THE IMPACT OF REPLENISHMENT FREQUENCY DRIVEN PRODUCT ALLOCATION IN A RETAIL SUPPLY CHAIN

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Bachelor of Technology

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2011

Submitted to the Faculty of the
Graduate College of
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
Master of Science
July 2015

THE IMPACT OF REPLENISHMENT FREQUENCY DRIVEN PRODUCT ALLOCATION IN A RETAIL SUPPLY CHAIN

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Date of Degree: July 2015

Title of Study: THE IMPACT OF REPLENISHMENT FREQUENCY DRIVEN PRODUCT ALLOCATION IN A RETAIL SUPPLY CHAIN

Major Field: INDUSTRIAL ENGINEERING AND MANAGEMENT

Scope and method of study: Distribution Centers perform a key role in the order fulfillment process by intermittently stocking products to be redistributed to different retail stores. An important strategic decision that has implications on cost and service levels in the long run is the allocation of products to the distribution centers. When fast moving products that generate large truckload volumes and/or have high replenishment frequency are stocked at distribution centers located closer to the retail stores, the miles traveled will be reduced resulting in the reduction of transportation costs. This product allocation strategy is called replenishment frequency driven distribution strategy. Explicit consideration of replenishment frequency requirements during product allocation decisions may be advantageous in comparison to imposing the requirements post decision making. Two optimization models were formulated to aid in product allocation decisions with and without replenishment frequency driven considerations. A numerical study was performed to yield insights into potential cost savings due to the explicit consideration of replenishment frequency driven distribution strategy.

Findings and Conclusions: The models aid in product allocation decision-making with or without replenishment frequency driven considerations. A post processing technique was employed to compare costs of the two models. The numerical study indicated potential cost savings in the range of 10% to 33%. An analysis on the computational performance of the GUROBI® solver indicated the need for performance improvement strategies. A greedy first-fit heuristic was introduced to solve large problem instances. The use of the heuristic in conjunction with tuning GUROBI® parameters yielded modest performance improvements. As retail supply chains become larger and more complex due to a broad product portfolio of present day retailers, it is clear that it would be advantageous to incorporate a replenishment frequency driven strategy for product allocation to realize cost savings as opposed to imposing the replenishment frequency requirements post product allocation decisions. We believe this study is a first step in this direction.

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CHAPTER 1

INTRODUCTION

A supply chain network is a network of facilities which form the infrastructure for the production and distribution of goods from the producer to the consumer. Physical locations in the network represent supplier locations which provide raw materials for the production of goods, manufacturing facilities which facilitate the production of goods, storage warehouses where finished goods are temporarily stored, carriers that transport finished good to downstream nodes, major distribution centers which are used for storing goods and also to provide value added services such as packaging of goods, testing and repairs (Heragu et al., 2005), and retail stores from which the end customers purchase the goods. A generic abstraction of a supply chain network is shown in Figure 1.1.

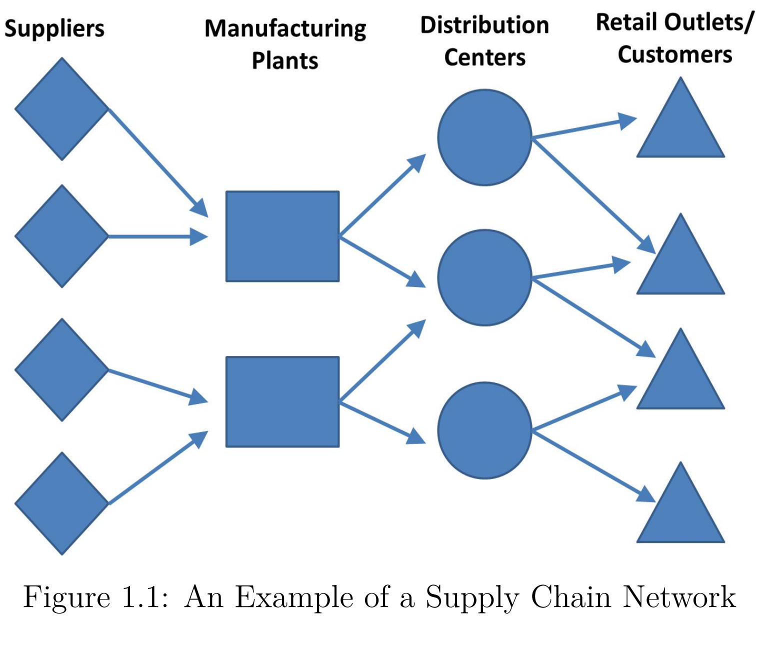

Figure 1.1: An Example of a Supply Chain Network

Generally, upstream facilities, e.g., manufacturing plants and distribution centers are fewer in number. This is because centralization of production and storage at a few locations is more efficient. The downstream facilities such as retail stores are typically more in number and geographically dispersed so more customers may be served.

1.1 Classifying Distribution Centers

In today's competitive business environment, distribution centers are viewed as strategic investments in the supply chain because they can decrease costs while providing improved service to customers. Therefore, in a supply chain network, different types of distribution centers varying in size, the amount of value added services they provide and the type of products they store, exist. Generally, large regional distribution centers are located quite far away from the retail stores and they provide storage, consolidation as well as cross docking facilities whereas smaller, local distribution centers which are closer to the retail stores temporarily store goods that are then transported to the retail stores nearby. Also, the large regional distribution centers supply goods to the smaller local distribution centers apart from directly supplying to the retail stores. Therefore, distribution centers which differ in size, function and the type of products they handle are being setup by organizations. An example of the same is given in the next section with the help of the description of the distribution center network of one of the largest retail organizations in the world, Walmart.

1.1.1 Walmart's US Distribution Network

Walmart has a huge distribution center network in the US consisting of 157 distribution centers. The total square footage of its US distribution centers is 118 million square feet (MWPVL, 2014). Walmart has defined its distribution centers as described in Table 1.1 (MWPVL, 2014).

