can be served by multiple facilities or just by one facility (Romeijn et al., 2010). Dupont (2008) considers a UFLP in which both the production and the shipment costs are concave functions of the output at each facility. He showed that there exists an optimal solution, in which any customer is supplied by a single facility.

CFLP is very similar to the UFLP other than one major difference. Capacitated facility location problems (CFLP) are primarily different from UFLP by considering capacities at facility location. Each facility has a fixed capacity which acts as a hard upper bound on the amount of demand which can be served or stored by the facility.

For example, there are various types of the capacitated facility location problem with different properties of approximation algorithms. One such difference is between soft and hard capacities. In hard capacities, each facility is either opened at some location or not, whereas in soft capacities, one may specify any number of facilities to be opened at that location which make problem easier. Shmoys, Tardos, & Aardal (1997) gave the first constant approximation algorithm for this problem based on an LP-rounding technique. A general technique was given by Jain and Vazirani (2001) to convert approximation algorithm results for the uncapacitated problem to algorithms which can handle soft capacities. Korupolu, Plaxton and Rajaraman(2000) gave the first approximation algorithm for CFLP which provides constant performance guarentees. Chudak & Williamson (1999) improved this performance guarantee to 5.83 for the uniform capacity case.

Similar to the UFLP, several variations of CFLP can be obtained by relaxing or changing certain assumptions. For example, Lu (2010) studied the CFLP with concave cost functions. The concave cost functions were used to model the economies of scale. Harkness and Revelle (2003) and Desrochers, Marcotte and Stan (1995) studied the CFLP with convex cost functions which was used to model the congestion at facilities.

The p-median problem differs from the UFLP and CFLP in two respects: (i) there is no cost associated with opening the facilities, and (ii) there is an upper bound p, on the number of facilities that can be opened. All other input parameters are similar. The objective in p-median problem is to locate p facilities which minimize the total cost of transporting the commodities (Korupolu, Plaxton, Rajaraman, 1998; Bartal, 1998).

2.2 Facility Location Problem Solution Techniques

Overviews of the different techniques which have been successfully used to solve the different variants of facility location are discussed below.

The first type of solution techniques involves greedy heuristics. Hochbaum (1982) was the first to propose the approximation algorithms that are based on greedy heuristics for facility location problems. The facility location problem was reduced to variants of set cover problems and greedy heuristics were used to solve the set cover problem. Jain, Mahdian, Markakis, Saberi and Vazirani (2002) applied similar solution techniques and derived constant factor approximation for UFLP. The greedy algorithms normally use heuristics which exploit the special structure of the problem.

The facility location problems are integer programming problems. The second category of solution techniques rely on generating integer solutions that are based on rounding the fractional optimal solution to the LP relaxation of the original integer programs (Shmoys, Tardos, Aardal , 1997). The filtering idea that was proposed by Lin and Vitter (1992) was used by them to round the fractional solution to the LP and obtain constant factor approximations for many facility location problems. This idea was also combined with randomization by Chudak and Shmoys (1999).

Jain and Vazirani (2001) proposed approximation algorithms for facility location based on primal-dual techniques. A two-phase primal-dual scheme was used to solve the uncapacitated facility location problem. They also proved a stronger approximation theorem for uncapacitated facility location. This allowed them to obtain approximation algorithms for a variety of facility location problems including the p-median problem using the Lagrangian relaxation technique.

The approximation algorithms for facility location based on local search are perhaps the most versatile. For many years practitioners have been using local search heuristics and one such heuristic was proposed by Kuehn and Hamburger (1963). For certain variants of facility location problems, local search are the only technique which gives constant factor approximations.

2.3 Cross-dock

Cross-docking is a special warehousing policy moving goods from inbound trucks (ITs) to outbound trucks (OTs) without storage or just temporary storage. In a typical logistics distribution network, products are sent to a warehousing facility for storing, retrieving, sorting and reconsolidating (Sunil and Meindl (2002); Berg and Zijm (1999); Zäpfel and Wasner, 2006). Products are subsequently sent out to retailers upon requests (Baker, 2008). There are many reasons why cross-docking is important in Transportation industry. The process of cross-docking is adopted in order to decrease the overall costs of the network and to deliver products on time. In the case of Wal-Mart, cross-docking is often regarded as a key driver of the retailer's superior logistics management (Hammer 2004).

As the inventory costs are the main costs in a supply chain, cross-docking becomes an attractive alternative to warehousing. In cross-docking products move quickly and directly from inbound trucks (ITs) to outbound trucks (OTs), after being consolidated with limited storage needs, normally not exceeding 24 hours (Saxena 2007; Laumar 2008). These types of facilities are generally used in "hub-and-spoke" arrangements, where (de)consolidation of cargo occurs as in the case of transshipment, with products delivered to customers in truckloads (TL) as shown in the figure below.

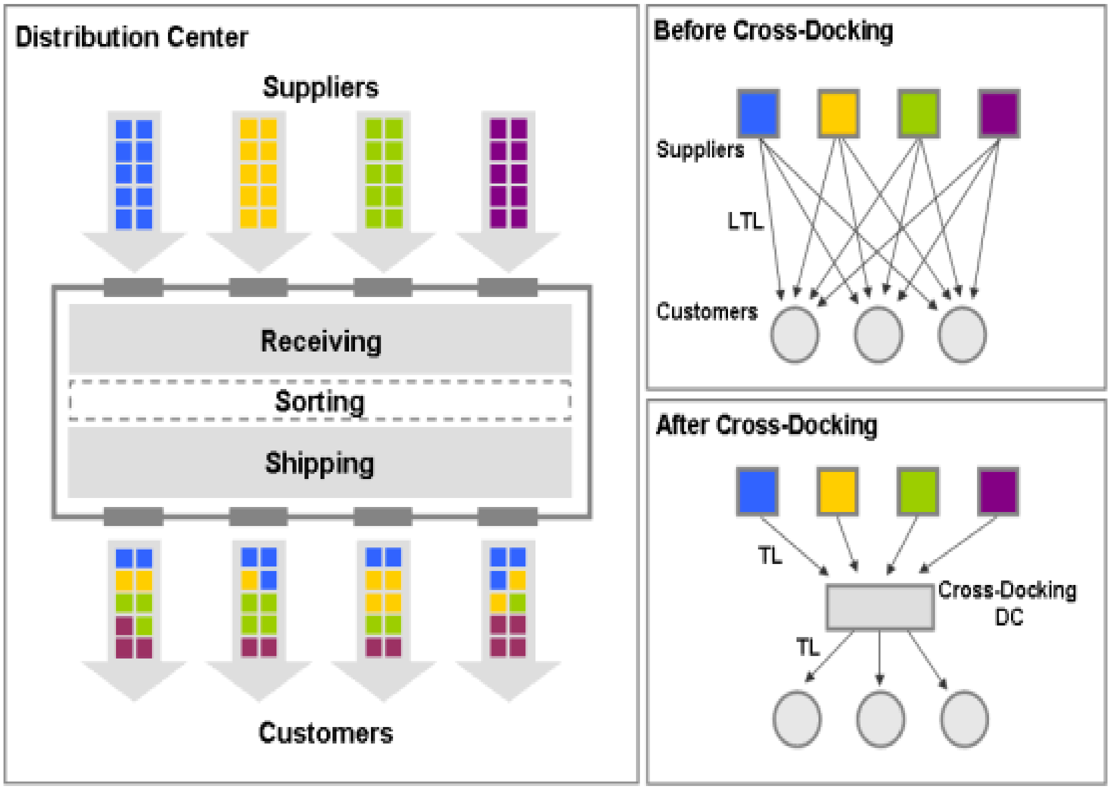

Figure 2: Cross-docking Operation Process (The Geography of Transport Systems)

Moore and Roy (1998) and Schaffer (1997) discussed the important factors to implement cross docking successfully. They explained about what kind of relationship must be maintained between the suppliers and the customers in a supply chain so that the customers truly rely on the suppliers. The products must be delivered in right time, in right quantity and of right quality. A detailed explanation was given by Schaffer (1998) on how the efficiency can be improved by using cross docking. To determine the flow of material in a facility, Gue (1995) constructed a LP-model which uses a parameter in which assigning incoming trailers to dock doors affect is captured. Apte and Vishwanathan (2000) discussed techniques which can be used in improving the efficiency of logistics and distribution operation in a cross dock. The design of physical and informational flows in cross-dock, analysis and management systems for cross-docking and other strategies for improving channel efficiencies were discussed in their paper.

Magableh, Rossetti and Mason (2005) used simulation to model the various operations in a cross-docking facility. This model incorporates five aspects which also include resource contention for dock doors, flexible assignment of loads to inbound and outbound doors, worker resource requirements, material handling contention and outbound load building. Bartholdi and Gue (2000a) used a simulated annealing approach to interchange designations of dock doors to minimize the worker's travel distance and waiting time due to congestion. Roodbergen and Vis (2002) modeled the cross-docking operation problem as a network which minimizes travel distance in a cross dock and solved it as a cost flow problem. Note that most of these works focus on operations within a cross-dock facility. The focus of this thesis is on where to locate the cross-docks in a large network.

2.3.1 Cross-docking Facilities Layout

An actual layout of a cross-docking operation was compared to a major automotive JIT (Just In Time) manufacturing plant with a newly designed layout by Hauser and Chung (2003). Peck (1983), Tsui and Chang (1990, 1992). Gue (1999) and Bartholdi and Gue (2000a) addressed the operational problem of labor costs due to placement of trailers into doors. Bartholdi and Gue (2004) in their paper say that the *shape matters* for a cross dock. They showed that the best shape of cross dock depends on the size of facility and the pattern of freight flows. Their results suggested that many large cross docks in practice suffer from poor design which also increases the labor costs on the docks. The most common shapes that are used for docks are L, I, T. There are also some unusual shapes like U and H as shown in the figure below.

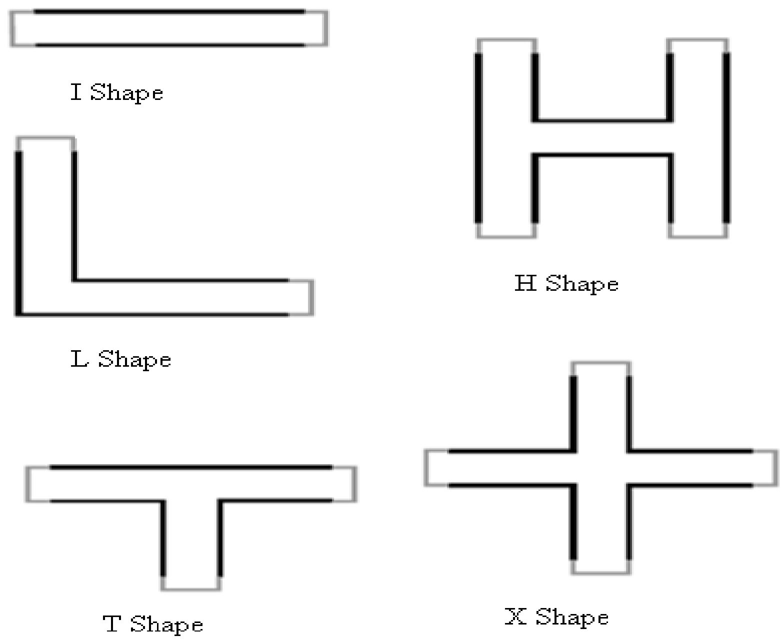

Figure 3: Shapes of Cross docks (Bartholdi and Gue 2004)

The best shape for a crossdock was discussed in detail by Bartholdi and Gue (2004). "As size increases, the most labor-efficient shapes for a crossdock are I, T and X-shapes successively". Depending on the number of receiving doors and the concentration of flows, the T-shape dock is preferred to I-shape and X-shape is preferred to T-shape. From the experiments the results suggested that for the docks which have less than 150 doors, I-shape dock is the most efficient one. For docks which have 150-200 doors, T-shape best suits and for docks which have more than 200 doors X-shape is the best. While Bartholdi and Gue (2000) propose some other measures of performance, they mention that minimizing weighted door-to-door distances can exacerbate congestion. As more activity is squeezed into a smaller area of the dock, delays will occur. Congestion on dock leads to excessive labor cost and can result in shipments missing service commitments.

2.3.2 Models for cross-docking facility operation and locations

According to Donald, et al.1999; Sung and Song 2003; Dobrusky 2003; Lee, et al. 2006; Wen, et al. 2008, the problems that consider the cross-dock facility as a node within larger transportation network include: (i) the routing of vehicles from/to the cross dock facility, (ii) the location and demand allocation to the facility, and (iii) design of the supply chain network given the cross dock facility.

According to Miao, et al. 2006; Song and Chen 2007; Wang et al.2008; Bozer and Carlo 2008; Yu and Egbelu 2008, Boysen, et al. 2008, the problems that focus on the operations of the facility (i.e., inbound doors, staging and outbound doors) include: (i) optimization of operations at the inbound doors (IDs) and the outbound doors (ODs), and (ii) optimization of operations within the storage area of the cross dock facility. Optimizing different operations can become somewhat tedious depending on the complexity of the cross-dock facility.

Several researchers have used simulation based methods to evaluate cross-docking operations. Rohrer (1995) oriented his paper towards practitioners who need to model cross-docking systems, as well as distribution mangers who are evaluating cross docking. The paper describes the application of simulation to ensure efficiency in cross-docking systems by determining optimal hardware configuration and software control, as well as establishing failure strategies before cross docking problems are encountered. An important factor that effects cross docking performances is queueing or congestion effect. Wang (2010) in his paper uses the simulation methods to analyze staging queueing and also provides several insights for improving cross dock performance from the results obtained from simulation. The results included smoothing trailer arrivals, installing suitable staging size, balancing demand distribution and avoiding high worker utilization.

As the scheduling of inbound and outbound transportation is a part of planning of a cross dock, this makes the problem more dynamic than the mere warehousing operations. Improvements in this area have appeared only recently (Laumar 2008). Soltani and Sadjadi (2009) used two robust hybrid meta-heuristics search methods – hybrid simulated annealing and hybrid variable neighborhood search to sequence and schedule the inbound and outbound trucks in the cross-dock. Larbi, Alpan, Baptiste, Penz (2010) presented different solution techniques in order to schedule the outbound trucks in a cross docking facility. For small time horizons these operations can be scheduled without degrading the system performance by Sathasivan, Ng, Waller (2010) developed a robust surrogate heuristic algorithm to solve a robust scheduling optimization model for loading or unloading of trucks at cross docks. This algorithm is easy to use and gives the results which are closer to the optimal solution.

By assuming that the outbound trucks cannot start service till the inbound trucks have finished loading Golias, Ivey, Haralambides, Saharidis (2010) discussed about the scheduling of trucks i.e., inbound and outbound trucks to the available inbound and outbound doors at the cross-dock facility. The truck scheduling had two objectives - maximization of facility's total throughput and minimizing the costs incurred by cross docks from early and tardy departures of trucks at both the inbound and outbound doors. The scheduling of inbound trucks at cross docks was done by Golias, Ivey, Haralambides, Saharidis (2011) by assuming the arrival times of trucks as stochastic with known lower and upper bounds. Vahdani, Zandieh (2009) used five meta-heuristic algorithms to schedule the trucks of cross-docking systems. The algorithms that are applied are: genetic algorithm (GA), tabu search (TS), simulated annealing (SA), electromagnetism-like algorithm (EMA) and variable neighborhood search (VNS). The result was compared with the heuristic method that was proposed by Yu and Egbelu (2008) and found better solutions. Arabani, Ramtin, Rafienejad (2009) used simulated annealing to find the best sequence of inbound and outbound trucks which minimize the make span. Ley, Elfayoumy, Member (2007) used genetic algorithms to create a truck schedule in order to decrease the time a truck must spend unloading and loading at a cross dock warehouse. The results of the efficiency and accuracy testing shows that using genetic algorithms to schedule cross dock trucking operations provides an accurate and timely solution. Boysen (2009) considered a truck scheduling problem in the cross docks of food industry, in which no intermediate storage of food is permitted. All the products are instantaneously loaded into the outbound trucks which have the refrigerators in order to keep the food cool. Flow time, processing time and tardiness of outbound trucks are taken as objective functions and are minimized. The methods that were used are Simulated Annealing and the Dynamic Programming Approach and these methods have been implemented in C# (Visual Studio 2003). The coordination of inbound and outbound trucks can be done by computerized scheduling procedures. To solve more complex real-world truck scheduling problems, Boysen, Fliedner, Scholl (2010) introduced a base model for scheduling trucks at cross docking terminals. This model relies on a set of assumptions in order to derive fundamental insights into underlying problem's structure i.e., its complexity and to develop a building block solution procedure.