A natural question may arise as to why such an extensive infrastructure may be required. One could argue that Walmart sees a broad product portfolio as a strategic advantage for greater profitability, and hence, needs a vast infrastructure in the form of distribution centers to store and transport the goods efficiently and effectively to the retail stores. Product portfolio can be defined as the list of items that an organization sells. In today's

Table 1.1: Types of Distribution Centers in Walmart's US Supply Chain Network

Type of Distribution Center	**Total Number in the US**	**Warehouse Size (in million sqft)**	**Details**
Regional General Merchandise Distribution Center	42	50.1	Designed for non-food items like electronics, beauty products etc. and the average one way distance to the retail stores is 124 miles.
Grocery and Perishables Distribution Center	42	34.7	Designed for all grocery items like dry grocery, frozen foods, meat products, dairy products etc.
Fashion Distribution Center	7	7.6	Designed for storing clothes and other fashion merchandise
Import Distribution Center	11	15.5	Main function is to receive shipments from across the world and then redistribute the shipments to the nearby regional general merchandise and grocery distribution centers. These do not send shipments directly to the retail stores.
Sam's Club Distribution Centers	26	2.5	Primarily operate for Sam's Club products
Specialty Distribution Centers	25	6.2	Service different products such as those sold only on walmart.com, optical products, pharmaceuticals, tires, returned products, etc.
Center Point Distribution Centers	11	1.6	Mainly act as consolidating centers that combine goods from different domestic suppliers based on their destinations. Consolidation reduces the total number of trips from an origin to a destination and thereby reduces the transportation costs for the distribution network

business world where there is increased competition in almost every sector, companies are looking to expand their product portfolios as a strategy to leverage growth. The reason for this is simple - tapping new markets which will increase the company's chances for greater profitability and also to build a stronger brand value. According to Anand (2008) a prime example of product portfolio expansion, which has driven an organization to a path of greater profitability is Apple's expansion into the music industry with the iPod and into the smartphone segment with the iPhone, which changed the fortunes of the company and has made it one of the technological giants of the world. It is natural that with a broad product portfolio, the variety of products that a firm sells is large too. In the case of consumer products, some products have very high demand and hence, have very high inventory turns. These products are called fast moving goods and some examples of these are toiletries and soft drinks. Then there is a second class of items, which do not move off the shelves as quickly as the fast moving goods but do make a sizeable proportion of the total business. These goods are called medium moving goods. The final class of products is called slow moving goods. These goods move very slowly off the shelves when observed over a longer time period but there might be sudden spikes in demand for the goods followed by a time period where there is no demand. These significant differences in the replenishment frequency of the products make it important for a firm to carefully manage its distribution strategies.

1.2 Replenishment Frequency-driven Distribution Strategy

Within the distribution center network of Walmart, the regional general merchandise distribution centers and the grocery and perishables distribution centers were originally intended to only handle non-food items and groceries of all kinds respectively. But starting in 2006, Walmart began to adopt a different approach in which 4,000 of the fastest moving items in groceries and general merchandise were mixed and allocated to the appropriate general merchandise and grocery distribution centers. This resulted in the fast moving items getting stocked in the distribution centers closer to the retail stores and the slower moving items getting stocked at fewer distribution centers and at farther locations (MWPVL, 2014). This strategy has two main advantages, which are listed below.

- Since the fast moving items typically require frequent replenishment, stocking the items in distribution centers closer to the retail stores will result in the reduction of the total travel distance for the movement of these items which will in turn reduce the transportation cost.

- Fast moving items getting stocked closer to the retail stores improves service levels of those products since proximity enhances flexibility to accommodate sudden upsurges in demand.

An example of product shuffle due to the adoption of this strategy is that the Grocery and Perishables distribution center located in Bartlesville, OK, which used to stock only grocery items, now stocks general merchandise like toiletries, which have high velocity. (Reference:Walmart Associate, Bartlesville, OK).The material discussed in the white paper (MWPVL, 2014) and a visit to the Walmart distribution center at Bartlesville, OK by the thesis author provided the motivation to pursue the line of research, which aims to explore decision making in product allocation across different distribution centers in a supply chain network in the presence of replenishment frequency requirements at the retail stores.

Considerable research has been reported in the areas of facility location, warehouse design and layout, product allocation within a warehouse storage area and improving operations in a warehouse such as storage, receiving and shipping. Whereas, there has been no explicit attempt to study the issue of product allocation among distribution centers in the presence of replenishment frequency requirements at the retail level.

The focus of this research is on understanding the impact of replenishment frequency requirements on product allocation decisions. The approach was to build and solve optimization models to make product allocation decisions with and without replenishment frequency constraints. Numerical study also involved the development of realistic datasets to define scenarios for the numerical experiments.

1.3 Outline of the Document

This chapter presented an introduction to a general supply chain network followed by the description of Walmart's distribution network and a discussion of the replenishment frequency driven distribution strategy and its importance in the context of product allocation among distribution centers. Chapter 2 presents a review of relevant literature published. Chapter 3 discusses the problem statement and the anticipated outcomes of this thesis effort. Chapter 4 presents two integer programming models, one which explicitly considers replenishment frequency driven constraints during product allocation and the other taking into account freight consolidation factors to form full truckloads alone. Chapter 5 includes the dataset generation methodology and the scenarios which were designed as part of the numerical experimentation. Chapter 6 further includes the preliminary cost savings results from the experiments, observations on the computational complexity of the models, description of the heuristic developed to address large problem instances and strategies for improving model performance in GUROBI®. Chapter 7 concludes the document by including a summary of this research effort and a brief discussion on avenues for future research.

CHAPTER 2

LITERATURE REVIEW

The literature review presented here covers topics related to the storage and the subsequent distribution of goods to retail locations. Section 2.1 presents some of the research done in receiving and shipping operations of a warehouse, Section 2.2 discusses research in the area of storage operations in a warehouse, Section 2.3 reviews some of the integrated models developed to jointly address facility location and inventory policy decisions, and finally, Section 2.4 discusses some of the research done in the field of freight consolidation.

2.1 Storage Operations in a Warehouse

One of the main functions of a warehouse is storage. The main decisions that affect this function are the amount of inventory that needs to held, the frequency and amount of replenishment of each stock keeping unit (SKU) and finally the allocation of different SKUs to different storage areas within the warehouses (Gu et al., 2007). This section will discuss the research related to the last decision of allocation of different SKUs to different storage areas.