Shakeri, Low, Lee (2010) proposed a Mixed Integer Programming (MIP) model in order to formulate the truck scheduling problem. Two observations were made with the help of experimental data – (i) truck interdependencies correlation has a positive impact on the behavior of the truck scheduling problem, (ii) in the course of scheduling trucks, capacity of cross dock did not turn out to be a bottleneck. Another paper by Shakeri, Low, Li, Lee (2010) was also on scheduling of trucks at cross-docking terminals where it consists of two optimization problems –

(i) truck sequencing, and (ii) door assignment. They developed a dependency ranking constructive heuristic for truck scheduling, and machine fitness (MF) based heuristic for door assignment. The solutions from the heuristic were found to be very close to the CPLEX solution.

The rest of the literature review will focus on studies whose objective is to determine optimal locations of cross-docks in a supply chain and logistics network. Gumus and Bookbinder (2004) develop models to determine the potential locations between origin and destination nodes for cross-dock operations. The cost functions discussed in this paper included transportation and facility costs, inventory costs at manufacturers and retailers, and in-transit inventory cost. The first model they developed was on the single product, single manufacturer and multiple seed customers and got a solution by using LINGO 2008. The second model was on the single manufacturer; multiple products and seed customers and the solution was obtained by using a heuristic approach based on consolidation priorities. The third model built was on multiple manufacturers and seed customers; single product, and the fourth model was for multiple manufacturers, products and seed customers in which the solution was obtained by using CPLEX 7.5.

Galbreth, Hill and Handley (2008) compared total costs by using two supply chain networks, one without cross-docks and one with cross-docks. The supply chain network was a stylized multi-echelon supply chain which consisted of a single supplier, three cross-dock locations and eight customer locations. In this paper, the value of cross-docking is defined as the percentage of total costs saved by using cross-docks in the supply chain, with higher savings corresponding to the higher number of cross-docks used. Sung and Song (2003) developed a path-based formulation problem for determining cross-dock facility location and vehicle allocation from origin nodes to cross-docks and cross-docks to destination nodes for a set of freight demands. The mathematical model's objective function was to minimize the total transportation costs through cross-docks and direct deliveries and the facility location costs. Tabu-search-based solution algorithm was used in order to obtain the solution.

Lee, Jung, Lee (2006) develop an integrated model which considers both the cross-docking and the scheduling of the vehicle routes. Wen, Larsen, Clausen, Francois, Laporte (2009) discussed Vehicle Routing Problem with cross-docking (VRPCD). Homogeneous fleet of vehicles is used for pickup and delivery process. The main objective of developing a model is to minimize the total distance traveled by respecting the time window constraints at nodes and time horizon for the entire transportation operation.

Ratliff and Vate, developed a mixed integer programming model to determine the number and location of cross docks in a load driven cross-docking network.. There are two important steps to design a load-driven cross docking system are: (i) location decisions: they deal with the number and location of cross docks. (ii) routing decisions: they deal with the path through which the flow should be routed. In this problem the objective was to minimize the average delay between the time a vehicle is produced and the time it reaches its destination ramp. The two types of delay they dealt with are: (i) transportation delay (time for traveling) , (ii) loading delay (waiting for the truck to be loaded). For this model, a linear programming relaxation provides an integral optimal solution. The model was tested in the context of North American automobile delivery systems.

Chen, Guo, Lim and Rodrigues (2006) studied a network of cross-docks. Delivery and pickup time windows, warehouse capacities and inventory-handling costs were taken into consideration. Because of the complexity of the problem, several local search techniques were developed and used with simulated annealing and tabu search heuristics. Results showed that the heuristics do better than CPLEX within practical computational times.

A survey of the literature reveals that several models have been developed for locating cross-docks in a supply chain network. This thesis is makes a contribution over the existing models in the literature along two main directions. First we provide a cross-dock facility location problem formulation which is consistent with a p-median facility location. In our case, the objective is to choose p facilities to locate cross-docks so that the total transportation cost is minimized. All of the works in the cross-dock facility location problem assume deterministic parameters. They assume that all freight demands are known, capacity and travel times are known and do not vary. However, in reality all of these parameters are uncertain. This thesis develops two optimization formulations to account for one form of uncertainty – capacity uncertainty. The next section provides a deterministic cross dock facility location formulation.

CHAPTER 3 DETERMINISTIC MODEL FORMULATIONS FOR CROSS DOCK FACILITY LOCATION PROBLEM

3.1 Introduction

The focus of modeling is on developing models for regional long haul freight transportation. The trucks directly travel from origins which are the pickup locations to the destination which are either the cross dock locations or the delivery nodes. Two models are presented in this chapter by assuming that every route modeled satisfies the time related constraints.

The first model (which is called Model A) assumes that the cross docking facilities have already been established and in this we have to choose P facilities from the existing established cross docks. In this model we choose P facilities so that the total transportation and facility handling costs are minimized. In the second model (which is called Model B), P cross dock facilities are needed to be operated. In this model we also minimize the handling costs in addition to the other two costs mentioned in the first model.

3.2 Problem Definition and Formulation

A number of freight agents (shippers or carriers) need to transport goods from origins to destinations. The origins and destinations correspond to supplier and retailer locations respectively. A third party logistics firm (3PL) has the responsibility of optimizing the routing of the goods and is considering using cross-docks to consolidate the goods for efficient usage of truck capacities. The notations used in the problem are defined next.

Consider a freight network $G = (N, A)$ where N represents the set of nodes and A represents the set of directed arcs. There are three types of nodes considered in this work: (i) the set of origin nodes O which are the locations from which the goods are picked up, (ii) the set of destination nodes D which are the locations at which the goods are delivered, and (iii) the set of potential cross dock locations K. Note that $N = O \cup D \cup K$. Every arc $(i, j) \in A$ corresponds to direct routes between nodes i and j. There are three types of arcs in this network: (i) arcs linking the set of origin nodes and cross dock locations, (ii) arcs connecting cross dock locations to destination nodes, and (iii) arcs connecting origin nodes and destination nodes directly. Let s_{ij} denote the distance between nodes i and j or the length of arc $(i, j) \in A$.

Let L represent the set of commodities. We model three types of commodities in this work –dry, refrigerated and frozen. Note that the truck type used to transport the commodity will vary depending on the type of goods. We cannot use a truck used to transport refrigerated goods to transport dry goods. Let q_{ij}^{l} denote the demand for commodity $l \in L$ which needs to be transported from origin node $i \in O$ to destination node $j \in D$. The unit of demand is the number of pallets of each commodity which needs to be transported. Every freight agent has two options for routing the commodities. The commodities can be routed through a cross dock location in which case the route would consist of two legs and can be represented as $[(i, k), (k, j)]$ where $i \in O$, $j \in D$ and $k \in K$. If the freight careers feels that routing through a cross-dock does not deliver significant cost savings, he can send the goods directly to the destination in which case the route would be a single leg and would correspond to the arc (i, j) where $i \in O$ and $j \in D$.

Associated with every truck is a capacity which corresponds to maximum number of pallets which can be loaded on to the single truck. Let U denote the capacity of the trucks. Note that the truck capacity is independent of the commodity type. The model presented in this research can be easily extended to the case where the truck capacity depends on commodity type.

For truckload transportation it is common to assume a unit transportation cost per mile per truckload. Let c_{ij}^{l} denote the unit truckload cost for transporting commodity $l \in L$ from node $i \in N$ to node $j \in N$. Due to the consolidation opportunities available from cross-dock locations to the destinations, normally the freight carriers get a discounted rate for that leg. Let γ denote the discount made on the transportation costs for the cross dock to destination leg. Therefore the unit truckload cost for transporting commodity $l \in L$ from cross dock node $i \in K$ to destination node $j \in D$ becomes γc_{ij}^{l}. Note that $\gamma \leq 1$.

In this research, we focus on developing models for regional long haul freight transportation where trucks travel directly from the pickup location (origin nodes /cross dock locations) to the delivery locations (cross dock locations/delivery nodes). We assume that the origin nodes and destination nodes are far apart so that there is no tour based routing possible where a truck can do multiple pickups in one tour or multiple deliveries in a single tour. Tour based routing is more common for deliveries within urban areas and is not the focus of this work. In this research we also do not explicitly model the time element. We assume that every route modeled satisfies the time related constraints and are feasible in terms of delivery start times, delivery end times, cross-dock processing times, driver work hours, etc.

Associated with every cross-dock $k \in K$ is a fixed cost of setting up the cross-dock f_k and a variable unit handling cost per pallet h_k. The fixed costs and variable costs vary from location to location depending on the land price and wages. Let W denote the capacity of the cross-docks. The notations (sets, indices and parameters) used in this model are summarized below followed by the description of the decision variables and the base routing constraints.

<u>Sets and Indices</u>

O	Set of all origin nodes
D	Set of all destination nodes
K	Set of potential cross-dock locations
N	Set of nodes
A	Set of arcs
L	Set of commodities
Z_+	Set of positive integers
i, j, k	Indices for nodes $i, j, k \in N$
l	Index for a commodity $l \in L$

Parameters (Inputs to the model)

q_{ij}^{l} Amount in pallets of commodity $l \in L$ which needs to be transported from origin node $i \in O$ to destination node $j \in D$

U Truck capacity

W Warehouse capacity

c_{ij}^{l} Unit truckload cost for transporting commodity $l \in L$ from node $i \in N$ to node $j \in N$

γ Discount parameter

f_k Fixed cost of establishing a cross-dock at location $k \in K$

h_k Unit cost of handling a pallet in a cross-dock at location $k \in K$

Decision variables and Base Routing Constraints

The objective of the 3PL firm is to efficiently route the freight commodities from origins to destinations in order to minimize the total system transportation costs and facility location and operational costs. The base constraints of the optimization model correspond to routing constraints on the flow of goods. The decision variables needed to fully characterize the routing process and the various constraints are described first. The equations represented the constraints are then provided followed by the detailed descriptions.

Decision variables (Outputs from the model)

x_{ijk}^{l} Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ through cross-dock location $k \in K$ and 0 otherwise

y_{ij}^{l} Number of trucks transporting commodity $l \in L$ from node $i \in N$ to node $j \in N$

v_{ij}^{l} Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ directly without using a cross-dock and 0 otherwise

z_k Takes the value 1 if a cross-dock facility is established at location $k \in K$ and 0 otherwise

Base Routing Constraints

$$\sum_{k \in K} x_{ijk}^{l} + v_{ij}^{l} = 1 \qquad \forall i \in O, j \in D, l \in L \qquad (1)$$

$$\sum_{j \in D} q_{ij}^{l} x_{ijk}^{l} \leq U y_{ik}^{l} \qquad \forall i \in O, k \in K, l \in L \qquad (2)$$

$$\sum_{i \in O} q_{ij}^l x_{ijk}^l \leq Uy_{kj}^l \qquad \forall j \in D, k \in K, l \in L \qquad (3)$$

$$q_{ij}^l v_{ij}^l \leq Uy_{ij}^l \qquad \forall i \in O, j \in D, l \in L \qquad (4)$$

$$x_{ijk}^l \leq z_k \qquad \forall i \in O, j \in D, k \in K, l \in L \qquad (5)$$

$$\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^l x_{ijk}^l \leq Wz_k \qquad \forall k \in K \qquad (6)$$

$$z_k \in \{0,1\} \qquad \forall k \in K \qquad (7)$$

$$x_{ijk}^l \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L, k \in K \qquad (8)$$

$$v_{ij}^l \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L \qquad (9)$$

$$y_{ij}^l \in Z_+ \qquad \forall i \in N, j \in N, l \in L \qquad (10)$$

Constraint (1) ensures that all demands are transported to their destinations. To be more specific constraint (1) ensures that commodity $l \in L$ from origin node $i \in O$ to destination node $j \in D$ is either transported through a cross-dock location $k \in K$ or transported directly to the destinations without using a cross-dock. Constraints (2, 3, and 4) enforces the capacity constraints on trucks. To be specific, constraint (2) ensures that the total volume of commodity $l \in L$ from origin node $i \in O$ to cross-dock node $k \in K$ is lesser than the total truck capacity for that specific commodity for that route. Similarly constraint (3) ensures that that the total volume of commodity $l \in L$ transported from cross-dock node $k \in K$ to destination node $j \in D$ is less than the total truck capacity for that specific commodity for that route. Constraint (4) ensures that the total volume of commodity $l \in L$ transported directly from origin node $i \in O$ to destination node $j \in D$ is lesser than the total capacity of trucks traveling directly between from origin node $i \in O$ to destination node $j \in D$. Constraint (5) ensures that commodity $l \in L$ from origin node $i \in O$ to destination node $j \in D$ is either transported through a cross-dock location $k \in K$ only if a cross dock is located at $k \in K$. Constraint (6) enforces capacity constraints on cross-dock locations. Constraint (5) ensures that the total volume of goods handled at cross-dock location $k \in K$ is lesser than total capacity of cross-dock at that location. Constraints (7, 8, 9, 10) enforces binary and integrality restrictions on the corresponding decision variables.

Given the above problem definition, two types of models are defined – Model A and Model B. The integer programming formulations of both model types are described next.

3.3 Model A Problem Formulation

Model A assumes that the cross-docking facilities have already been established. The objective of the 3 PL firm in Model A is to choose P facilities out of existing established cross-docks in order to minimize the total transportation and facility handling costs subject to the base routing constraints. The mathematical programming formulation of Model A is given below.

$$Min \quad \sum_{i\in O}\sum_{k\in K}\sum_{l\in L} c_{ik}^{l} s_{ik} y_{ik}^{l} + \sum_{k\in K}\sum_{j\in D}\sum_{l\in L} c_{kj}^{l} s_{kj} y_{kj}^{l} + \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} c_{ij}^{l} s_{ij} y_{ij}^{l} \qquad (11)$$

$$+ \sum h_k \sum\sum\sum d_{ij}^{l} X_{ijk}^{l}$$

Subject to:

$$\sum_{k \in K} z_k = P \tag{12}$$

Base Routing constraints (1, 2, 3, 4, 5, 6, 7, 8, 9, 10)

The objective function in model A, corresponding to equation (11) comprises of four terms. The first term corresponds to the total routing costs from origin nodes to cross-docks, the second term corresponds to total routing costs from cross-docks to destination nodes, the third term represents the total routing costs of all goods which are transported directly from origins to destinations and the fourth term denotes the total handling costs at each cross-docks. Constraint (12) ensures that the total number of cross-docks used in the model is equal to P . In addition, the routing strategies must also satisfy the base routing constraints. The above integer programming formulation belongs to the category of P-median facility location problems.

3.4 Model B Problem Formulation

Model B relaxes the assumption that P cross-dock facilities need to be operated. In model B we relax the assumption that facilities are already in operation. The objective in Model B is to minimize the total transportation, facility location and handling costs. The mathematical programming formulation of model B is provided below.

$$Min \qquad \sum_{i \in O} \sum_{k \in K} \sum_{l \in L} c_{ik}^{l} s_{ik} y_{ik}^{l} + \sum_{k \in K} \sum_{j \in D} \sum_{l \in L} c_{kj}^{l} s_{kj} y_{kj}^{l} + \sum_{i \in O} \sum_{j \in D} \sum_{l \in L} c_{ij}^{l} s_{ij} y_{ij}^{l} \tag{13}$$

$$+ \sum h_k \sum \sum \sum d_{ij}^{l} X_{ijk}^{l} + \sum f_k z_k$$

Subject to:

Base Routing constraints (1, 2, 3, 4, 5, 6, 7, 8, 9, 10)

The objective function in model B, corresponding to equation (13) comprises of five terms. The first four terms are the transportation and handling costs and is the same as that of Model A objective function. In model B, we have an additional fifth term which corresponds to the total cross-dock facility location costs. The constraints of this model correspond to the base routing constraints. The above integer programming formulation belongs to the category of capacitated facility location problems.

In this chapter we provide two different formulations for the cross dock facility location problem. However one major assumption made in the formulation provided in this chapter is the deterministic assumption. We assume that all parameters are known with certainty. The next chapter relaxes this assumption and provides formulations which account for uncertainty in capacity.