It is known that there are different departments within a warehouse and in the case that an SKU can be stored in different departments, then decisions regarding the SKU allocation among the departments need to be made taking into consideration the cost of storage, material handling, etc. Hackman et al. (1990) consider the problem of product allocation in an automated storage and retrieval system (AS/RS). The authors construct a nonlinear optimization model consisting of a binary variable indicating whether a product has been allocated to the AS/RS or otherwise as well as a continuous decision variable determining the space allocated to a product in the AS/RS with an objective to maximize the profit arising due to allocation of products to the AS/RS. A heuristic procedure is developed to solve the problem and priori and posteriori tests for optimality of the heuristic are provided. Research in the field of warehousing and AS/RS prior to Hackman et al. (1990) dealt with the optimal design, storage & scheduling policies and optimal storage assignment problem to minimize the one way travel time in these systems, but did not address the problem of product allocation in the AS/RS. Heragu et al. (2005) consider the problem of product allocation in several functional areas of the warehouse, namely, reserve storage area, forward area where order collation takes place & cross-docking based on the flows of the products through the functional areas and at the same time determine the magnitude of the warehouse areas that need to be allocated to the three functional areas. The cost tradeoff was between the material handling cost and the storage cost. A heuristic was developed based on the mixed integer model developed to minimize the total costs. The research contribution is the joint consideration of the problem of determining the size of the functional area as well as product allocation to each of the areas, as opposed to the sequential consideration of these problems.

The Storage Location Assignment Problem (SLAP) addresses the assignment of incoming products to storage locations/departments in a warehouse. The constraints and performance criteria related to this problem are the capacity of each storage area, compatibility of the products and the storage area, picker capacity and efficiency (Gu et al., 2007). Three variants of the problem exist which are the SLAP with item information (SLAP - II) in which the details about the incoming individual items are available, the SLAP with product information (SLAP-PI) in which the incoming details about each product is available and the SLAP with no information (SLAP-NI) in which no information about the incoming products/items are available (Gu et al., 2007). The SLAP-II and SLAP-PI are addressed adequately in the literature and the reader is directed to Gu et al. (2007) for a comprehensive review of the problems. In the SLAP-NI, simple stocking policies can be constructed such as closest open location, farthest open location, random and longest open location. It is interesting to note that Gu et al. (2007) suggest that the difference in the performance metrics between the four policies have not been studied.

2.2 Receiving and Shipping Operations in a Warehouse

Warehouse operations of receiving and shipping are mainly carried out to bring inbound items into the warehouse (receiving), place them in storage, and pick and ship items to the customers or the next downstream point via shipping docks. In the case of a cross-docking operation, goods received are immediately sent to the shipping docks for outbound shipments without ever having to be stored. The common inputs of the receiving/shipping operations are information about the incoming shipments such as arrival times and contents, demand for items, warehouse layout, and different material handling resources (Gu et al., 2007). The constraints include resources required to complete the set of receiving/shipping operations for the aggregate orders, layout of the warehouse which imposes area and resource handling constraints, management policies like one customer per shipping dock, etc. and the performance criteria are typically operational metrics like loading/unloading times, etc. (Gu et al., 2007). The decisions that need to be taken for these operations are assignment of inbound and outbound carriers to the respective inbound and shipping docks, service schedule of the carriers for each dock and allocation of the warehouse material handling and the labor resources (Gu et al., 2007).

Decision making and management of the receiving/shipping operations is addressed adequately in the literature. Tsui and Chang (1990) deal with the optimal assignment of inbound and outbound trucks to strip/receiving and strap/shipping doors. The authors formulate a bilinear programming model which aims to minimize the total distance travelled by the forklifts to unload the contents of the inbound trailers and transfer the contents to outbound trailers. An algorithm is developed to find a local optimal solution and is implemented in software. The model developed by Tsui and Chang (1990) addresses the operation of individual freight yards and the implementation of the algorithm in the computer removes any manual calculation of the solution, thereby speeding up decision making. Tsui and Chang (1992) develop a branch and bound algorithm to find the optimal solution for the problem described in Tsui and Chang (1990). Gue (1999) develops a cost optimization model to assign inbound trucks to the strip doors and also assigns destinations to the stack doors. A local search procedure was then incorporated to find an efficient door layout based on the optimization model. The research in (Gue, 1999) extends previous work in this area by including the dependence of the material flows on the layout of the freight terminal to create an efficient layout. Bartholdi III and Gue (2000) model the door layout in a cross-docking environment with an objective to minimize the total travel time and the waiting time due to congestion. A simulated annealing algorithm is incorporated to find an efficient door layout. The contribution of the research is addressing the problem of designing the layout of doors in a cross docking environment which will translate into better efficiency of the workers doing the cross docking operations. Also, the authors provide a set of general guidelines based on the results of the model to design efficient door layouts.

2.3 Joint Facility Location and Inventory Policy Models

Traditionally facility location and inventory policy decisions such as safety stocks and replenishment frequency were determined separately and in a sequential manner. But the joint facility location and inventory policy models combine both the facility location and the inventory decisions thereby providing an integrated framework aimed at minimizing overall system costs which include inventory costs, transportation costs and the facility location costs.

(Üster et al., 2008) develop an integrated location-inventory model for a three-tier distribution network consisting of a single supplier, multiple retailers and a single intermediate warehouse whose location needs to be determined. The model explicitly considers the inventory costs and the distance based transportation costs and the decision variables are the location of the warehouse and the reorder interval between the warehouse and the retailer. The research contribution is the explicit consideration of the impact of coordinated replenishments in the location of facility and the decision of inventory policies in a multi-echelon setting.

Nozick and Turnquist (2001) consider the problem of determining the location of distribution centers along with the required safety stocks for products based on their demands in a two-echelon system. The authors develop a nonlinear optimization model to minimize the total inventory holding costs and the expected penalties for stock outs at the distribution centers. The cost components are constructed using queueing theory techniques with to the assumption of Poisson demands at the retail locations. The research is an extension of the authors previous work in Nozick and Turnquist (1998) in which a fixed charge facility location model is developed with explicit consideration of inventory costs in a single-echelon inventory-distribution system.

2.4 Freight Consolidation

Freight consolidation is a truck loading strategy that is aimed at dispatching full truck loads so that the number of trips is minimized for fulfilling the demand in the supply chain network. The reason freight consolidation is discussed is to get an idea of the often used strategies to reduce transportation costs.

Qin et al. (2014) discuss the freight consolidation and containerization problem which takes into account the allocation of shipments into trucks as well as loading the shipments into a truck considering the volume limit. An integer programming model which minimizes the container transportation cost and the parcel delivery costs was developed and a memetic algorithm based heuristic was designed to solve the problem practically. The research contribution is that the freight consolidation and the containerization problem is a relatively new problem in itself. The integer programming model developed is shown to be NP-hard and a heuristic method is developed based on the memetic algorithm.

Song et al. (2008) consider the coordination between the suppliers and the customers in a consolidation center in a supply chain network. A nonlinear discrete optimization model was developed which aims at minimizing the total transportation costs that include the transportation cost from the suppliers to the consolidation center, the transportation cost from the consolidation center to the customers and total holding cost. The research contribution is that transportation cost structures are modeled to be dependent on the time of delivery, which was assumed as stationary in the previous literature. Also the model is proved to be NP-hard and an efficient Lagrangian dual-based heuristic algorithm is developed to solve the problem practically.

2.5 Summary

All of the abovementioned research addresses different problems related to areas of supply chain network design, warehouse/distribution center design, warehouse operations and freight transportation. The joint facility location and inventory policy models address the initial supply chain network design problem along with inventory policy decisions. Once the locations of the distribution centers are fixed, warehouse/distribution center design determines the dimensions of the different functional areas of the warehouse like forward area, reserve area and cross docking. When the distribution center becomes functional, the improvement of warehouse operations like storage, receiving and shipping need to be addressed. The freight consolidation problem is a transportation operations optimization problem aiming at reducing the number of trips between an origin and a destination. The distribution strategy is concerned with the product allocation to distribution centers in a supply chain network so as to minimize associated physical distribution costs. This normally occurs after the location and distribution center design decisions are made. Product allocation to distribution centers will be followed by the warehouse operation improvement and freight consolidation. Product allocation decisions typically occur at the supply chain network design stage. These could also become relevant at a later stage when the supply chain network is fully functional and when there is a significant product portfolio expansion or significant changes in demand for the different products. These changes can introduce the need to streamline the distribution strategies and replenishment frequency driven distribution strategy could be an effective strategy that can help in reducing costs without significant changes in the supply chain network such as adding a new distribution center.

The literature review also reveals some gaps in the academic research. Though there have been models aimed at addressing the joint facility location and inventory decisions, the improvement of the different operations in a warehouse, the product allocation to different storage areas within a warehouse and freight consolidation, there has been no attempt to explicitly consider the replenishment frequency at the retail level when modeling product allocation between distribution centers and the resulting cost savings realized in comparison to transportation costs in the absence of this strategy.

CHAPTER 3

RESEARCH STATEMENT

This chapter discusses the motivation for this research effort in Section 3.1, the problem statement in Section 3.2, the scope and limitations of this research in Section 3.3, the objectives of this research in Section 3.4 and finally the deliverables of the research in Section 3.5.

3.1 Motivation

The thesis author's interest in this area was sparked by the white paper (MWPVL, 2014) which discusses the distribution center expansion strategy of Walmart in detail. According to MWPVL (2014), starting around 2006, Walmart has been explicitly considering the speed of product movement as indicated by its replenishment frequency to change the product mixes at distribution centers thereby allowing for the faster moving items to be stocked closer to the retail stores and the slower moving items farther away from the retail stores. Also, a field trip to the Walmart distribution center at Bartlesville, Oklahoma helped to support the claims of the white paper. A review of the literature indicated that there has not been an attempt to explicitly model product allocation to distribution centers in the presence of replenishment frequency requirements. An experimental study on the impact of the consideration of replenishment frequency requirements while making product allocation decisions as opposed to the imposition of these requirements post production allocation decisions could provide additional insight to companies with large supply chain networks and a broad product portfolio and help them develop effective strategies to support product allocation decisions.

3.2 Problem Statement

A review of the literature indicated that though there have been models aimed at addressing joint facility location and inventory decisions, the improvement of the different operations in a warehouse, the product allocation to different storage areas within a warehouse and freight consolidation, there have been no studies on product allocation to distribution centers under replenishment frequency constraints.

This study investigated and emperically assessed the impact of replenishment frequency considerations on transportation cost and potential for cost savings.

3.3 Scope and Limitations

The scope and limitations of the research are as follows.

1. The structural details of the supply chain network are already known, i.e., the locations of the distribution centers, the locations of the retail stores and which distribution center services which retail outlet.

2. The supply chain network considered is two-echelon network consisting of the distribution centers and retail stores.

3. The demand for the products is assumed to be deterministic and known at the retail store level.

4. Transportation costs of a trip from distribution centers to the retail locations are assumed to be known.

5. The truck fleet is assumed to be held privately resulting in no restrictions on fleet availability.

6. There are no milk runs in a transportation route, that is, only one retail store is serviced by a truck leaving from a distribution center. Once the items are delivered to a retail store, an empty truck comes back to the distribution center.

7. The demand for a product at a retail store is fulfilled by one distribution center.

3.4 Research Goal and Objectives

The goal of this research was to investigate the impact of replenishment frequency requirements on production allocation decisions. To achieve this goal the following objectives were defined.

(a) To develop integer programming formulations for making product allocation decisions in the presence of replenishment frequency requirements at the retail level and freight consolidation to form full truckloads.

(b) To develop realistic datasets involving retail store and distribution center locations, product characteristics, transportation distances and costs to define scenarios for the numerical experiments.

(c) To perform numerical experiments to emperically estimate the savings in transportation costs due to the consideration of replenishment frequency requirements.

(d) To study the computational effort required to solve large problem instances of the product allocation problem and to develop a heuristic approach to solve large problem instances.

3.5 Deliverables

The deliverables of the research effort are as follows:

(a) Integer programming based optimization models that will aid in decision-making with respect to which product will be stored in which distribution center based on the speed of product movement and freight consolidation.

(b) Results of the numerical study to assess the impact of replenishment frequency requirements on product allocation decisions.

(c) A heuristic approach to improve the efficiency of solving large instances of the problem.