CHAPTER 4 CROSS DOCK FACILITY LOCATION PROBLEM ACCOUNTING FOR CAPACITY UNCERTAINTY

Designing a facility involves determination of capacity, location and layout of facility. Capacity is defined as a measure of an ability of the organization to provide the demanded goods in the requested quantity and also in a timely frame. There are two types risks associated with capacity: (i) operational uncertainty and (ii) disruption. Operational uncertainties correspond to day-to-day variation in capacities. Short term operational uncertainties correspond to variation in day to day capacities which causes changes in the amount of goods which can be handled by a cross dock. Disruptions correspond to complete shutdown of operations at a cross-dock and can be caused by natural and man-made disasters. This section provides two integer programming formulation for capacity uncertainty under day-to-day operational uncertainty and disruptions.

4.1 Capacity Uncertainty

As described above, there are two sources of capacity uncertainties. The first is the day-to-day operational uncertainty in capacity which is caused due to worker and equipment related issues. The factors that affect the job-site productivity can be influenced by labor characteristics, project work conditions and some non-productive activities.

The labor characteristics include the age, skill of labor, experience and motivation of workforce. The project work conditions include the job size and complexity, availability of labor, local climate conditions, handling equipment and utilizing it. The non-productive activities include maintaining the progress of project by employing indirect labor, time off for union activities, wasted time which includes late starts and early quits, non-working holidays and strikes. All the factors discussed above affects the on-site labor efficiency and also the productive labor available resulting in variations in capacity in terms of number of goods which can he handled at that facility. In addition to the human centric issues, factors which can cause variations in amount of goods which can be handled at a facility include equipment repairs and software failures in Information Technology systems due to bugs or crashes (Chopra et al., 2004; Spekman et al., 2004).

Disruptions are defined as the major breakdowns in a supply chain's production or distribution nodes. The causes of disruptions are due to severe weather, political/industrial crisis, machine breakdown, fire, unexpected increase in capacity which creates bottleneck and natural disasters like earthquakes, floods. The supply-chain disruptions have recently begun to receive attention from practitioners and researchers. The reason for this interest is because of the high-profile disruptions like 9/11 and hurricanes like Katrina and Rita in 2005. The other reason for the increasing interest is that the firms are growing and their supply chains are increasingly global. A few decades ago, the firms used to manufacture products from scratch but in today's world firms tend to assemble final products from increasingly complex components procured from suppliers rather than produced in-house.

Due to supply chain disruptions, significant physical costs and subsequent losses due to downtime occur. Kembel, 2000 in his recent study estimated the cost of downtime in terms of lost revenue for several online industries like Ebay, Amazon. The cost of one hour of downtime for Ebay is estimated as $225,000, for amazon.com it was $180,000 and for brokerage companies it was $6,450,000. All these numbers do not include cost of paying employees who cannot work because the system suffered from outage (Patterson, 2002). A company which experiences a disruption will face significant declines in sales growth, stock returns and shareholder wealth for two years or more that depends on the incident occurred (Hendricks and Singhal, 2003, 2005a, 2005b).

As shown in the literature review, all the past works in cross-dock facility location do not consider the impact of capacity uncertainty on facility location and costs. In this chapter we provide two models to account for the impact of the two types of capacity uncertainty described above. Note that in our work we will focus on the impact of capacity uncertainty on Model A alone. The methodology can be easily extended to the formulation of Model B also.

4.2 Operational Uncertainty

In order to model the day-to-day capacity uncertainty we assume that the capacity of the cross-dock is uncertain and can be described by a pre-specified probability distribution. We replace the cross dock capacity constraint by a probabilistic chance constraint (see equation 8).

$$Min \quad \sum_{i\in O}\sum_{k\in K}\sum_{l\in L} c_{ik}^{l} s_{ik} y_{ik}^{l} + \sum_{k\in K}\sum_{j\in D}\sum_{l\in L} c_{kj}^{l} s_{kj} y_{kj}^{l} + \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} c_{ij}^{l} s_{ij} y_{ij}^{l} \qquad (1)$$

$$+ \sum h_k \sum\sum\sum d_{ij}^{l} X_{ijk}^{l}$$

$$\sum_{k\in K} z_k = P \qquad (2)$$

$$\sum_{k\in K} x_{ijk}^{l} + v_{ij}^{l} = 1 \qquad \forall i \in O, j \in D, l \in L \qquad (3)$$

$$\sum_{j \in D} q_{ij}^{l} x_{ijk}^{l} \;\leq\; U y_{ik}^{l} \qquad \forall i \in O, k \in K, l \in L \qquad (4)$$

$$\sum_{i \in O} q_{ij}^{l} x_{ijk}^{l} \;\leq\; U y_{kj}^{l} \qquad \forall j \in D, k \in K, l \in L \qquad (5)$$

$$q_{ij}^{l} v_{ij}^{l} \qquad \leq \; U y_{ij}^{l} \qquad \forall i \in O, j \in D, l \in L \qquad (6)$$

$$x_{ijk}^{l} \qquad \leq \quad z_k \qquad \forall i \in O, j \in D, k \in K, l \in L \qquad (7)$$

$$\Pr\left(\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^{l} x_{ijk}^{l} \;\leq\; W \right) \geq \alpha_k \qquad \forall k \in K \qquad (8)$$

$$z_k \quad \in \{0,1\} \qquad \forall k \in K \qquad (9)$$

$$x_{ijk}^{l} \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L, k \in K \qquad (10)$$

$$v_{ij}^{l} \;\; \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L \qquad (11)$$

$$y_{ij}^{l} \;\in\; Z_+ \qquad \forall i \in N, j \in N, l \in L \qquad (12)$$

The primary difference between the deterministic formulation and the current formulation is the capacity constraint (8). Essentially in constraint (8) we provide probabilistic guarantees on the capacity constraint being met. The probabilistic guarantees are described by the parameter α_k

for each cross dock facility location. For each facility location, the probability of capacity constraint being met has to be greater than α_k. This implies that there is a $1 - \alpha_k$ chance of the capacity constraint not being met. We can then control the level of infeasibility tolerated at each facility location by changing the parameter α_k. Higher the values of α_k , lower the chances of capacity constrain not being met and thus lower the risks. This is referred to in literature as the chance constrained problem formulation (Charnes and Cooper, 1963; Birge and Louveaux, 1997).

In the problem variation studied in this thesis, we assume that the capacity is normally distributed. Normal distribution is described by two parameters: mean μ_k and standard deviation σ_k. We assume that the freight planners know the mean and standard deviation of the capacity of each cross dock location. This can be estimated from historical records using statistical techniques.

$$\Pr\left(\sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^l x_{ijk}^l \le W\right) = 1 - Pr\left(W \le \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^l x_{ijk}^l\right)$$

$$= 1 - \Pr\left(\frac{W - \mu_k}{\sigma_k} \le \frac{\sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^l x_{ijk}^l - \mu_k}{\sigma_k}\right)$$

$$= 1 - \Phi\left(\frac{\sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^l x_{ijk}^l - \mu_k}{\sigma_k}\right)$$

In the above equations, Φ denotes the cumulative distribution function of the standard normal distribution. Now equation (8) can be rewritten as:

$$1 - \Phi\left(\frac{\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^{l} x_{ijk}^{l} \ - \mu_k}{\sigma_k}\right) \geq \quad \alpha_k \qquad \forall k \in K$$

$$\Phi\left(\frac{\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^{l} x_{ijk}^{l} \ - \mu_k}{\sigma_k}\right) \quad \leq \quad 1 - \alpha_k \qquad \forall k \in K$$

$$\frac{\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^{l} x_{ijk}^{l} \ - \mu_k}{\sigma_k} \quad \leq \quad \Phi^{-1}(1 - \alpha_k) \qquad \forall k \in K$$

$$\sum_{i \in O} \sum_{j \in D} \sum_{l \in L} q_{ij}^{l} x_{ijk}^{l} \quad \leq \quad \mu_k + \ \sigma_k \Phi^{-1}(1 - \alpha_k) \qquad \forall k \in K \qquad (13)$$

Thus the chance constrained problem formulation can be obtained by replacing constraint (8) with constraint (13).

4.3 Disruptions

In this section we will develop a model to account for large scale disruptions in capacity of the warehouse. We assume that there are two major scenarios: (i) regular operating condition denoted by R and (ii) disrupted conditions denoted by Ω. Let $\omega \in \Omega$ index one specific disruption scenario in the set of disruption scenarios. Based on historical records we assume that the freight planner is able to estimate the probability of normal operating conditions P^R and the probability of disrupted conditions P^{ω}. Depending on the disruption scenario, $\omega \in \Omega$, the capacity of cross-dock established at location $k \in K$, W_k^{ω} is equal to W or 0. Note that:

$$P^R + \sum_{\omega \in \Omega} P^{\omega} = 1$$

In this case, the freight decision maker establishes the facility locations, he is aware of the probability distribution of the disruption scenarios and the associated capacities at each location. The freight decision maker has the freedom to change his routing decisions depending on the nature of the disruptions, i.e, for each disruption scenario; there will be different routing decisions. The decision variables for this formulation are given below:

<u>Decision variables (Outputs from the model)</u>

x_{ijk}^{lR} Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ through cross-dock location $k \in K$ under regular operating conditions and 0 otherwise

y_{ij}^{lR} Number of trucks transporting commodity $l \in L$ from node $i \in N$ to node $j \in N$ under regular operating conditions

v_{ij}^{lR} Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ directly without using a cross-dock under regular operating conditions and 0 otherwise

z_k Takes the value 1 if a cross-dock facility is established at location $k \in K$ and 0 otherwise

$x_{ijk}^{l\omega}$ Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ through cross-dock location $k \in K$ under disrupted operating condition scenario $\omega \in \Omega$ and 0 otherwise

$y_{ij}^{l\omega}$ Number of trucks transporting commodity $l \in L$ from node $i \in N$ to node $j \in N$ under disrupted operating condition scenario $\omega \in \Omega$

$v_{ij}^{l\omega}$ Takes the value 1 if commodity $l \in L$ is transported from origin node $i \in O$ to destination node $j \in D$ directly without using a cross-dock under under disrupted operating condition scenario $\omega \in \Omega$ and 0 otherwise

The constraints for the current problem formulation are given below.

$$\sum_{k \in K} z_k = P \tag{14}$$

$$\sum_{k \in K} x_{ijk}^{lR} + v_{ij}^{lR} = 1 \qquad \forall i \in O, j \in D, l \in L \tag{15}$$

$$\sum_{k \in K} x_{ijk}^{l\omega} + v_{ij}^{l\omega} = 1 \qquad \forall i \in O, j \in D, l \in L, \omega \in \Omega \tag{16}$$

$$\sum_{j\in D} q_{ij}^{lR} x_{ijk}^{lR} \le U y_{ik}^{lR} \qquad \forall i \in O, k \in K, l \in L \qquad (17)$$

$$\sum_{j\in D} q_{ij}^{l\omega} x_{ijk}^{l\omega} \le U y_{ik}^{l\omega} \qquad \forall i \in O, k \in K, l \in L, \omega \in \Omega \qquad (18)$$

$$\sum_{i\in O} q_{ij}^{lR} x_{ijk}^{lR} \le U y_{kj}^{lR} \qquad \forall j \in D, k \in K, l \in L \qquad (19)$$

$$\sum_{i\in O} q_{ij}^{l\omega} x_{ijk}^{l\omega} \le U y_{kj}^{l\omega} \qquad \forall j \in D, k \in K, l \in L, \omega \in \Omega \qquad (20)$$

$$q_{ij}^{lR} v_{ij}^{lR} \le U y_{ij}^{lR} \qquad \forall i \in O, j \in D, l \in L \qquad (21)$$

$$q_{ij}^{l\omega} v_{ij}^{l\omega} \le U y_{ij}^{l\omega} \qquad \forall i \in O, j \in D, l \in L, \omega \in \Omega \qquad (22)$$

$$x_{ijk}^{lR} \le z_k \qquad \forall i \in O, j \in D, k \in K, l \in L \qquad (23)$$

$$x_{ijk}^{l\omega} \le z_k \qquad \forall i \in O, j \in D, k \in K, l \in L, \omega \in \Omega \qquad (24)$$

$$\sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^{l} x_{ijk}^{lR} \le W^{R} \qquad \forall k \in K \qquad (25)$$

$$\sum_{i\in O}\sum_{j\in D}\sum_{l\in L} q_{ij}^{l} x_{ijk}^{l\omega} \le W^{\omega} \qquad \forall k \in K, \omega \in \Omega \qquad (26)$$

$$z_k \quad \in \{0,1\} \qquad \forall k \in K \qquad (27)$$

$$x_{ijk}^{lR}, x_{ijk}^{l\omega} \ \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L, k \in K, \omega \in \Omega \qquad (28)$$

$$v_{ij}^{lR}, v_{ij}^{l\omega} \ \in \{0,1\} \qquad \forall i \in O, j \in D, l \in L, \omega \in \Omega \qquad (29)$$

$$y_{ij}^{lR}, y_{ij}^{l\omega} \ \in \ Z_+ \qquad \forall i \in N, j \in N, l \in L, \omega \in \Omega \qquad (30)$$

The constraints are similar in logic to the deterministic formulation constraints described in the previous chapter. Constraint (14) ensures that only P cross-docks are located. Constraints (15) and (16) ensure that for regular operating conditions and for each disruption scenarios, all demands are transported to their destinations either through a cross dock or shipped directly. Constraints (17, 18, 19, 20, 21 and 22) enforce the capacity constraints on trucks for regular operating conditions and for each disruption scenarios. Constraints (23 and 24) ensures that for regular operating conditions and for each disruption scenarios commodity $l \in L$ from origin node $i \in O$ to destination node $j \in D$ is either transported through a cross-dock location $k \in K$ only if a cross dock is located at $k \in K$. Constraint (25 and 26) enforces capacity constraints on cross-dock locations for regular operating conditions and for each disruption scenarios. Constraints (27, 28, 29, 30) enforces binary and integrality restrictions on the corresponding decision variables.

The objective function in this model is to minimize the total expected routing costs. The objective function can be written as:

$$Min \quad P^R\Psi^R + \sum_{\omega\in\Omega} P^\omega\Psi^\omega$$

Where:

$$\Psi^R = \sum_{i\in O}\sum_{k\in K}\sum_{l\in L} c_{ik}^l s_{ik} y_{ik}^{lR} + \sum_{k\in K}\sum_{j\in D}\sum_{l\in L} c_{kj}^l s_{kj} y_{kj}^{lR} + \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} c_{ij}^l s_{ij} y_{ij}^{lR}$$
$$+ \sum_{k\in K} h_k \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} d_{ij}^l X_{ijk}^{lR}$$

$$\Psi^\omega = \sum_{i\in O}\sum_{k\in K}\sum_{l\in L} c_{ik}^l s_{ik} y_{ik}^{l\omega} + \sum_{k\in K}\sum_{j\in D}\sum_{l\in L} c_{kj}^l s_{kj} y_{kj}^{l\omega} + \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} c_{ij}^l s_{ij} y_{ij}^{l\omega}$$
$$+ \sum_{k\in K} h_k \sum_{i\in O}\sum_{j\in D}\sum_{l\in L} d_{ij}^l X_{ijk}^{l\omega}$$

In this chapter we provide two stochastic variations of the cross-dock facility location problem. The first model formulation accounts for day-to-day capacity uncertainty. The second problem variation accounts for disruptions. The next chapter conducts a detailed numerical analysis.

CHAPTER 5 NUMERICAL RESULTS

The focus of this chapter is to demonstrate the value of cross-docking on two real world freight networks with operational uncertainty and disruptions. The next section describes the data set used in this study. Then the experimental runs conducted in this thesis is described followed by analysis of salient results.

5.1 Description of Networks

The computational runs in this thesis were conducted on two networks. The first network includes 10 origin nodes (these are the nodes from which supply takes place), 10 potential cross-dock locations and 10 destination nodes (the points to which supply has to be reached) and the second dataset includes 20 origin nodes, 10 potential cross-dock locations and 20 destination nodes. Even though we did not have access to actual freight networks due to privacy concerns, the network used in this study is consistent with real world freight networks. Figure 3 shows the origin nodes, destination nodes and cross-dock locations for the two networks. The freight network transports three types of commodities: (i) dry goods, (ii) refrigerated goods, and (iii) frozen goods. The unit transportation costs for transporting dry, refrigerated and frozen goods are taken to be \$ 1.4, \$ 1.6, and \$ 1.8 per mile respectively. The truck capacity was taken to be 28 pallets. The handling cost at cross-docks is fixed at \$ 3 per pallet. These values are consistent with real world freight networks.

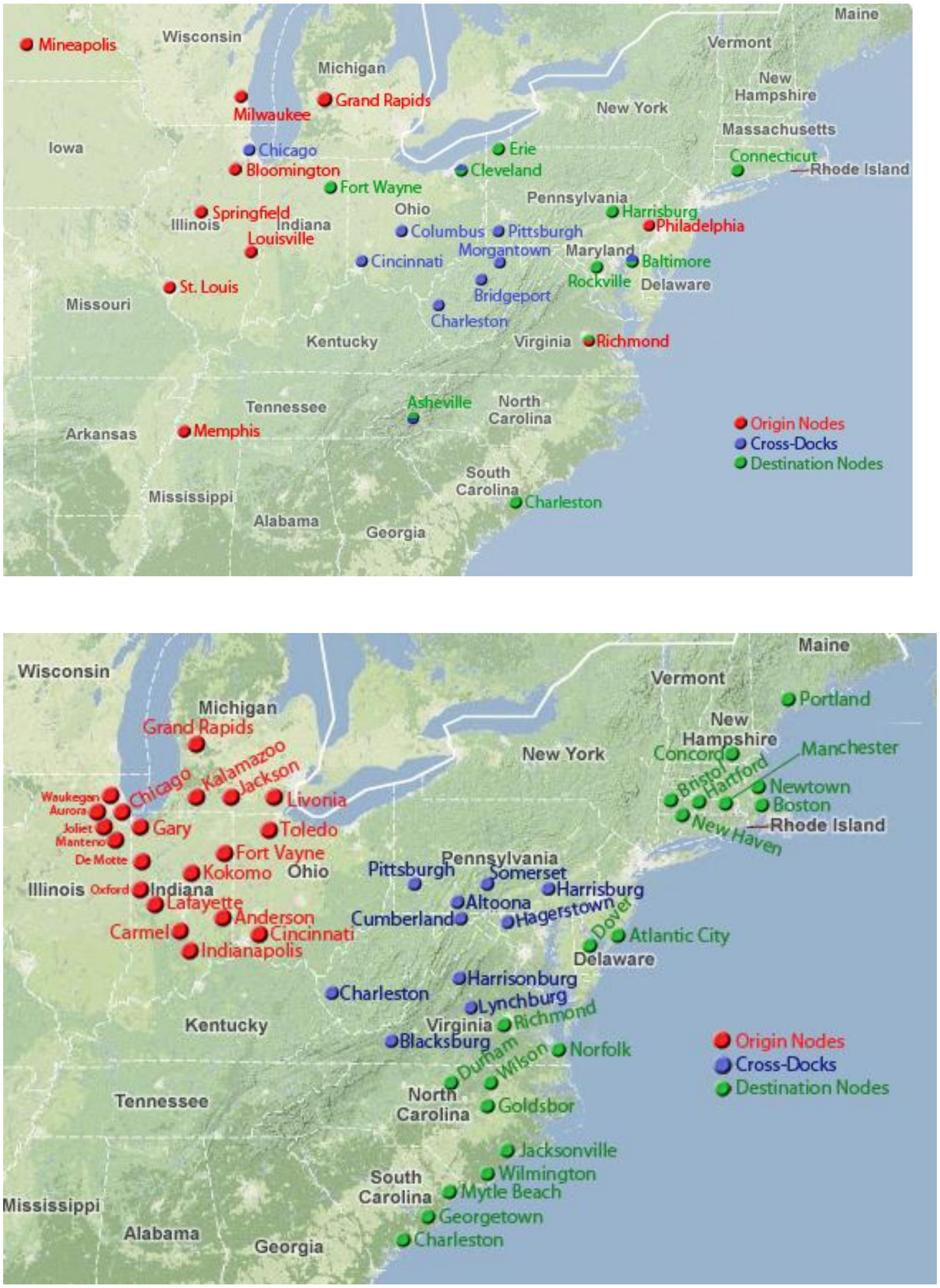

Figure 4: Location of origin nodes, cross-dock facilities, destination nodes.

Five sets of demands were generated: (i) D1 with demand in the range 0 to 10, (ii) D2 with demand in the range 0 to 25, (iii) D3 with demand in the range 0 to 50, (iv) D4 with demand in the range 0 to 75, (v) D5 with demand in the range 0 to 100. The demand units were in pallets. The first set of runs studied the performance of the integrating cross-docks under operational capacity uncertainty using the chance constrained model. The benefit of cross-docking was measured by the savings term (S) :

$$S = \frac{Z_{REG} - Z_{CD}}{Z_{REG}} \times 100$$

where Z_{REG} is the total routing cost under direct routing, and Z_{CD} is the routing cost with cross-docks.

5.2 Operational Uncertainty

In this section we study the impact of operational uncertainty on benefits of cross-docking by varying the numerous parameters and studying its impacts on the savings as defined above.

5.2.1 Impact of Demand Scenarios

I studied the impact of various demand scenarios on the savings term for both the networks at two different levels of means of cross-dock capacity – 250 and 500. The standard deviation of capacity was set at 50. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The α_k term which bounds the probability of the cross-dock capacity being met is fixed at 0.9. The number of cross-docks to be opened is fixed at 4. Table 1 and 2 show the savings obtained by cross-docks for the various demand scenarios at two levels of capacity.

Table 1: Variation of Savings with Demand Scenario for mean cross-dock capacity of 250

Demand Scenario	Savings (Capacity=250)	
	Network 1	**Network 2**
D1 [0 10]	48.127	24.208
D2 [0 25]	18.58	13.599
D3 [0 50]	4.393	6.15
D4 [0 75]	0	0
D5 [0 100]	0	0

Table 2: Variation of Savings with Demand Scenario for mean cross-dock capacity of 500

Demand Scenario	Savings (Capacity=500)	
	Network 1	**Network 2**
D1 [0 10]	58.072	44.683
D2 [0 25]	23.233	27.863
D3 [0 50]	6.082	11.0739
D4 [0 75]	0	7.418
D5 [0 100]	0	0

The benefit of cross-docking is highest for the smaller demand scenarios. For the larger demand scenarios there is no benefit of cross-docking. This is an interesting insight and can be explained by the fact that when the demand sizes are small, there is more scope for consolidation of demand across multiple trucks into single trucks. When demand sizes are large there is less scope for consolidation of multiple truck trips into single truck trips. When demand sizes are very large there is no benefit in cross-docking and it is better for the suppliers to route their goods directly. In general the benefit of cross-docking is found to be higher for the smaller network 1 when compared to the larger network 2. Thus the variation of cross-docks with increase in network size has to be carefully studied and dealt with on a case by case basis.

5.2.2 Impact of Standard Deviation of Capacity

I studied the impact of various standard deviations of capacity on the savings term for both the networks at two different levels of means of cross-dock capacity – 250 and 500. The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The α_k term which bounds the probability of the cross-dock capacity being met is fixed at 0.9. The number of cross-docks to be opened is fixed at 4. Table 3 and 4 show the savings obtained by cross-docks for three standard deviation levels for the two networks.

Table 3: Variation of Savings with standard deviations for mean cross-dock capacity of 250

Capacity Standard Deviation	Savings (Capacity=250)	
	Network 1	**Network 2**
10	22.038	18.352
50	18.581	13.600
100	15.364	10.222

Table 4: Variation of Savings with standard deviations for mean cross-dock capacity of 500

Capacity Standard Deviation	Savings (Capacity=500)	
	Network 1	**Network 2**
10	23.945	29.104
50	23.233	27.864
100	23.610	24.962

As the standard deviation of operational capacity increased, the savings obtained by cross-docking decreases. The decrease in savings is more pronounces in the lower mean capacity case. This is expected as in the chance constrained formulation, increase in standard deviation makes the capacity constraint tighter which reduces the savings. This effect will be more pronounced when the mean capacity is lower.

5.2.3 Impact of mean capacity

This section studies the impact of various mean capacity levels on savings obtained from cross-docks (see table 5). The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The α_k term which bounds the probability of the cross-dock capacity being met is fixed at 0.9. The number of cross-docks to be opened is fixed at 4. The standard deviation of capacity is set to be equal to 50.

Table 5: Impact of Mean Capacity

Mean Capacity	**Savings**	
	Network 1	**Network 2**
200	18.863	10.589
250	18.581	13.600
500	23.233	27.864
750	23.256	35.663

As expected as the mean capacity of the cross-dock increases, the savings obtained from cross-docking increases. The increase in savings is more pronounced in the larger network 2 compared to network 1. One potential explanation is that the increase in capacity provides more opportunities for consolidation in the larger network which have higher demands.

5.2.4 Impact of α_k

The α_k parameter measures the probability of capacity constraint being met or 1- α_k chances of capacity constraint not being met. The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The mean capacity is set to 250 and the standard deviation of capacity is set to 50. The number of cross-docks to be opened is fixed at 4. Table 6 shows the variation in savings with α_k parameter.

Table 6: Impact of α_k

α_k	Savings	
	Network 1	Network 2
0.8	20.499	17.107
0.85	20.238	16.706
0.9	18.581	13.600
0.99	17.551	10.967

As the probabilistic guarantee on capacity constraint being met increases, the savings obtained decreases. This is expected as in the chance constrained formulation, increase in the probabilistic guarantees makes the capacity constraint tighter which reduces the savings. The decrease in savings is more pronounced for the larger network.

5.2.5 Impact of Discount Factor

This section studies the impact of variation of discount factor obtained from consolidation on the cross-dock savings for the mean capacity of 250 and 500 for the two networks (see table 7 and 8). The demand scenario was fixed to be D2. The α_k term which bounds the probability of the cross-dock capacity being met is fixed at 0.9. The number of cross-docks to be opened is fixed at 4. The standard deviation of capacity is set to be equal to 50.

Table 7: Impact of discount factor for mean capacity level of 250

Discount Factor	Savings (Capacity=250)	
	Network 1	Network 2
0.5	21.884	16.468
0.6	20.309	16.043
0.7	19.266	16.364
0.8	18.581	13.600
0.9	17.175	15.718

1	17.252	12.609

Table 8: Impact of discount factor for mean capacity level of 500

Discount Factor	Savings (Capacity=500)	
	Network 1	**Network 2**
0.5	29.351	28.181
0.6	26.501	27.819
0.7	24.888	27.539
0.8	23.233	27.864
0.9	21.349	27.275
1	19.359	26.274

As the discount factor increase we get lesser savings on consolidation. Therefore as expected as the discount factor increases the cross-dock savings decreases. For the smaller network, the reduction in savings are more pronounced for the higher mean capacity whereas the reduction in savings are more pronounces for the lower mean capacity for the larger network.

5.2.6 Impact of number of cross-docks

This section studies the impact of variation in number of cross-docks on the cross-dock savings for the mean capacity of 250 and 500 for the two networks (see table 9 and 10). The demand scenario was fixed to be D2. The α_k term which bounds the probability of the cross-dock capacity being met is fixed at 0.9. The discount factor is fixed at 0.8. The standard deviation of capacity is set to be equal to 50. As expected as the number of cross-docks increases the savings obtained increases. This is because as the number of cross-docks increases there is more capacity available in the network. The increase in number of cross-docks is analogous and is expected to have the same impact as the increase in capacity of the existing cross-docks.

Table 9: Impact of number of cross-docks for mean capacity level of 250

# Cross-docks	Savings (Capacity=250)	
	Network 1	Network 2
1	10.212	3.016
2	10.348	11.215
3	18.772	13.923
4	18.581	13.600
5	20.325	17.257

Table 10: Impact of number of cross-docks for mean capacity level of 500

# Cross-docks	Savings (Capacity=500)	
	Network 1	Network 2
1	18.790	14.403
2	21.765	19.528
3	22.573	23.145
4	23.233	27.864
5	24.736	31.106

5.3 Disruption

In this section we study the impact of disruption on benefits of cross-docking by varying the numerous parameters and studying its impacts on the savings as defined above.

5.3.1 Impact of Demand Scenarios

I studied the impact of various demand scenarios on the savings term for both the networks at two different levels of cross-dock capacity – 250 and 500 and considering 50% reduction in capacities i.e., 125, 250 for the disrupted cross-dock. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4. The probability that normal routing takes place is taken as 0.8 and the probability that the routing takes place during disrupted conditions is taken as 0.2. Table 11 and 12 show the savings obtained by cross-docks for the various demand scenarios at two levels of capacity.

Table 11: Impact of Demand Scenarios for mean capacity level of 250

Demand Scenario	Savings (Capacity=250)	
	N1	N2
D1 [0 10]	50.897	27.728
D2 [0 25]	19.376	17.614
D3 [0 50]	4.235	6.258
D4 [0 75]	0	0
D5 [0 100]	0	0

Table 12: Impact of Demand Scenarios for mean capacity level of 500

Demand Scenario	Savings (Capacity=500)	
	N1	N2
D1 [0 10]	55.228	45.835
D2 [0 25]	23.987	27.927
D3 [0 50]	5.709	12.291
D4 [0 75]	0	0
D5 [0 100]	0	0

From the results we got, for the cross-docking with lesser demand scenarios the savings were more which is beneficial. Similar to the Operational uncertainty case, there is an interesting insight that when demand sizes are small there is more scope for consolidation of demand across multiple trucks into single truck. When demand sizes are large there is not much for consolidation of multiple truck trips into single truck trips. In general the smaller network 1 gives higher benefits when compared to the larger network 2.

5.3.2 Impact of Capacity Reduction when a disruption occurs

This section studies the impact of various capacity reduction levels on savings obtained from cross-docks. The capacities of 250 and 500 are considered in this section and for different percentage reductions the savings were calculated (see table 13 and 14). The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4. The probability that regular routing takes place is taken as 0.8 and the probability that the routing takes place during disrupted conditions is taken as 0.2.

Table 13: Impact of Capacity Reduction for capacity level of 250

Reduction in Capacity	Savings (Capacity=250)	
	N1	N2
50%	19.375	17.614
60%	19.166	16.963
70%	18.756	16.899
90%	17.227	16.076

Table 14: Impact of Capacity Reduction for Capacity level of 500

Reduction in Capacity	Savings (Capacity=500)	
	N1	N2
50%	23.987	27.927
60%	22.963	27.021
70%	22.637	26.460
90%	19.612	24.974

As expected, as the capacity of cross-dock decreases, the savings obtained from the cross-dock decreases. One potential explanation is that the decrease in capacity provides less opportunities for consolidation in the networks which have higher demand.

5.3.3 Impact of change in Probabilities (i.e., under normal conditions, disrupted conditions)

This section studies the impact of different probabilities under normal and disrupted conditions on savings obtained from cross-docks. The capacity of 250 is considered in this section and considering 50% reduction in capacity i.e., 125 for the disrupted cross-dock. The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4. The probabilities for normal conditions (NC) and disrupted conditions (DC) are shown in Tables 15.

Table 15: Impact of change in probabilities for capacity level 250

Probability [NC,DC]	Savings (Capacity=250)	
	N1	N2
[0.9 0.1]	19.764	18.465
[0.8 0.2]	19.376	17.615
[0.7 0.3]	19.277	16.672
[0.6 0.4]	18.838	16.067

An interesting insight from the above table is that, as the probability of disrupted conditions increase, the savings that occur are getting reduced. Therefore, under more disrupted conditions we get significantly lesser amounts of savings.

5.3.4 Impact of Number of Cross-docks

I studied the impact of number of cross-docks on the savings term for both the networks at two different levels of cross-dock capacity – 250 and 500 and considering 50% reduction in capacities i.e., 125, 250 for the disrupted cross-dock. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The probability that regular routing takes place is taken as 0.8 and the probability that the routing takes place during disrupted conditions is taken as 0.2. Table 16 and 17 show the savings obtained for various number of cross-dock scenarios.

Table 16: Impact of Number of Cross-docks for capacity 250

# Cross-docks	Savings (Capacity=250)	
	N1	N2
1	11.602	3.282
2	13.871	13.059
3	18.082	13.173
4	19.376	17.615
5	22.138	20.186

Table 17: Impact of Number of Cross-docks for capacity 500

# Cross-docks	Savings (Capacity=500)	
	N1	**N2**
1	18.907	14.543
2	20.682	20.632
3	23.180	23.059
4	23.988	27.928
5	24.279	30.948

As expected, the increase in number of cross-docks increases the savings that were obtained. This is because as the number of cross-docks increases there is more capacity available in the network.