CHAPTER 4

MODELING APPROACH

This chapter presents the problem description in Section 4.1, the objectives of the models in 4.2, the formulation of product allocation model with replenishment frequency constraints in Section 4.3, the description of product allocation model without replenishment frequency constraints in Section 4.4 and finally concluding remarks in Section 4.5.

4.1 Problem Description

Though a supply chain network consists of suppliers, manufacturing plants, distribution centers and retail outlets, only the product flow from the distribution centers to the retail stores is considered in this study. Given a set of distribution centers and retail stores, it is assumed that we know which distribution center services which retail store(s). Given a list of products, order quantity information in unit loads of each product is considered at the retail store level. It is assumed that the number of replenishments per year for each product at a retail store level is predetermined and fixed. According to the Senior Vice President of Process Engineering at a major retailer, an entity in the retail supply chain is usually responsible for deciding the replenishment frequencies based on the demand expected at the retail stores.

Other input parameters of the product are the weight and the volume information of a unit load of the product, the distribution center capacity, the average time (in years) spent in storage by a product at a distribution center which is assumed to be half the time between two successive replenishments of a product at the distribution center level. The cost factor that is considered in the network is the transportation cost of a round trip which is assumed to be dependent upon the distribution center and retail store combination. Note that the transportation cost is different from the cost coefficient considered in the classical transportation problem. The truck volume limit and the truck weight limit during freight transportation from a distribution center to a retail store are also enforced.

The decisions that need to be made are the distribution center to which the demand for a product at a retail store is allocated and the number of trips required to be taken between a retail store and distribution center pair per week.

4.2 Objectives of the Models

The supply chain distribution network modeled consists of various distribution centers and several retail stores with demands for a set of products at the retail store level. The decisions that need to be made are which product demands need to be allocated to which of the distribution centers either in the presence or absence of the replenishment frequency constraints so as to minimize transportation costs while considering physical distribution constaints such as the weight and the volume limits of the trucks and the storage constraints such as the distribution center capacities.

The first model makes the product allocation decisions constrained by the replenishment frequency requirements at the retail store level and the second model makes the production allocation decisions without considering replenishment frequencies. Both models include freight consolidation - combining shipments to form full truckloads.

4.3 Product Allocation with Replenishment Frequency Constraints

In addition to the integer programming formulation, this section includes a description of the inputs, decision variables, objective function and the constraints of the product allocation model with replenishment constraints (PAWR).

Index Sets:

$P = \{1, 2, ..., n\}$ denotes the set of all products,

$S = \{1, 2, ..., m\}$ denotes the set of all distribution centers,

$R = \{1, 2, ..., r\}$ denotes the set of all retail stores,

$T = \{1, 2, ..., 52\}$ denotes the set of all weeks in a year,

$R_j \subseteq R$, denotes the set of retail stores that a distribution center $j \in S$ can supply, and

$S_k \subseteq S$, denotes the set of distribution centers that can supply retail store $k \in R$.

Input Parameters:

D_{ik} denotes annual demand of product $i \in P$ at retail store $k \in R$ in unit loads,

G_{ikl} denotes forecasted number of replenishment(s) for product $i \in P$ to retail store $k \in R$ in week $l \in T$,

V_i denotes the volume required to store a unit load of product $i \in P$ in distribution center/truck,

W_i denotes the weight of a unit load of product $i \in P$,

M_j denotes storage capacity of distribution center $j \in S$,

K_i denotes the average time spent in storage (years) by a unit load of product $i \in P$ in a distribution center,

α denotes volume limit of a truck,

β denotes weight limit of a truck,

C_{jk} denotes the transportation cost of a round trip between distribution center $j \in S$ and retail location $k \in R$.

Derived Parameters:

V'_{ikl} denotes the total volume required to transport product $i \in P$ to retail store $k \in R$ in week $l \in T$. This is calculated by the formula $V'_{ikl} = G_{ikl}(\frac{D_{ik}}{\sum_{l=1}^{52} G_{ikl}})V_i$ for product $i \in P$ to retail store $k \in R$ in week $l \in T$.

W'_{ikl} denotes the total weight required to transport product $i \in P$ to retail store $k \in R$ in week $l \in T$. Similar to V'_{ikl} this quantity is calculated by the formula $W'_{ikl} = G_{ikl}(\frac{D_{ik}}{\sum_{l=1}^{52} G_{ikl}})W_i$ for product $i \in P$ to retail store $k \in R$ in week $l \in T$.

A_{ik} denotes the maximum storage space needed in a distribution center for product $i \in P$ to satisfy demand at retail store $k \in R$ occupies. This parameter can be calculated as $A_{ik} = 2D_{ik}K_iV_i$ under EOQ model assumptions.

Decision Variables:

$x_{ijk} = 1$ if demand of product $i \in P$ at retail store $k \in R$ is allocated to distribution center $j \in S_k$; 0 otherwise,

y_{jkl} = number of trips required from distribution center $j \in S_k$ to retail store $k \in R$ in week $l \in T$.

Assumptions:

(a) Constraints of capacity like storage space available in a distribution center and volume and weight limits of trucks are all enforced at an aggregate level.

(b) A delivery trip serves only one retail store; milk run routes are not considered.

(c) It is assumed trucks can always be packed if aggregate volume and weight limits are met. Factors like shape of the unit loads have not been considered.

Model PAWR:

$$Min \sum_{l \in T} \sum_{k \in R} \sum_{j \in S_k} y_{jkl} C_{jk} \tag{4.1}$$

$$\sum_{j \in S_k} x_{ijk} = 1 \quad \forall i \in P, k \in R \tag{4.2}$$

$$\sum_{i\in P}\sum_{k\in R_j} x_{ijk}A_{ik} \le M_j \quad \forall j \in S \tag{4.3}$$

$$y_{jkl}\alpha \ge \sum_{i\in P} x_{ijk}V'_{ikl} \quad \forall j \in S_k, k \in R, l \in T \tag{4.4}$$

$$y_{jkl}\beta \ge \sum_{i\in P} x_{ijk}W'_{ikl} \quad \forall j \in S_k, k \in R, l \in T \tag{4.5}$$

$$y_{jkl} \ge x_{ijk}G_{ikl} \quad \forall i \in P, k \in R, l \in T, j \in S_k \tag{4.6}$$

$$y_{jkl} \in \mathbb{Z}_+ \quad \forall j \in S_k, k \in R, l \in T \tag{4.7}$$

$$x_{ijk} \in \{0,1\} \quad \forall j \in S_k, k \in R, i \in P \tag{4.8}$$

The objective function (4.1) minimizes the total transportation cost which is expressed as the product of the number of trips required per week multiplied by the cost of one round trip and summing over all possible week, retail store and distribution center combinations. Constraint (4.2) ensures that demand for product $i \in P$ in retail store $k \in R$ is allocated to only one distribution center $j \in S_k$. Constraint (4.3) assures that the storage capacity of each distribution center is not violated. Constraint (4.4) checks whether the volume limit constraint of the truck is met for each week for all retail store-distribution center combinations. Constraint

(4.5) checks whether the weight limit of the truck is met for each week, similar to constraint (4.4). Constraints (4.4) and (4.5) take into account the freight consolidation aspects of transportation at an aggregate level. Constraint (4.6) assures the forecasted number of replenishments constraint is met for all product, retail store and week combinations if an allocation is made to a distribution center. Constraint (4.7) ensures the number of trips between distribution center $j \in S_k$ and retail store $k \in R$ on week $l \in T$ is a non-negative integer. Constraint (4.8) emphasises that the decision variable x_{ijk} is binary in nature. Note that this implies that the demand for a product $i \in P$ in retail store $k \in R$ is wholly allocated to a distribution center $j \in S_k$. This is included as it is easier from a retailer's perspective to be receiving a certain product from one distribution center rather than from multiple distribution centers.

4.4 Product Allocation Without Replenishment Frequency Constraints

To evaluate the impact of constraint (4.6), which ensures that the replenishment frequency requirements are met at the retail store level for all products, we use Model PAWR without constraint (4.6). We refer to this as Model PAWOR. So Model PAWOR would yield product allocation decisions based only on the demand for products at the retail stores. However, to compare the cost of the solution from Model PAWR to that obtained from Model PAWOR, the replenishment frequency requirements must be applied to the product allocation solution from Model PAWOR. This post processing step is explained later in Section 6.1.

4.5 Remarks

How often a retail store needs to be replenished for a product could depend on many factors such as product demand, shelf space allocated to the product and perishability. As indicated by the Senior Vice President of Process Engineering at a major retailer, the replenishment schedules for various products at the retail store level are decided by a separate entity within the retail supply chain. Distribution centers must honor these replenishment schedules as they supply products to retail locations. The purpose of the two models developed in this chapter is to investigate the potential benefits of explicitly considering replenishment related requirements while making product allocation decisions at the distribution center level.

CHAPTER 5

DATA GENERATION

The purpose of the planned numerical study was to get realistic estimates of the benefits that can be realized through transportation cost savings if the product allocation at the distribution center explicitly considered the product replenishment schedule at the retail stores. Hence, the datasets used for the experiments were carefully constructed to ensure realistic figures of potential cost savings resulting from the experiments. In this section, we discuss how the product related datasets were created in Section 5.1, the supply chain network of retail stores and distribution centers was defined in Section 5.2 and finally how the transportation cost matrix and freight consolidation factors were defined in Section 5.3.

5.1 Product-related Data

This section discusses how the datasets related to individual products were created. The datasets include the product portfolio defining the product categories; weight and volume of an unit load of the product and the demand and replenishment frequency of the products at the retail store level. The data generation methodology for the various datasets is explained in the following paragraphs.

- The product portfolio was selected to resemble the product portfolios of leading retail giants like Walmart and Kroger's. An initial product set consisting of 26 products was selected from the Walmart's official website Walmart (2015). Products include diary products like milk, eggs; food products like ketchup, vegetable oil, beans, cornflakes, noodle soup and popcorn. Beverages include water, soda and beer; electronics like television, printer, vacuum cleaner and car batteries. Furniture products consisted of office chair, office table; sports products consisted of basketballs; paper products like office paper and paper cups and finally travel products included a luggage set.

- The volume of the initial product set was derived from Walmart's official website Walmart (2015). A unit load of a product was assumed to be a standard carton of 24" $\times$ 24" $\times$ 24". If the physical dimension of a particular product was bigger than the assumed unit load's dimension, then the unit load of the particular product was assumed to be the packaging dimension of a single unit of the product. Volume was measured in cubic inches.
- The weight of the unit load of the item was obtained from Walmart's official website (Walmart, 2015). Weight was measured in pounds. The weights of the products for datasets replicated from the initial product set. Weights were generated randomly so as to fall between 75% to 125% of the original weight.
- To generate the replenishment frequency the products were first categorized as fast movers and slow movers. The dairy products, food products and beverages were classified as fast movers and electronics, furniture, sports products and paper products were classified as slow movers. The replenishment frequency of the fast movers was randomly generated from the range of 313 to 365 replenishments per year and the replenishment frequency of the slow movers were randomly generated from the range of 52 to 104 replenishments per year.
- To generate the demand dataset, first, the order quantity (in unit loads) of the individual products was randomly generated according to the product movements. For example, the order quantity of sodas was randomly generated using a range of 8 to 12 and the order quantity of office tables was generated randomly from a range of 2 to 5 unit loads. Then, the annual demand was derived by multiplying the retail order quantity with the annual replenishment frequency.

5.2 The Distribution Center and Retail Store Network

From a cost perspective, the generation of a realistic supply chain distribution network was key since the transportation costs mainly depend on the spatial distribution of the retail stores and the distribution centers. A list of Walmart's existing distribution center locations was obtained from MWPVL (2014). The list of retail stores was obtained from a publicly available source (Priceviewer, 2015). To carry out the numerical experimentation, a set of twelve scenarios was designed as shown in Table 5.1.

Table 5.1: List of Scenarios

Scenario	DCs	Retail Stores	Products
1	2	20	50
2	2	20	100
3	2	20	150
4	2	20	200
5	3	30	50
6	3	30	100
7	3	30	150
8	3	30	200
9	4	40	50
10	4	40	100
11	4	40	150
12	4	40	200

Two separate instances of each scenario were created, differing in the proportion of the fast movers in the product mix. The variations in the scenarios were 30% fast movers and 70% fast movers.