5.4 Deterministic case

In this section we study the benefits of cross-docking by varying the numerous parameters and studying its impacts on the savings as defined above.

5.4.1 Impact of Demand Scenarios

I studied the impact of various demand scenarios on the savings term for both the networks at two different levels of cross-dock capacity – 250 and 500. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4. Table 18 and 19 show the savings obtained by cross-docks for the various demand scenarios at two levels of capacity.

Table 18: Variation of Savings with Demand Scenario for cross-dock capacity of 250

Demand Scenario	Savings (Capacity=250)	
	N1	**N2**
D1 [0 10]	54.706	23.332
D2 [0 25]	21.645	10.482

D3 [0 50]	4.930	0.000
D4 [0 75]	0.000	0.000
D5 [0 100]	0.000	0.000

Table 19: Variation of Savings with Demand Scenario for cross-dock capacity of 500

Demand Scenario	Savings (Capacity=500)	
	N1	**N2**
D1 [0 10]	58.352	39.305
D2 [0 25]	24.621	19.381
D3 [0 50]	5.786	5.640
D4 [0 75]	0.000	0.000
D5 [0 100]	0.000	0.000

From the results we got, cross-docking is beneficial for the smaller demand scenarios. For larger demand scenarios there is no benefit of cross-docking.

5.4.2 Impact of Capacity.

This section studies the impact of various capacities on savings obtained from cross-docks. The demand scenario was fixed to be D2. (See Table 20). The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4.

Table 20: Impact of Capacity

Capacity Scenario	Savings	
	N1	**N2**
200	20.246	9.674
250	21.645	10.481
500	24.620	19.380
750	22.636	23.984
1000	25.250	25.359

As expected, as the capacity of cross-dock increases, the savings obtained from cross-docking increases.

5.4.3 Impact of Discount Factor.

This section studies the impact of variation of discount factor obtained from the consolidation on the cross-dock savings for capacities 250 and 500. (see Table 21 and 22). The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The number of cross-docks to be opened is fixed at 4. As the discount factor increase we get lesser savings on consolidation. Therefore, as the discount factor increases the cross-dock savings decreases.

Table 21: Impact of Discount Factor for capacity of 250

Discount Factor	Savings (Capacity=250)	
	N1	N2
0.5	25.021	13.061
0.6	24.187	12.369
0.7	23.287	11.888
0.8	21.645	10.481
0.9	20.705	10.406
1	18.458	10.814

Table 22: Impact of Discount Factor for capacity of 500

Discount Factor	Savings (Capacity=500)	
	N1	N2
0.5	28.226	20.250
0.6	26.028	19.881
0.7	25.040	19.648
0.8	24.620	19.380
0.9	21.996	18.463
1	19.588	17.693

5.4.4 Impact of number of cross-docks

This section studies the impact of variation in number of cross-docks on the cross-dock savings for capacities 250 and 500. (see Table 23 and 24). The demand scenario was fixed to be D2. The discount factor for the cross-dock to the destination leg was set equal to 0.8. The discount factor from cross-dock to destination leg was considered to be 0.8. As expected as the number of cross-docks increases the savings obtained increases. The reason for this is because as number of cross-docks increases there is more capacity available on the network. The increase in number of cross-docks is analogous and is expected to have the same impact as the increase in capacity of existing cross-docks.

Table 23: Impact of number of cross-docks for capacity of 250

# Cross-docks	Savings (Capacity=250)	
	N1	N2
1	12.875	2.059
2	15.743	7.989
3	19.548	10.332
4	21.645	10.481
5	22.022	12.944

Table 24: Impact of number of cross-docks for capacity of 500

# Cross-docks	Savings (Capacity=500)	
	N1	N2
1	19.809	11.838
2	22.625	14.739
3	23.593	17.111
4	24.620	19.380
5	23.203	21.370

CHAPTER 6 CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

6.1 Summary

With the increase in demand to deliver goods in a timely manner, there is a great need for innovative solutions to improve the efficiency of the network operations and decrease the operation costs in the transportation sector. Cross-docking is a special warehousing policy moving goods from inbound trucks (ITs) to outbound trucks (OTs) without storage or just temporary storage. Cross-docking has the potential to reduce the number of truck trips through effective consolidation of goods and better usage of truck capacity. Several large businesses like Walmart and Goodyear have used cross-docks for improving the efficiency of their supply chain.

In this thesis different models were developed to demonstrate how truck carriers can integrate their operations and get significant cost savings. The first model termed Model A, presented in Chapter 3, and demonstrates the effect of cross-docks in a network to minimize the total transportation and facility handling costs. A carrier of interest can increase their profit by establishing cross-docks as the intermediate points. The goal of model A was to choose exactly P locations to locate cross-docks so that the transportation and handling costs are minimized. In addition we developed another model, called model B, whose objective is to locate as many cross-docks as needed so that total routing, handling, and facility location costs are minimized.

We then studied two extensions of Model A which accounts for two types of capacity uncertainty at cross-docks : day-to-day operational capacity uncertainty and capacity reductions due to disruptions. The first model which models operational uncertainty replaces the cross-dock capacity constraint from Model A by a probabilistic chance constraint to provide probabilistic guarantees on the capacity constraint being met. he second model operates under two major scenarios 1) regular routing conditions 2) disrupted conditions. Based on the historic records we assume that the freight planner is able to estimate the probability of normal operating conditions and the probability of disrupted conditions and change his decision accordingly depending on the nature of disruptions.

6.2 Conclusions

The performance of the cross-dock formulations were tested on two realistic freight networks with parameters which are consistent with real world freight operations. The performance metric used was savings obtained from using cross-docks when compared to the case where all shipments are sent directly. For this we have considered two networks Network 1 consists of 10 origin nodes, 10 cross-docks and 10 destination nodes, Network 2 consists of 20 origin nodes, 10 cross-docks and 20 destination nodes. From the results we have obtained in the thesis, we could say that using cross-docks as the intermediate points for delivering the products will be beneficial. Establishing cross-docks helps in reducing number of trucks to be operated which helps to reduce the air pollutants that the trucks emit and increase the savings made due to delivery through cross-dock.

Numerical analysis on deterministic model reveals the percentage of maximum cost savings for smaller demand scenarios as 58.35% for Network 1 and 39.305% for network 2 when cross-dock capacity was taken as 250. As the cross-dock capacity increased the savings also increased. For the demand range of [0 25], the cost savings also increased for larger capacity scenarios, for smaller discount factors and when number of cross-docks established was more.

Numerical analysis on the model with operational uncertainty reveals that for the mean capacity of cross dock as 250 and for smaller demand scenario, the savings obtained for Network

1 was 48.127% and Network 2 was 24.208%. As the capacity increased the savings also increased. For lower capacity standard deviations there were higher savings.

Numerical analysis on the model with disruptions reveals that for smaller demand range and capacity of cross-dock as 250, the savings obtained were 50.89% for Network 1 and 27.72% for Network 2. For larger capacities the savings increase and if the probability of disruption occurring is less then the savings are more.

6.3 Directions for future research

The work in this thesis can be extended in multiple directions. First area in which we may improve is to model the impact of freeway congestion on a supply chain with cross-dock operations. There is also a need to model other forms of uncertainties such as demand uncertainties.

In addition we assume that every shipper in the network cooperates to minimize the total routing costs. This might not be the case. We may need to provide incentives for shippers to participate in the coalition. Modeling these incentives to ensure cooperation will significantly enhance the complexity of the work.

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APPENDIX

Table 25: Network 1,2 - Location of Origins, Cross-docks and Destinations

Network 1: 10 Origins, 10 Cross-docks, 10 Destinations		
Origins	**Cross-docks**	**Destinations**
Philadelphia	Pittsburgh	FortWayne
Richmond	Morgantown	cleveland
StLouis	Cincinnatti	Asheville
Memphis	Asheville	Charleston
GrandRapids	Baltimore	Connecticut
Minneapolis	Chicago	Erie
Bloomington	Columbus	Baltimore
Louisville	Bridgeport	Rockville
Milwaukee	Cleveland	Richmond
Springfield	Charleston	Harrisburg

Network 2: 20 Origins, 10 Cross-docks, 20 Destinations		
Origins	**Cross-docks**	**Destinations**
Grand Rapids		Boston
Kalamazoo	Pittsburgh	Hartford
Fort Wayne		Manchester
Jackson	Altoona	Bristol
Livonia		Concord
Toledo	Harrisburg	Newton
Chicago		Portland
Waukegan	Hagerstown	New Haven
Lafayette		Atlantic City
Indianapolis	Cumberland	Dover
Kokomo		Norfolk
Cincinnatti	Harrisonburg	Richmond
Carmel		Jacksonville
Anderson	Somerset	Durham
Gary		Wilmington
Manteno	Charleston	Myrtle Beach
Oxford		Charleston
De Motte	Lynchburg	Georgetown
Joliet		Wilson
Aurora	Blacksburg	Goldsboro

Table 26: The distances between each origin, destination and cross-docks are taken from Google Maps.

Table 27: Commodity 1 for Demand range [0 10] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	0	1	5	10	4	0	8	3	2	0
Richmond	10	9	1	0	4	9	5	10	0	2
StLouis	7	4	4	1	8	1	3	2	1	4
Memphis	7	1	2	5	5	9	10	0	4	8
GrandRapids	5	7	7	1	0	9	10	1	0	7
Minneapolis	5	1	2	5	2	9	5	8	3	6
Bloomington	9	3	6	10	9	0	2	0	8	10
Louisville	2	7	6	1	10	10	4	7	9	9
Milwaukee	3	6	2	5	10	9	9	1	0	3
Springfield	10	1	8	2	2	3	0	6	10	3

Table 28: Commodity 2 for Demand range [0 10] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	4	6	3	6	4	1	10	7	0	3
Richmond	9	6	10	6	8	6	3	3	6	9
StLouis	4	7	8	1	9	4	5	2	9	2
Memphis	9	7	8	9	1	7	1	0	10	2
GrandRapids	3	6	4	8	9	8	0	1	10	4
Minneapolis	4	8	8	2	7	4	4	4	6	9
Bloomington	5	0	6	2	9	5	3	3	2	3
Louisville	9	2	5	1	3	0	3	6	10	9
Milwaukee	8	9	4	10	1	6	1	7	6	6
Springfield	10	9	10	0	5	3	1	7	0	1

Table 29: Commodity 3 for Demand range [0 10] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	9	6	9	8	8	10	10	5	6	0
Richmond	9	5	7	6	10	3	9	7	1	1
StLouis	3	8	4	2	6	2	0	0	8	5
Memphis	4	7	10	1	5	3	10	0	2	0
GrandRapids	3	9	2	6	3	5	6	3	9	6
Minneapolis	2	10	9	6	4	7	9	0	6	5
Bloomington	8	6	9	3	10	2	3	8	4	9
Louisville	0	4	0	5	0	10	8	9	0	8
Milwaukee	10	3	10	5	4	3	6	0	10	7
Springfield	0	10	6	10	8	0	5	1	2	1

Table 30: Commodity 1 for Demand range [0 25] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	1	10	7	23	6	14	13	13	16	15
Richmond	6	6	3	11	9	2	21	22	19	6
StLouis	23	22	0	24	20	4	3	3	15	8
Memphis	5	3	8	6	4	6	13	0	5	23
GrandRapids	8	16	7	15	2	16	24	11	23	4
Minneapolis	3	11	8	19	24	4	3	23	12	18
Bloomington	6	17	1	9	25	15	5	2	16	1
Louisville	0	1	24	19	23	18	10	0	2	20
Milwaukee	24	24	14	16	25	22	11	2	21	8
Springfield	19	5	16	18	2	0	7	22	1	19

Table 31: Commodity 2 for Demand range [0 25] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	21	19	10	14	4	11	6	22	19	6
Richmond	25	5	18	17	15	12	7	20	22	16
StLouis	1	19	7	8	15	1	2	11	17	24
Memphis	0	9	13	17	9	22	10	14	7	12
GrandRapids	2	17	20	15	0	21	15	14	5	6
Minneapolis	15	20	5	19	11	9	12	11	17	17
Bloomington	1	21	1	14	19	15	13	8	8	19
Louisville	6	2	4	18	24	25	15	12	13	1
Milwaukee	8	15	6	7	24	6	9	20	11	3
Springfield	5	10	13	16	21	25	9	4	4	6

Table 32: Commodity 3 for Demand range [0 25] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	16	10	1	0	1	6	15	13	19	14
Richmond	20	25	15	24	23	1	6	11	12	5
StLouis	8	9	6	22	15	4	16	16	4	23
Memphis	14	20	2	18	20	3	24	16	13	5
GrandRapids	24	7	6	24	13	11	18	21	2	15
Minneapolis	15	19	19	23	16	2	12	7	24	6
Bloomington	25	13	1	23	2	17	7	0	2	20
Louisville	12	16	5	6	19	11	18	16	8	18
Milwaukee	3	6	3	24	5	5	11	10	9	22
Springfield	9	23	23	23	13	9	4	15	17	23

Table 33: Commodity 1 for Demand range [0 50] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	9	5	36	33	3	27	2	31	40	0
Richmond	43	40	14	7	44	44	34	26	15	46
StLouis	27	39	43	12	12	35	27	2	38	11
Memphis	5	35	13	49	41	7	13	30	24	11
GrandRapids	19	32	44	40	16	42	20	1	24	20
Minneapolis	48	26	46	22	45	18	49	11	22	43
Bloomington	27	40	15	41	10	21	27	47	45	40
Louisville	37	14	33	34	1	21	3	48	33	24
Milwaukee	22	2	34	46	10	25	37	40	19	38
Springfield	28	44	39	41	19	47	30	49	45	34

Table 34: Commodity 2 for Demand range [0 50] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	13	12	18	22	28	25	37	42	0	8
Richmond	13	46	18	46	19	50	25	21	48	46
StLouis	40	35	2	31	12	20	38	22	5	40
Memphis	3	35	6	25	27	10	6	21	19	16
GrandRapids	0	38	22	34	36	27	41	22	8	12
Minneapolis	35	22	2	45	25	20	43	20	4	16
Bloomington	45	0	45	25	8	48	33	20	17	36
Louisville	12	13	7	14	35	8	44	1	34	14
Milwaukee	15	22	30	19	13	7	26	42	31	21
Springfield	41	11	37	36	1	45	31	31	42	4

Table 35: Commodity 3 for Demand range [0 50] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	26	10	9	29	8	27	43	35	34	21
Richmond	36	20	7	22	12	16	9	5	5	26
StLouis	46	2	3	17	14	19	42	28	46	16
Memphis	17	25	21	26	8	22	6	28	20	1
GrandRapids	37	1	37	35	45	15	38	34	30	6
Minneapolis	31	26	41	15	24	34	25	37	25	46
Bloomington	23	31	30	31	17	26	18	46	45	47
Louisville	21	25	12	34	29	6	7	26	35	17
Milwaukee	28	43	24	42	9	2	41	26	36	6
Springfield	0	42	31	6	42	15	13	36	5	49

Table 36: Commodity 1 for Demand range [0 75] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	30	31	14	7	63	67	46	31	73	30
Richmond	42	56	6	36	37	38	56	17	16	66
StLouis	72	54	5	39	16	15	51	27	62	48
Memphis	22	68	17	49	12	21	66	39	68	45
GrandRapids	19	72	69	28	11	45	4	74	73	11
Minneapolis	13	58	53	3	51	23	40	47	3	63
Bloomington	12	41	23	53	51	23	26	50	29	43
Louisville	24	72	32	51	1	25	30	36	3	10
Milwaukee	31	55	52	62	43	70	20	19	29	64
Springfield	39	27	24	40	42	22	44	58	7	22

Table 37: Commodity 2 for Demand range [0 75] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	61	35	72	27	15	43	33	30	20	11
Richmond	57	23	56	64	16	23	54	19	37	65
StLouis	51	30	67	30	70	23	21	44	73	22
Memphis	45	15	19	32	39	43	44	9	14	8
GrandRapids	33	6	42	68	24	46	35	44	42	12
Minneapolis	25	47	34	41	9	40	47	75	44	24
Bloomington	4	34	51	64	69	40	11	61	0	15
Louisville	27	46	0	14	2	74	72	37	43	71
Milwaukee	51	39	67	27	38	29	39	17	60	52
Springfield	66	61	17	23	41	51	61	4	49	68

Table 38: Commodity 3 for Demand range [0 75] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	13	63	73	6	44	65	74	37	5	13
Richmond	13	66	23	50	15	17	60	59	7	24
StLouis	36	31	71	21	25	40	65	23	73	55
Memphis	29	37	64	31	6	75	71	56	64	59
GrandRapids	41	8	28	65	47	35	60	64	25	19
Minneapolis	32	73	59	32	25	12	12	47	47	20
Bloomington	8	55	24	42	50	10	73	72	33	3
Louisville	16	39	8	32	38	0	40	56	15	50
Milwaukee	8	65	29	75	15	53	25	42	18	45
Springfield	2	35	60	16	12	14	72	75	39	17

Table 39: Commodity 1 for Demand range [0 100] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	35	92	98	42	65	41	30	15	24	75
Richmond	5	32	59	85	85	68	3	21	14	48
StLouis	7	41	1	47	61	35	69	42	80	82
Memphis	44	78	28	65	18	32	2	59	96	99
GrandRapids	54	22	19	56	60	9	97	56	8	18
Minneapolis	81	1	1	78	85	46	50	91	6	16
Bloomington	52	59	52	32	5	27	11	94	79	39
Louisville	77	4	61	8	21	39	72	42	13	52
Milwaukee	73	23	88	82	67	76	47	81	14	8
Springfield	66	93	21	67	75	14	76	91	53	23

Table 40: Commodity 2 for Demand range [0 100] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	78	8	46	36	36	41	22	17	46	46
Richmond	58	38	41	47	89	31	64	86	76	29
StLouis	68	20	29	21	54	65	68	29	100	100
Memphis	100	75	24	36	58	74	30	70	23	52
GrandRapids	29	71	94	85	8	35	75	55	96	47
Minneapolis	94	92	88	54	98	65	89	79	5	81
Bloomington	49	72	35	41	84	39	30	100	14	22
Louisville	79	8	79	44	97	81	40	49	88	4
Milwaukee	66	79	25	82	5	99	69	25	85	19
Springfield	82	41	38	35	84	44	21	68	78	84

Table 41: Commodity 3 for Demand range [0 100] - Network 1

O-D	FortWayne	Cleveland	Asheville	Charleston	Connecticut	Erie	Baltimore	Rockville	Richmond	Harrisburg
Philadelphia	65	26	38	9	45	3	93	22	31	4
Richmond	73	31	55	29	36	13	79	30	25	97
StLouis	19	25	4	36	88	37	34	33	61	94
Memphis	92	67	9	41	44	24	62	82	33	28
GrandRapids	13	59	51	52	18	70	81	7	62	90
Minneapolis	44	49	8	38	79	4	85	80	48	50
Bloomington	45	91	7	60	52	8	24	42	62	35
Louisville	75	82	48	76	15	21	78	44	14	61
Milwaukee	95	93	36	16	57	89	46	77	79	86
Springfield	53	65	38	40	87	58	100	56	55	31

Table 42: Commodity 1 for Demand range [0 10] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	0	1	10	10	0	10	1	8	2	2	4	5	0	3	0	5	8	5	0	5
Kalamazoo	5	10	6	6	2	4	6	3	2	3	8	10	10	4	3	10	2	6	1	9
Fort Wayne	10	1	10	6	9	4	10	10	6	0	8	5	2	1	5	1	7	0	0	1
Jackson	0	8	2	4	9	3	2	10	2	10	5	5	0	1	5	0	3	0	2	4
Livonia	9	10	8	0	7	5	0	8	6	9	6	2	6	0	6	2	5	10	1	9
Toledo	3	9	7	4	5	6	4	9	1	1	8	7	1	4	9	5	4	7	7	5
Chicago	4	10	4	1	8	10	8	9	10	7	8	0	5	8	2	6	7	6	7	6
Waukegan	6	1	6	1	0	10	8	0	3	10	0	7	4	1	0	4	7	2	3	2
Lafayette	4	9	9	8	6	6	10	0	0	2	7	6	8	10	7	1	2	10	9	0
Indianapolis	0	5	0	3	10	6	9	2	9	1	0	10	10	5	6	4	4	1	3	1
Kokomo	7	3	1	6	5	7	1	9	10	10	8	7	0	2	7	4	9	2	5	6
Cincinnatti	1	0	3	4	6	4	6	9	4	3	2	4	3	5	1	10	1	8	4	7
Carmel	3	1	4	6	7	0	6	7	6	3	7	1	4	4	1	8	4	2	5	6
Anderson	2	2	0	8	1	8	10	3	4	9	4	4	4	5	1	5	4	1	1	8
Gary	6	2	2	3	10	1	5	9	8	4	5	4	1	7	4	10	5	2	5	1
Manteno	5	2	3	8	5	7	9	7	4	5	6	0	6	8	8	9	3	8	9	5
Oxford	7	7	3	4	4	2	10	0	8	1	4	9	9	6	8	8	1	9	4	1
De Motte	10	0	6	3	8	3	5	8	3	5	5	1	0	3	2	10	8	7	6	7
Joliet	10	0	10	4	3	4	6	7	8	10	2	8	0	3	6	7	3	6	2	3
Aurora	5	7	9	2	5	5	4	6	4	10	9	5	5	5	2	7	10	4	6	2

Table 43: Commodity 2 for Demand range [0 10] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	1	8	0	9	2	2	9	0	8	0	2	7	10	2	9	10	7	2	10	2
Kalamazoo	9	7	8	3	8	3	5	7	7	7	8	9	9	1	2	0	6	10	8	8
Fort Wayne	8	3	0	5	1	4	1	4	4	4	8	2	5	4	9	6	0	5	2	8
Jackson	1	8	0	5	9	6	9	0	0	1	9	0	6	6	4	3	4	0	2	10
Livonia	8	2	3	4	8	7	0	3	6	2	4	4	4	8	7	10	0	5	4	0
Toledo	2	4	7	1	7	5	9	7	5	5	9	7	8	8	7	2	0	5	5	2
Chicago	7	8	8	3	3	6	4	1	4	7	5	4	10	8	2	8	8	0	0	0
Waukegan	6	2	2	8	0	6	3	8	10	7	3	5	1	0	4	8	3	1	5	5
Lafayette	2	2	10	4	5	2	4	9	8	5	8	4	8	3	10	9	8	3	2	1
Indianapolis	10	8	6	8	6	6	9	10	4	3	9	1	9	1	3	3	2	0	3	7
Kokomo	8	0	2	0	4	6	9	2	2	3	0	5	10	9	3	8	0	5	2	0
Cincinnatti	7	10	1	1	9	5	6	2	1	6	4	7	0	9	7	8	3	9	5	3
Carmel	0	7	10	7	10	7	8	7	5	10	10	6	9	5	1	1	2	4	0	6
Anderson	10	9	2	3	5	2	4	9	9	10	2	8	7	9	9	4	6	2	4	0
Gary	3	7	3	0	10	5	9	9	6	7	10	4	8	4	8	0	6	1	3	6
Manteno	5	0	7	9	6	2	7	2	4	3	9	8	3	4	3	9	5	9	5	8
Oxford	2	2	7	4	0	5	8	6	10	0	4	4	8	3	6	6	7	10	1	1
De Motte	6	9	2	9	4	3	1	0	8	4	1	9	7	10	4	10	6	0	8	5
Joliet	8	2	10	2	2	2	9	7	0	3	7	8	1	9	9	0	2	9	0	0
Aurora	1	9	1	7	5	9	1	5	2	1	1	10	0	3	2	2	1	2	2	4

Table 44: Commodity 3 for Demand range [0 10] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	5	10	10	4	8	6	4	8	0	8	3	10	2	4	8	3	4	1	9	7
Kalamazoo	2	5	1	7	8	7	0	6	6	8	10	10	7	2	6	9	8	0	4	2
Fort Wayne	2	7	5	5	0	2	4	0	10	4	1	8	8	6	9	8	6	7	2	3
Jackson	9	5	7	7	8	2	8	8	9	5	5	5	7	5	5	3	9	5	5	0
Livonia	5	10	10	9	1	2	9	6	1	9	1	3	4	8	5	2	1	2	6	8
Toledo	9	2	4	3	1	6	3	6	5	5	4	4	5	5	6	7	2	2	10	8
Chicago	5	8	9	4	4	5	5	2	0	9	2	0	8	3	0	0	0	7	3	0
Waukegan	5	7	1	10	9	6	0	3	4	0	2	10	7	0	3	3	2	2	5	10
Lafayette	8	0	5	6	2	4	9	10	7	7	8	6	9	0	6	8	4	10	7	2
Indianapolis	8	0	6	4	4	5	6	9	6	0	6	6	9	9	1	0	5	6	5	10
Kokomo	3	2	10	0	8	1	3	4	9	9	5	5	10	1	2	0	9	5	9	9
Cincinnatti	6	4	1	3	9	3	5	4	1	9	4	5	3	9	0	7	4	9	9	6
Carmel	7	8	8	0	10	2	4	6	5	5	1	5	1	2	2	10	5	3	7	0
Anderson	6	2	7	8	2	5	5	5	4	10	0	7	1	0	8	7	5	1	8	0
Gary	8	7	1	10	6	7	9	8	3	2	4	2	8	8	9	7	2	5	7	8
Manteno	9	8	8	0	5	6	7	0	9	4	5	3	3	6	6	0	0	6	8	6
Oxford	0	4	7	10	1	10	10	2	4	3	8	2	1	4	0	5	5	2	7	8
De Motte	1	10	1	3	7	6	9	1	6	1	7	1	5	1	4	3	1	6	5	0
Joliet	0	6	4	4	4	7	3	8	3	10	1	4	5	3	7	9	0	4	3	9
Aurora	7	5	5	8	0	8	9	4	9	3	5	3	5	6	1	9	1	10	10	8

Table 45: Commodity 1 for Demand range [0 25] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	21	9	6	19	16	5	25	18	24	19	15	22	5	1	7	9	23	21	2	17
Kalamazoo	13	5	3	7	11	17	4	10	13	24	22	4	2	4	15	2	7	3	1	6
Fort Wayne	18	10	22	8	16	6	4	17	0	1	25	9	12	7	24	21	8	17	20	13
Jackson	18	17	10	18	22	21	17	16	8	25	17	19	12	12	15	4	21	18	22	11
Livonia	1	10	4	20	3	16	8	17	12	24	13	5	20	4	7	2	20	18	8	12
Toledo	4	16	17	23	7	19	25	11	12	2	9	14	1	23	13	13	7	11	0	25
Chicago	23	1	6	21	16	8	23	7	22	4	10	14	17	24	19	19	16	18	17	17
Waukegan	2	4	1	21	23	23	5	3	8	9	4	8	16	24	4	11	8	23	20	22
Lafayette	7	15	17	1	15	23	1	4	16	7	21	23	10	25	11	17	10	15	1	7
Indianapolis	15	24	11	5	21	2	3	21	1	23	13	9	8	24	23	3	10	11	4	13
Kokomo	6	21	9	14	22	0	17	0	2	2	0	22	1	2	0	14	24	8	1	18
Cincinnatti	8	12	23	5	7	7	0	24	7	0	19	2	12	2	20	20	12	22	18	20
Carmel	8	17	14	6	7	9	21	6	6	15	21	11	19	8	21	23	7	5	14	4
Anderson	23	1	8	20	6	20	16	6	10	23	24	25	5	18	8	14	1	22	24	6
Gary	6	21	5	25	9	24	23	12	6	6	14	18	4	20	11	18	17	21	18	10
Manteno	16	14	13	9	25	25	10	22	6	25	20	15	10	9	9	8	23	4	20	16
Oxford	25	14	6	5	9	4	25	4	16	15	0	19	23	8	23	25	5	14	0	10
De Motte	3	5	20	17	3	15	16	21	9	17	6	24	2	6	21	12	17	0	24	3
Joliet	7	8	25	8	0	6	17	2	21	10	2	13	20	10	7	21	23	11	17	20
Aurora	16	13	15	22	6	24	1	17	3	6	10	12	20	4	4	9	22	20	4	15

Table 46: Commodity 2 for Demand range [0 25] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	25	20	7	8	0	12	10	8	17	11	16	13	18	16	11	1	14	4	2	17
Kalamazoo	14	8	23	17	1	11	15	1	10	20	9	5	18	5	2	18	24	14	20	4
Fort Wayne	12	23	25	21	17	25	23	22	0	19	9	14	13	8	8	2	4	4	12	5
Jackson	18	8	13	14	12	11	21	1	20	2	3	22	13	19	24	18	12	23	5	1
Livonia	14	13	13	22	0	8	15	23	11	9	23	4	6	20	6	20	7	8	17	7
Toledo	13	2	7	3	2	5	1	8	16	3	16	17	17	17	3	17	25	8	20	13
Chicago	0	11	19	6	12	6	17	24	13	22	17	2	0	7	17	13	10	4	3	22
Waukegan	15	7	22	15	7	22	6	21	22	2	0	1	12	16	7	11	2	25	17	14
Lafayette	24	5	19	14	20	0	19	2	3	16	16	7	16	18	3	17	23	14	13	24
Indianapolis	19	13	19	25	12	11	1	0	10	7	3	7	3	17	20	18	20	13	0	8
Kokomo	16	24	15	1	17	4	22	23	8	22	14	7	13	6	11	15	6	10	3	11
Cincinnatti	11	7	6	13	1	18	18	4	11	3	4	22	10	5	14	9	12	6	7	20
Carmel	0	6	25	17	22	15	10	7	23	23	22	12	25	9	11	21	14	6	8	2
Anderson	2	16	24	9	6	23	24	7	1	19	16	7	23	14	9	6	20	7	23	1
Gary	2	4	15	3	5	8	15	3	15	12	3	5	9	2	21	10	20	10	18	16
Manteno	5	14	15	22	20	4	23	0	22	23	3	19	11	15	19	23	9	25	18	21
Oxford	7	21	6	15	5	21	2	25	2	21	8	12	2	9	2	20	8	11	13	19
De Motte	19	11	17	6	9	11	25	23	15	11	0	10	7	7	20	25	6	2	22	15
Joliet	7	12	0	3	7	9	22	16	3	6	21	17	7	22	5	1	5	12	17	9
Aurora	19	8	6	11	6	22	10	8	7	7	13	7	24	24	11	1	21	4	21	11

Table 47: Commodity 3 for Demand range [0 25] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	18	6	19	13	7	23	19	3	14	15	0	19	20	1	22	22	11	9	7	5
Kalamazoo	23	18	16	21	23	25	17	4	18	12	13	2	9	8	11	0	24	17	20	14
Fort Wayne	8	7	17	9	6	12	8	23	21	19	9	10	14	0	14	0	1	16	17	23
Jackson	15	6	16	5	13	18	3	13	4	21	3	19	6	19	13	25	25	15	25	16
Livonia	0	2	16	9	17	11	9	14	1	0	16	21	0	1	5	9	8	3	20	2
Toledo	1	20	19	2	2	0	25	21	11	18	9	1	20	13	5	18	14	14	15	13
Chicago	7	5	25	5	17	8	4	19	6	15	19	2	19	25	2	13	1	22	6	2
Waukegan	25	11	20	18	12	22	16	23	0	1	19	10	16	0	7	24	2	3	13	7
Lafayette	4	2	4	2	9	23	16	19	5	6	20	20	24	19	11	11	10	6	21	16
Indianapolis	1	10	7	9	23	1	13	12	9	25	19	25	15	0	0	14	15	7	5	6
Kokomo	0	5	9	23	6	7	4	25	4	13	4	1	13	7	25	18	12	19	0	2
Cincinnatti	15	17	23	10	14	15	22	4	16	25	8	18	11	15	0	8	13	3	9	6
Carmel	25	4	7	15	10	10	24	12	17	21	1	11	16	11	1	7	24	7	12	21
Anderson	1	7	16	24	6	17	4	14	4	1	19	0	7	19	0	24	0	20	4	16
Gary	3	17	1	22	5	24	10	0	23	12	11	12	1	5	10	6	0	10	5	8
Manteno	12	23	16	8	18	5	25	14	6	22	3	9	12	19	5	24	3	21	24	14
Oxford	18	3	25	21	22	19	13	19	13	18	24	16	7	22	6	15	20	5	24	14
De Motte	20	4	15	17	22	25	5	1	14	1	4	23	22	10	16	10	14	2	9	11
Joliet	7	0	15	3	24	4	3	14	4	20	20	6	20	18	9	24	1	1	23	4
Aurora	12	1	2	18	2	17	8	5	18	25	4	3	1	3	23	5	5	23	10	18