It can be observed that the number of distribution centers and retail stores are (2,20); (3,30) and (4,40) respectively. To generate supply chain networks with the respective configurations for the various scenarios, retail store and distribution center locations from the State of Illinois were selected. The total number of retail stores was 155 and the total number of distribution centers was 4. Out of the 155 retail stores, subsets of size 20; 30 and 40 were randomly selected. The distribution center and retail store locations for the various configurations can be found in Figures 5.1 through 5.3. Note that the markers with an "R" on them signify retail stores and the markers with a ”D” on them signify distribution centers. The maps were generated using Google® Fusion Tables. It was assumed that each distribution center can service every retail store since the supply chain network considered in the above mentioned scenarios was small and it was desired to keep all combinations of product allocation to the various distribution centers possible.

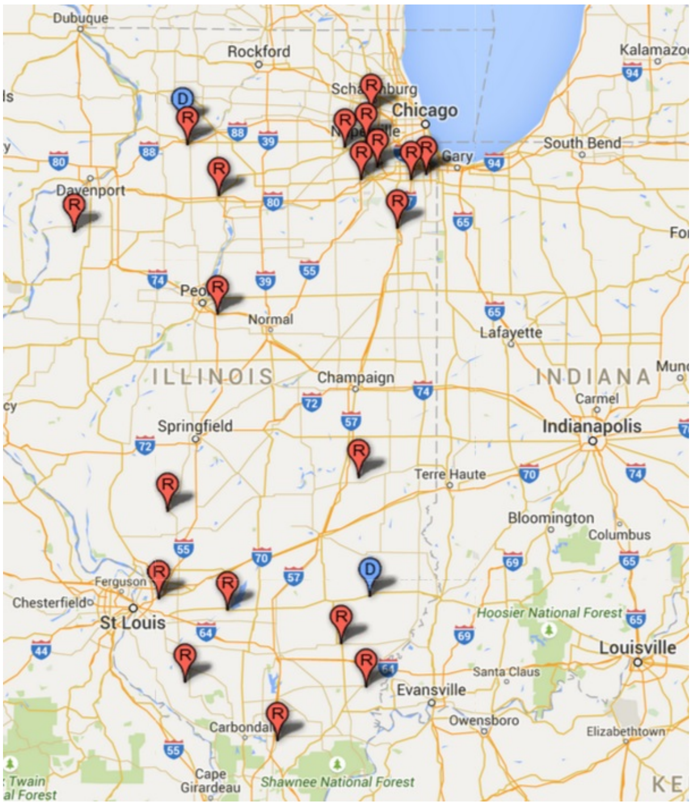

Figure 5.1: 2 Distribution Centers and 20 Retail Stores

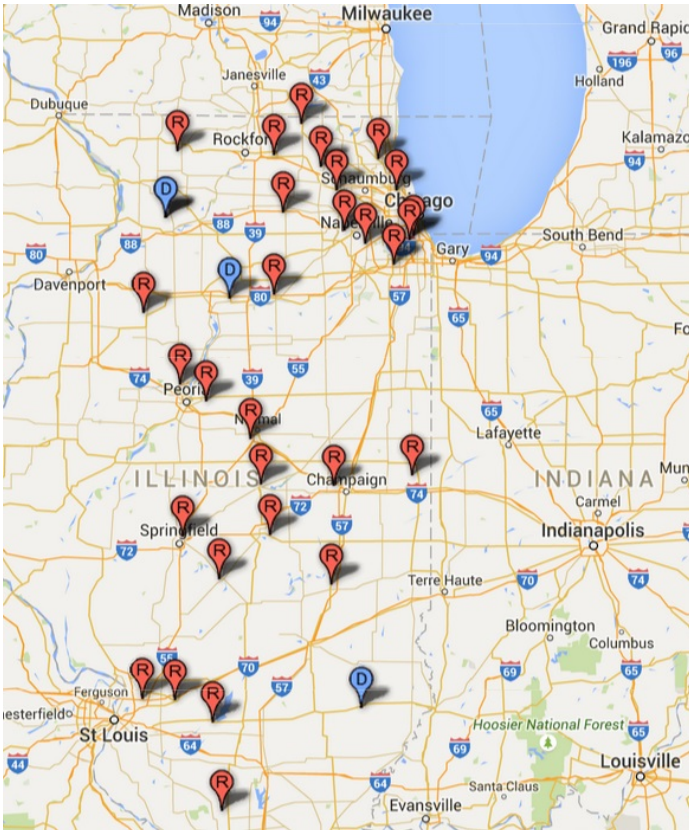

Figure 5.2: 3 Distribution Centers and 30 Retail Stores

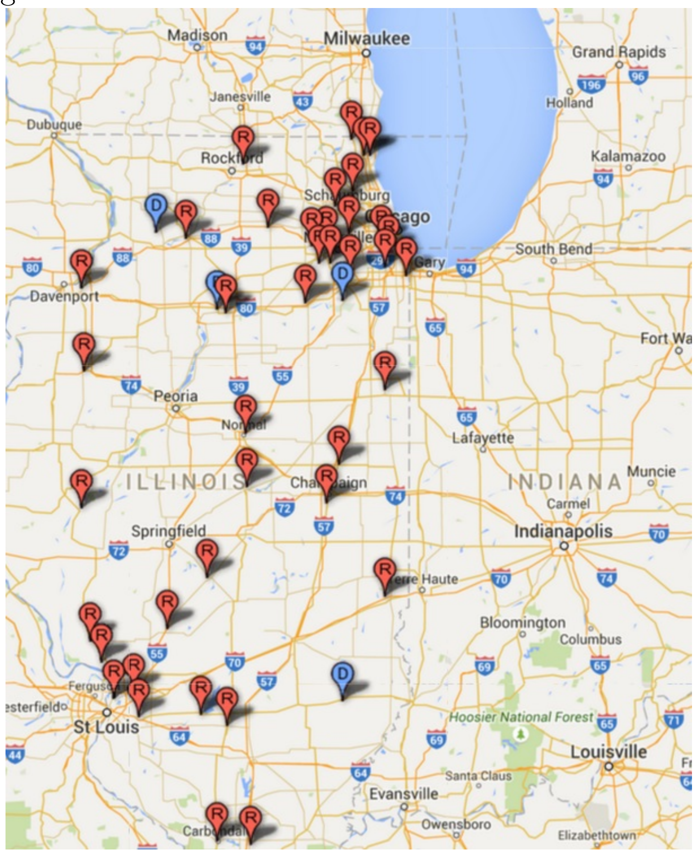

Figure 5.3: 4 Distribution Centers and 40 Retail Stores

5.3 Transportation Costs and Freight Consolidation Factors

Once the locations of distribution centers and the retail stores were determined, the one way distance between each distribution center and retail store pair was determined by a software called PC*Miler (2015), which employs an industry standard for calculating zip to zip distances. The distance then was converted into trip based transportation costs by multiplying the round trip distance by the average per mile trucking operational costs of $1.38 as quoted in TheTruckersReport (2015).