Table 48: Commodity 1 for Demand range [0 50] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	33	8	24	21	43	30	19	9	25	22	40	39	27	24	9	44	8	27	3	24
Kalamazoo	26	22	1	3	30	20	29	8	19	29	49	19	14	20	46	13	46	36	1	22
Fort Wayne	18	25	4	38	48	10	27	31	11	12	8	36	36	16	1	36	15	50	48	33
Jackson	13	44	45	50	38	15	1	36	25	37	2	16	14	7	18	35	44	2	39	27
Livonia	8	14	43	41	10	6	19	24	35	38	7	26	29	48	45	48	29	1	46	16
Toledo	13	26	16	41	19	14	12	16	23	17	11	27	19	13	39	25	30	16	37	44
Chicago	0	11	23	13	33	38	10	22	4	37	47	28	29	18	16	42	26	14	20	20
Waukegan	26	28	47	6	35	5	18	39	31	28	3	1	26	15	45	23	6	23	31	44
Lafayette	40	24	21	48	32	7	37	22	30	44	25	40	43	12	8	25	39	30	12	7
Indianapolis	35	0	0	38	3	49	35	35	44	25	3	0	42	11	40	39	32	29	28	16
Kokomo	48	4	7	49	25	24	36	29	48	42	34	45	50	24	39	25	49	22	11	35
Cincinnatti	3	12	3	39	41	47	41	11	40	8	39	14	20	21	36	2	1	21	40	32
Carmel	19	29	44	26	23	2	32	5	36	1	48	40	35	41	46	4	11	25	44	40
Anderson	47	8	25	43	29	41	3	11	22	3	45	21	8	44	4	38	4	5	33	21
Gary	0	16	41	8	17	29	7	2	4	46	41	11	35	29	33	38	7	6	22	43
Manteno	0	49	24	45	29	37	42	8	50	28	38	30	20	34	26	49	9	8	42	16
Oxford	18	31	16	42	28	12	41	33	32	4	21	45	47	13	15	20	38	19	35	5
De Motte	15	37	9	26	29	27	22	36	47	47	33	25	47	3	20	14	38	45	16	17
Joliet	5	13	35	22	39	44	48	46	25	39	18	38	3	49	4	42	48	20	49	10
Aurora	26	43	42	14	24	35	8	36	16	5	17	12	9	40	17	7	32	15	25	36

Table 49: Commodity 2 for Demand range [0 50] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	17	38	8	17	49	46	13	26	6	42	25	32	9	22	35	1	29	43	30	0
Kalamazoo	1	13	39	39	48	26	30	41	38	36	1	45	23	10	19	14	15	47	2	40
Fort Wayne	10	4	45	29	11	12	40	27	39	41	20	36	34	35	24	17	0	10	24	18
Jackson	40	30	42	42	31	16	23	11	24	7	38	2	42	15	33	36	25	42	49	9
Livonia	28	3	45	24	32	25	37	15	3	18	34	41	45	37	21	48	36	3	39	48
Toledo	50	34	17	1	11	7	13	15	23	1	29	34	10	33	19	23	4	18	10	31
Chicago	12	12	50	42	48	29	16	41	7	43	6	40	6	27	19	22	11	6	2	13
Waukegan	25	1	8	22	25	32	48	9	1	0	2	36	48	31	34	42	10	38	18	11
Lafayette	33	16	45	11	26	33	3	34	24	26	3	37	15	10	8	35	40	35	23	9
Indianapolis	16	50	22	33	46	4	5	0	13	19	13	40	24	32	42	0	37	34	11	36
Kokomo	36	6	2	19	45	37	43	32	1	4	9	50	1	1	35	44	43	35	2	33
Cincinnatti	8	3	21	47	35	2	48	22	0	5	20	45	41	28	45	3	13	21	7	22
Carmel	31	37	35	6	22	46	45	36	48	50	43	48	17	1	14	29	5	2	50	44
Anderson	1	48	13	7	50	6	15	10	41	24	33	33	30	11	28	45	5	50	40	20
Gary	14	2	50	8	6	23	32	36	29	8	37	27	29	28	49	10	17	31	28	48
Manteno	13	43	14	49	28	23	49	19	16	29	46	37	31	14	11	34	45	45	21	16
Oxford	12	30	44	17	22	14	20	44	18	10	32	47	11	13	10	38	0	39	47	3
De Motte	39	35	27	30	10	24	43	46	48	21	19	28	38	35	0	7	44	28	30	30
Joliet	32	33	38	44	26	15	4	39	14	38	38	4	13	25	48	34	47	46	22	19
Aurora	50	11	28	13	11	35	8	29	25	45	27	34	11	46	9	18	0	19	29	21

Table 50: Commodity 3 for Demand range [0 50] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charlestor	Georgetown	Wilson	Goldsboro
Grand Rapids	34	35	10	24	17	38	45	7	3	19	3	33	22	20	16	18	12	20	6	15
Kalamazoo	26	7	13	4	48	28	41	25	11	31	33	16	33	11	20	21	0	10	50	16
Fort Wayne	48	35	42	50	10	18	29	3	50	4	38	8	42	17	36	10	12	38	22	39
Jackson	50	17	4	19	32	40	7	33	0	31	38	34	22	23	11	29	5	25	16	23
Livonia	28	12	40	0	48	6	24	21	20	3	25	9	30	0	29	41	26	1	40	38
Toledo	13	35	15	23	39	25	3	22	48	38	22	13	13	24	31	43	50	41	7	18
Chicago	28	47	41	29	37	45	31	38	35	29	30	3	41	3	16	40	8	41	11	1
Waukegan	35	15	45	49	8	22	23	39	14	38	8	45	41	39	13	41	6	12	9	12
Lafayette	14	50	36	25	13	48	44	34	35	48	42	9	8	28	35	47	38	35	16	27
Indianapolis	27	47	14	46	47	16	4	19	14	41	46	29	0	37	7	3	26	28	28	22
Kokomo	22	49	27	2	29	5	5	24	20	43	8	10	29	23	39	36	21	6	0	23
Cincinnatti	39	25	19	46	20	33	9	8	45	41	17	14	11	29	28	1	4	21	46	21
Carmel	17	44	21	37	32	27	24	45	2	44	40	30	8	27	50	49	16	13	45	6
Anderson	7	24	20	36	19	36	3	5	3	50	47	37	21	0	3	41	12	42	33	11
Gary	29	30	0	13	4	50	21	24	47	25	20	50	39	42	48	18	41	22	14	49
Manteno	8	23	39	12	45	50	7	18	12	25	36	4	16	2	46	13	12	24	5	0
Oxford	40	30	2	28	31	10	17	15	5	32	45	46	47	21	25	12	44	32	28	31
De Motte	45	6	37	9	20	5	16	38	42	4	38	21	37	50	18	15	1	41	15	0
Joliet	16	19	31	36	36	1	17	37	17	43	10	28	2	29	31	46	32	7	50	11
Aurora	31	18	30	0	22	48	38	48	22	11	44	10	17	3	10	10	21	43	3	47

Table 51: Commodity 1 for Demand range [0 75] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	67	17	17	35	60	14	20	42	25	57	24	20	18	22	68	53	46	2	62	55
Kalamazoo	39	41	34	58	13	13	15	39	16	58	53	25	42	34	29	43	49	40	59	46
Fort Wayne	64	59	45	0	42	69	16	6	43	60	22	36	69	22	19	20	74	3	16	0
Jackson	30	41	23	51	22	61	37	60	52	56	27	61	7	51	0	33	13	48	12	40
Livonia	21	65	5	14	20	27	33	5	33	38	70	22	54	6	49	21	14	65	35	39
Toledo	67	3	3	63	40	21	3	58	47	5	66	43	41	43	65	46	60	2	41	6
Chicago	10	23	33	57	14	54	1	41	19	24	13	33	74	34	22	61	61	2	29	14
Waukegan	44	22	47	56	2	55	3	16	22	16	62	71	19	59	75	64	29	49	55	34
Lafayette	0	54	35	39	8	8	44	8	24	4	36	66	17	8	72	33	67	42	6	25
Indianapolis	75	14	53	4	23	35	47	44	27	20	28	52	57	63	25	43	46	12	62	64
Kokomo	29	1	55	15	1	49	5	29	38	49	40	47	73	28	58	45	43	12	11	28
Cincinnati	37	39	64	22	3	40	43	65	74	60	48	50	49	32	42	26	19	71	60	14
Carmel	14	30	52	55	13	64	5	4	21	59	26	55	29	53	13	25	7	55	70	35
Anderson	37	64	74	64	56	25	66	46	20	60	42	38	63	26	70	23	31	70	45	64
Gary	62	64	68	58	6	5	62	4	14	45	4	71	62	75	74	67	19	62	26	43
Manteno	1	9	11	72	55	7	3	42	45	64	34	46	10	51	68	13	50	40	9	23
Oxford	2	59	43	33	16	62	40	37	45	57	25	20	46	62	5	35	20	22	41	20
De Motte	53	72	24	45	16	33	40	45	16	6	1	36	58	28	47	0	23	52	54	38
Joliet	21	51	67	69	12	58	29	63	33	56	61	12	29	56	1	73	44	2	58	21
Aurora	21	58	73	24	49	73	26	65	15	4	41	64	75	72	20	51	3	8	60	23

Table 52: Commodity 2 for Demand range [0 75] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	11	48	49	62	41	47	74	64	13	33	43	49	27	37	23	66	15	53	54	9
Kalamazoo	37	71	16	44	71	17	4	3	57	0	26	14	63	23	38	29	62	33	61	2
Fort Wayne	4	22	66	15	39	9	35	8	2	67	32	13	56	31	45	38	5	59	10	44
Jackson	37	27	34	3	46	42	64	69	20	3	0	52	40	44	23	28	28	74	9	0
Livonia	66	56	69	42	52	62	0	9	0	58	29	42	51	30	63	47	60	28	51	2
Toledo	25	19	30	54	50	2	44	52	44	45	67	9	18	44	28	24	1	26	50	41
Chicago	75	33	7	18	70	28	25	29	18	68	50	15	48	40	71	62	33	71	52	29
Waukegan	72	56	36	43	18	14	32	67	44	48	29	36	18	64	55	24	72	9	53	23
Lafayette	30	71	70	12	21	9	63	43	46	24	72	69	6	4	13	73	62	72	3	29
Indianapolis	17	71	37	18	10	65	41	64	55	42	52	5	19	60	27	53	5	8	27	53
Kokomo	28	49	52	72	59	51	42	1	55	32	0	58	75	17	23	50	3	46	13	41
Cincinnatti	3	53	60	1	31	50	4	31	28	19	20	32	40	51	14	2	75	30	3	24
Carmel	3	33	8	30	22	69	40	72	71	32	42	57	71	10	73	31	64	21	65	32
Anderson	17	63	5	70	7	61	53	30	14	29	6	18	48	19	23	34	75	49	9	8
Gary	75	0	72	28	25	6	32	47	64	11	26	2	70	65	5	23	67	19	25	37
Manteno	8	73	37	58	26	46	12	26	58	7	47	20	54	37	10	47	20	39	61	18
Oxford	72	73	27	61	5	59	29	17	44	5	27	56	55	66	66	14	75	12	24	66
De Motte	5	27	73	8	30	17	52	55	44	48	20	48	23	7	51	72	5	53	13	61
Joliet	37	2	60	32	16	9	53	35	17	34	44	43	50	2	74	64	60	75	6	4
Aurora	9	61	57	31	29	48	35	9	5	71	15	16	51	19	46	6	33	35	9	61

Table 53: Commodity 3 for Demand range [0 75] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	53	46	50	5	12	48	34	25	5	60	57	40	71	16	23	36	35	73	71	49
Kalamazoo	38	14	74	67	35	62	32	16	47	62	63	5	31	75	16	46	45	64	43	19
Fort Wayne	55	30	30	9	74	11	72	70	41	41	40	33	56	20	64	55	58	8	35	15
Jackson	65	65	60	54	59	72	61	74	31	71	25	53	4	72	8	75	17	46	47	71
Livonia	6	40	60	15	0	21	40	19	56	54	20	10	14	5	2	0	32	28	10	48
Toledo	26	35	35	12	61	58	0	24	33	63	46	60	8	71	54	30	68	16	25	10
Chicago	62	46	62	4	37	19	37	65	60	46	75	14	24	17	0	22	44	10	43	19
Waukegan	18	70	16	35	1	25	65	46	3	9	52	32	32	25	61	2	48	56	66	63
Lafayette	54	67	69	19	74	62	44	60	74	36	67	56	61	14	10	23	31	12	47	15
Indianapolis	32	48	64	42	55	38	34	61	25	0	20	29	20	8	23	48	44	46	4	57
Kokomo	8	49	72	74	3	5	62	31	18	16	16	41	74	18	23	72	41	73	72	70
Cincinnatti	66	71	75	26	51	48	39	5	61	10	40	46	70	43	6	32	11	42	24	4
Carmel	61	74	37	14	36	33	12	56	21	60	68	62	56	9	32	40	49	69	31	25
Anderson	63	70	33	2	3	1	64	56	31	10	40	56	21	74	60	18	54	75	53	45
Gary	67	71	6	53	4	18	23	17	19	29	20	73	73	21	75	36	64	26	61	52
Manteno	68	46	56	6	65	26	47	57	66	56	56	73	44	73	73	43	71	23	58	9
Oxford	49	30	25	12	5	38	9	30	72	48	42	31	22	67	30	24	62	60	75	23
De Motte	9	31	29	46	60	52	16	27	31	34	39	31	69	52	30	35	7	72	14	33
Joliet	38	5	14	16	3	59	1	15	62	63	49	74	18	45	19	26	55	42	35	27
Aurora	66	70	43	24	57	72	70	22	70	1	41	33	31	37	24	41	63	27	24	9

Table 54: Commodity 1 for Demand range [0 100] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	7	48	26	78	97	99	81	45	5	78	69	98	17	33	45	27	11	30	63	41
Kalamazoo	40	60	62	0	76	2	44	12	71	80	57	89	74	33	85	53	71	49	68	31
Fort Wayne	38	89	20	68	40	90	84	53	96	98	37	6	93	87	79	82	23	84	23	65
Jackson	54	6	83	46	41	18	77	97	10	66	3	78	17	85	44	1	70	51	20	38
Livonia	94	79	64	16	90	69	17	18	73	18	71	81	32	89	72	92	80	47	24	0
Toledo	65	40	20	71	94	90	91	98	15	45	28	14	66	46	16	22	8	87	78	23
Chicago	31	2	68	63	19	44	56	19	95	18	38	53	46	98	44	27	24	70	14	50
Waukegan	28	93	21	32	12	81	86	67	44	99	99	46	8	9	76	7	35	82	86	1
Lafayette	13	15	92	0	68	7	71	23	87	96	26	58	100	79	67	71	96	82	75	8
Indianapolis	63	17	34	80	91	37	34	27	76	10	93	10	77	15	62	64	1	88	26	46
Kokomo	78	36	80	14	49	81	75	67	40	22	25	7	35	4	22	35	37	80	55	47
Cincinnatti	32	50	91	44	90	38	97	24	18	92	74	89	17	77	9	59	78	84	36	42
Carmel	47	30	82	100	13	33	12	68	91	79	34	19	43	40	36	32	33	97	68	63
Anderson	92	66	61	69	12	54	15	51	74	43	94	77	70	45	6	71	14	100	55	46
Gary	83	42	64	19	11	11	72	95	70	66	47	34	71	83	35	63	49	94	60	3
Manteno	61	28	50	95	48	84	55	34	67	25	40	75	44	13	54	74	65	49	12	17
Oxford	11	62	43	49	3	66	100	4	100	75	63	33	82	94	39	100	52	66	89	97
De Motte	6	71	36	24	39	23	82	62	2	73	91	98	58	73	45	51	18	73	52	85
Joliet	22	46	46	26	35	14	44	97	4	47	73	71	39	51	87	43	6	37	86	35
Aurora	96	30	49	26	62	73	52	0	98	93	3	56	93	38	3	82	32	64	57	26

Table 55: Commodity 2 for Demand range [0 100] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	38	88	17	13	57	99	70	13	90	4	32	76	86	76	38	46	68	78	90	91
Kalamazoo	25	73	18	40	59	40	91	46	69	18	86	25	88	37	85	6	69	61	90	27
Fort Wayne	5	58	13	57	68	17	8	64	15	12	11	54	53	37	35	3	3	86	95	100
Jackson	40	78	58	43	97	23	47	15	75	41	76	52	1	9	14	27	86	52	46	84
Livonia	14	49	85	55	90	70	52	8	65	6	61	12	71	95	76	57	38	15	88	82
Toledo	81	17	11	69	15	48	77	0	72	69	25	1	24	69	24	85	21	24	3	3
Chicago	0	66	2	96	49	54	1	71	100	26	68	32	51	0	34	87	41	35	65	84
Waukegan	87	100	30	43	14	0	95	24	79	65	68	28	52	48	94	57	5	67	40	76
Lafayette	70	89	56	81	88	78	97	0	16	72	17	72	69	53	18	23	7	54	94	62
Indianapolis	85	43	60	83	75	64	61	68	10	11	24	79	32	93	35	90	46	3	16	73
Kokomo	55	0	30	51	7	31	49	55	41	36	26	63	62	35	45	55	99	70	61	67
Cincinnati	38	4	44	49	59	49	63	47	58	76	76	18	79	58	50	53	43	34	73	98
Carmel	9	57	47	39	48	56	3	76	78	57	13	10	98	43	29	10	61	84	21	1
Anderson	79	17	50	35	21	86	72	76	13	79	37	27	31	80	18	31	37	88	89	13
Gary	33	53	24	75	38	77	48	70	87	60	29	30	83	44	44	68	5	66	95	58
Manteno	32	46	61	19	30	32	84	48	19	60	8	81	7	98	61	99	21	14	92	6
Oxford	68	7	3	19	97	18	10	92	99	48	12	69	77	89	23	0	67	9	0	86
De Motte	40	69	30	50	23	19	93	71	60	0	81	7	85	79	82	36	33	36	82	10
Joliet	98	23	8	60	83	34	23	50	82	85	27	8	47	55	86	95	57	84	96	94
Aurora	20	3	75	35	4	72	81	15	1	40	57	12	2	68	2	62	96	40	57	79

Table 56: Commodity 3 for Demand range [0 100] - Network 2

O-D	Boston	Hartford	Manchester	Bristol	Concord	Newton	Portland	New Haven	Atlantic City	Dover	Norfolk	Richmond	Jacksonville	Durham	Wilmington	Myrtle Beach	Charleston	Georgetown	Wilson	Goldsboro
Grand Rapids	66	44	80	53	11	20	44	40	41	7	5	79	52	66	41	0	58	5	84	6
Kalamazoo	31	10	80	46	58	0	72	30	58	98	66	51	56	73	8	7	24	83	44	33
Fort Wayne	45	28	62	60	97	23	55	68	72	89	57	40	15	32	47	64	72	53	43	62
Jackson	5	67	7	5	72	79	87	26	86	11	79	75	80	83	31	48	23	90	11	100
Livonia	75	45	92	77	35	35	81	34	87	22	53	28	100	69	5	95	93	14	59	88
Toledo	86	88	62	90	80	32	45	0	30	83	12	15	88	43	69	3	62	53	77	8
Chicago	24	18	61	84	54	84	77	34	12	36	29	27	15	34	58	43	95	72	43	4
Waukegan	40	64	24	37	64	99	75	5	34	59	18	24	61	71	10	37	24	76	37	15
Lafayette	49	27	5	85	16	29	78	20	52	33	63	30	54	99	33	29	39	71	62	97
Indianapolis	32	48	74	23	64	60	13	76	61	62	27	100	50	76	38	1	56	5	23	35
Kokomo	34	91	57	40	52	8	18	74	100	77	59	92	90	10	60	54	19	17	33	62
Cincinnatti	20	72	8	94	42	98	0	95	28	59	41	73	21	69	1	20	84	29	35	19
Carmel	66	9	57	69	30	17	52	7	47	20	83	48	35	18	45	35	88	74	67	50
Anderson	84	24	59	23	38	20	56	53	6	68	31	70	88	29	58	3	71	94	49	5
Gary	75	94	16	25	70	45	15	63	18	57	4	27	85	85	65	89	90	79	31	18
Manteno	84	41	83	41	79	92	6	98	89	100	7	93	48	72	37	10	66	55	15	82
Oxford	88	84	53	86	10	17	84	33	57	59	39	70	55	48	14	77	37	56	93	43
De Motte	46	1	11	57	73	27	56	38	84	74	45	68	58	63	78	81	95	42	59	6
Joliet	13	46	29	94	68	43	51	40	41	36	42	79	40	91	52	59	76	65	52	14
Aurora	29	53	42	54	4	82	51	59	66	17	51	5	99	99	95	42	41	47	26	56

Table 57: GAMS CODE for the model with Operational Uncertainty

```
set i 'origin'/
$call =xls2gms r=b4:b13 i=book3.xls o=seti.inc
$include seti.inc
/;
set j 'destination' /
$call =xls2gms r=c3:l3 s="," i=book3.xls o=setj.inc
$include setj.inc
/;
set k 'crossdocks'/
$call =xls2gms r=c15:l15 s="," i=book3.xls o=setk.inc
$include setk.inc
/;
set l      'commodity'          /F, R, D/
table s(i,j)
$call =xls2gms r=b3:l13 i=book3.xls o=pard.inc
$include pard.inc
;
display i,j,s;
table s1(i,k)
$call =xls2gms r=b15:l25 i=book3.xls o=pard1.inc
$include pard1.inc
;
display i,j,s1;
table s2(k,j)
$call =xls2gms r=b27:l37 i=book3.xls o=pard.inc
$include pard.inc
;
display i,k,s2;
table c(l,i,j)
$call =xls2gms r=a41:m71 i=book3.xls o=pard.inc
$include pard.inc
```

```
;
display l,i,j,c;
table c1(l,i,k)
$call =xls2gms r=a73:m103 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,k,c1;
table c2(l,k,j)
$call =xls2gms r=a106:m136 i=book3.xls o=pard.inc
$include pard.inc
;
display l,k,j,c2;
table q(l,i,j)
$call =xls2gms r=a139:m169 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,j,q;
parameter h(k)  'handling cost';
h(k)=3 ;
parameter u  'truck capacity';
u =28;
parameter p 'number of cross docks';
p =4;
parameter w_mean 'mean of cross dock capacity';
w_mean =1000;
parameter w_std 'std of cross dock capacity';
w_std =100;
parameter phi_inverse 'inverse phi';
phi_inverse =-1.281;
parameter alpha  'discount factor';
alpha =0.8
variables
O 'objective variable'
```

```
;
Binary variables
x(i,j,l,k)
v(i,j,l)
z(k)
;
integer variables
y(i,j,l)
y1(i,k,l)
y2(k,j,l)
;
equations
obj
location
routing(i,j,l)
inequality1(i,k,l)
inequality2(j,k,l)
inequality3(i,j,l)
inequality4(i,j,k,l)
crossdock(k)
;
obj.. sum((i,k,l),c1(l,i,k)*s1(i,k)*y1(i,k,l))+sum((k,j,l),alpha*c2(l,k,j)*s2(k,j)*y2(k,j,l))+sum((i,j,l),c(l,i,j)*s(i,j)*y(i,j,l))+sum((k),
h(k))*sum((i,j,l,k),x(i,j,l,k)*q(l,i,j))=e=O;
location.. sum((k), z(k))=e=p;
routing(i,j,l).. sum((k), x(i,j,l,k))+ v(i,j,l)=e=1;
inequality1(i,k,l).. sum((j),q(l,i,j)*x(i,j,l,k))=l=u*y1(i,k,l);
inequality2(j,k,l).. sum((i),q(l,i,j)*x(i,j,l,k))=l=u*y2(k,j,l);
inequality3(i,j,l)..q(l,i,j)*v(i,j,l)=l=u*y(i,j,l);
inequality4(i,j,k,l).. x(i,j,l,k)=l=z(k);
crossdock(k)..sum((i,j,l),q(l,i,j)*x(i,j,l,k))=l=w_mean+phi_inverse*w_std;
model m/all/;
solve m minimizing O using MIP;
```

Table 58: GAMS CODE for the model operating under Disruptions

```
set  w     'scenario'      /medium/
;
set i 'origin'/
$call =xls2gms r=b4:b13 i=book3.xls o=seti.inc
$include seti.inc
/;
set j 'destination' /
$call =xls2gms r=c3:l3 s="," i=book3.xls o=setj.inc
$include setj.inc
/;
set k 'crossdocks'/
$call =xls2gms r=c15:l15 s="," i=book3.xls o=setk.inc
$include setk.inc
/;
set l      'commodity'          /F, R, D/
table s(i,j)
$call =xls2gms r=b3:l13 i=book3.xls o=pard.inc

$include pard.inc
;
display i,j,s;
table s1(i,k)
$call =xls2gms r=b15:l25 i=book3.xls o=pard1.inc
$include pard1.inc
;
display i,j,s1;
table s2(k,j)
$call =xls2gms r=b27:l37 i=book3.xls o=pard.inc
$include pard.inc
;
display i,k,s2;
table c(l,i,j)
```

```
$call =xls2gms r=a41:m71 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,j,c;
table c1(l,i,k)
$call =xls2gms r=a73:m103 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,k,c1;
table c2(l,k,j)
$call =xls2gms r=a106:m136 i=book3.xls o=pard.inc
$include pard.inc
;
display l,k,j,c2;
table q(l,i,j)
$call =xls2gms r=a139:m169 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,j,q;
parameter h(k)  'handling cost';
h(k)= 3;
parameter u  'truck capacity';
u = 28;
parameter p 'number of cross docks';
p =4;
parameter cap_r 'capacity at disruption';
cap_r =150;
parameter cap 'capacity of cross dock';
cap =500;
parameter t(w)  /medium=.2/;
parameter alpha 'discount factor';
alpha = 0.8
variables
```

```
EE
bb
ff(w)
Binary variables
x(i,j,l,k)
xs(i,j,l,k,w)
v(i,j,l)
vs(i,j,l,w)
z(k)
;
integer variables
y(i,j,l)
ys(i,j,l,w)
y1(i,k,l)
y1s(i,k,l,w)
y2(k,j,l)
y2s(k,j,l,w)
;
equations
oo
obj(w)
location
routing(i,j,l)
routings(i,j,l,w)
inequality1(i,k,l)
inequality1s(i,k,l,w)
inequality2(j,k,l)
inequality2s(j,k,l,w)
inequality3(i,j,l)
inequality3s(i,j,l,w)
inequality4(i,j,k,l)
inequality4s(i,j,k,l,w)
crossdock(k)
```

```
crossdocks(k,w)
expected_profit
;
oo.. sum((i,k,l),c1(l,i,k)*y1(i,k,l)*s1(i,k))+sum((k,j,l),alpha*c2(l,k,j)*y2(k,j,l)*s2(k,j))+sum((i,j,l),c(l,i,j)*y(i,j,l)*s(i,j))+sum((k),
h(k))*sum((i,j,l,k),x(i,j,l,k)*q(l,i,j))=e=bb;
obj(w)..
sum((i,k,l),c1(l,i,k)*y1s(i,k,l,w)*s1(i,k))+sum((k,j,l),alpha*c2(l,k,j)*y2s(k,j,l,w)*s2(k,j))+sum((i,j,l),c(l,i,j)*ys(i,j,l,w)*s(i,j))+sum((k),
h(k))*sum((i,j,l,k),xs(i,j,l,k,w)*q(l,i,j))=e=ff(w);
location.. sum((k), z(k))=e=p;
routing(i,j,l).. sum((k), x(i,j,l,k))+ v(i,j,l)=e=1;
routings(i,j,l,w).. sum((k), xs(i,j,l,k,w))+ vs(i,j,l,w)=e=1;
inequality1(i,k,l).. sum((j),q(l,i,j)*x(i,j,l,k))=l=u*y1(i,k,l);
inequality1s(i,k,l,w).. sum((j),q(l,i,j)*xs(i,j,l,k,w))=l=u*y1s(i,k,l,w);
inequality2(j,k,l).. sum((i),q(l,i,j)*x(i,j,l,k))=l=u*y2(k,j,l);
inequality2s(j,k,l,w).. sum((i),q(l,i,j)*xs(i,j,l,k,w))=l=u*y2s(k,j,l,w);
inequality3(i,j,l)..q(l,i,j)*v(i,j,l)=l=u*y(i,j,l);
inequality3s(i,j,l,w)..q(l,i,j)*vs(i,j,l,w)=l=u*ys(i,j,l,w);
inequality4(i,j,k,l).. x(i,j,l,k)=l=z(k);
inequality4s(i,j,k,l,w).. xs(i,j,l,k,w)=l=z(k);
crossdock(k)..sum((i,j,l),q(l,i,j)*x(i,j,l,k))=l=cap;
crossdocks(k,w)..sum((i,j,l),q(l,i,j)*xs(i,j,l,k,w))=l=cap_r;
expected_profit.. EE=e=sum(w,ff(w)*t(w))+bb*.8;
model m/all/;
solve m minimizing EE using MIP;
```

Table 59: GAMS CODE for the Deterministic model

```
set i 'origin'/
$call =xls2gms r=b4:b13 i=book3.xls o=seti.inc
$include seti.inc
/;
set j 'destenation' /
$call =xls2gms r=c3:l3 s="," i=book3.xls o=setj.inc
$include setj.inc
/;
set k 'crossdocks'/
$call =xls2gms r=c15:l15 s="," i=book3.xls o=setk.inc
$include setk.inc
/;
set l      'commodity'          /F, R, D/
table s(i,j)
$call =xls2gms r=b3:l13 i=book3.xls o=pard.inc
$include pard.inc
;
display i,j,s;
table s1(i,k)
$call =xls2gms r=b15:l25 i=book3.xls o=pard1.inc
$include pard1.inc
;
display i,j,s1;
table s2(k,j)
$call =xls2gms r=b27:l37 i=book3.xls o=pard.inc
$include pard.inc
;
display i,k,s2;
table c(l,i,j)
$call =xls2gms r=a41:m71 i=book3.xls o=pard.inc
$include pard.inc
;
```

```
display l,i,j,c;
table c1(l,i,k)
$call =xls2gms r=a73:m103 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,k,c1;
table c2(l,k,j)
$call =xls2gms r=a106:m136 i=book3.xls o=pard.inc
$include pard.inc
;
display l,k,j,c2;
table q(l,i,j)
$call =xls2gms r=a139:m169 i=book3.xls o=pard.inc
$include pard.inc
;
display l,i,j,q;
parameter h(k)  'handling cost';
h(k)=3 ;
parameter u  'truck capacity';
u =28;
parameter p 'number of cross docks';
p =4;
parameter w 'cross dock capacity';
w =500;
parameter alpha 'discount factor';
alpha = 0.5
variables
O 'objective variable'
;
Binary variables
x(i,j,l,k)
v(i,j,l)
z(k)
```

```
;
integer variables
y(i,j,l)
y1(i,k,l)
y2(k,j,l)
;
equations
obj
location
routing(i,j,l)
inequality1(i,k,l)
inequality2(j,k,l)
inequality3(i,j,l)
crossdock(k)
;
obj.. sum((i,k,l),c1(l,i,k)*s1(i,k)*y1(i,k,l))+sum((k,j,l),alpha*c2(l,k,j)*s2(k,j)*y2(k,j,l))+sum((i,j,l),c(l,i,j)*s(i,j)*y(i,j,l))+sum((k),
h(k))*sum((i,j,l,k),x(i,j,l,k)*q(l,i,j))=e=O;
location.. sum((k), z(k))=e=p;
routing(i,j,l).. sum((k), x(i,j,l,k))+ v(i,j,l)=e=1;
inequality1(i,k,l).. sum((j),q(l,i,j)*x(i,j,l,k))=l=u*y1(i,k,l);
inequality2(j,k,l).. sum((i),q(l,i,j)*x(i,j,l,k))=l=u*y2(k,j,l);
inequality3(i,j,l)..q(l,i,j)*v(i,j,l)=l=u*y(i,j,l);
crossdock(k)..sum((i,j,l),q(l,i,j)*x(i,j,l,k))=l=w*z(k);
model m/all/;
solve m minimizing O using MIP;
```