Freight consolidation factors which include weight limit and the volume limit of a truck were derived from specifications of a standard 53 foot trailer. The volume limit was set at 90 cubic meters or 5,492,000 cubic inches and the weight limit was set at 44,000 pounds which are industry standards for designing trucking solutions.

CHAPTER 6

NUMERICAL EXPERIMENTS AND COMPUTATIONAL RESULTS

This chapter first describes the computing infrastructure used to run the numerical experiments in Section 6.1. Section 6.2 discusses the experimental results obtained. Section 6.3 discusses the impact of replenishment driven frequency requirements on product allocation as observed through cost savings. An empirical analysis of the performance of the GUROBI® solver is included in Section 6.4. A heuristic is introduced to solve the problem for large instances in Section 6.5 followed by a comparison of the performance of the heuristic in terms of solution quality in Section 6.6. Finally, strategies adopted for performance tuning of the GUROBI® solver are described in Section 6.7.

6.1 Computing Specifications

To run the experiments, the Cimarron cluster in the OSU High Performance Computing Center (OSUHPCC) was used. The Cimarron cluster consists of ten compute nodes running 64-bit Linux CentOS operating system. Each compute node has dual quad core Intel Xeon E5620 2.40 GHz processors. Six of these nodes have 96 GB RAM and four have 144 GB RAM. The six nodes with 96 GB RAM were used in the experiments. The models were coded into GUROBI® using the python programming language. The default settings of GUROBI® were used and the time-limit set was 24 hours.

6.2 Experimental Results

This section dicusses the experimental results for the various supply chain network scenarios. Results are included for the 30% fast movers dataset and the 70% fast movers dataset. The objective function value (OFV) is in US Dollars, the running time reported is in seconds and the gap reported is in percentage. The results are summarized in tables A.1 and A.2 in Appendix A.

From the tabulated experimental results, we can observe that Model PAWR has solved to optimality for most of the scenarios. The scenarios for which it did not solve to optimality are scenarios 6, 7 and 10 for the 30% dataset and scenario 4 for the 70% dataset with the maximum gap being 0.6% for scenario 4 of the 70% dataset. On the other hand, Model PAWOR does not get solved to optimality for most of the instances and we can observe bigger gaps, some as large as 9.3% for scenario 6 in the 70% dataset. Also, for scenario 10 of the 70% dataset, Model 1 couldn't be solved as the program ran out of memory.

Scenarios 1 and 3 for both the 30% and 70% datasets has solved to optimality. For these scenarios, the cost savings was performed with the optimal solutions and for other scenarios the cost savings were calculated using the incumbent solution of Model PAWR or Model PAWOR.

6.3 Cost Savings

The main objective of this research is to quantify the potential cost savings when considering replenishment frequency driven product allocation strategy as opposed to imposing the replenishment frequency requirements after making product allocation decisions. To achieve this objective, Model PAWR was formulated which explicitly considered the replenishment frequency driven constraints during product allocation. Model PAWOR is nothing but Model PAWR without the replenishment frequency constraints. Once both the models were solved, allocation decisions from

Model PAWOR are fixed in Model PAWR to estimate PAWOR's true cost in the presence of replenishment frequency requirements.

It was observed that only 4 scenarios out of 24 scenarios resulted in optimal solutions for both the models. Cost savings were reported by comparing the optimal solutions for the these scenarios and the incumbent solutions from the models were used for the cost comparison for the other scenarios.

The technique used to calculate the cost savings after getting optimal solutions to both models was to fix the product allocation decision variables values of the optimal solution of Model PAWOR in Model PAWR and re-solve Model PAWR to get the true transportation costs. In other words, the replenishment frequency constraints are being forced on the product allocation decisions of Model PAWOR to get the true transportation costs. To quantify the relative difference between the costs, the ratio of the difference of the true transportation cost of Model PAWOR and the cost of Model PAWR to the true transportation cost of Model PAWOR was calculated which signifies the cost savings. The cost savings are shown in Tables A.3 and A.4 in Appendix A.

"Model PAWR Cost" represents the objective function value resulting from the optimal or incumbent solution of Model PAWR and "Model PAWOR true cost" is the true transportation costs when replenishment frequency driven requirements are imposed on the product allocation decisions of Model PAWOR. Scenarios 1 and 3 have been starred in tables A.3 and A.4 in Appendix A as we were able to obtain optimal solutions for both the models for these scenarios. The cost figures that have been reported in other scenarios were derived using the best incumbent solution obtained after 24 hours. It can be observed for scenario 1 shows 10% and 13% cost savings for the 30% and 70% fast movers datasets respectively. Similarly, scenario 2 shows 26% and 27% cost savings for the 30% and 70% fast movers datasets respectively. Cost savings of upto 33% can be observed in scenario 4 of the 30% and 70% dataset and scenario 2 of the 70% fast mover dataset. No cost savings have been reported for scenario 10 of the 70% dataset since GUROBI® ran out of memory while solving Model PAWR for that instance.

Cost savings figures suggest that substantial cost savings in the range of 10% to 33% can be realized by taking into account the replenishment frequency driven requirements during product allocation in a retail supply chain.

Since, it was observed that most of the scenarios resulted in sub-optimal solutions for both the models, a deeper analysis of the computational issues in solving the models was carried out and some model performance improvement strategies were tested out, which will be discussed in detail in the following sections.

6.4 Observations Regarding Computational Performance

Out of the 24 scenarios that were run during the numerical experimentation, only 4 scenarios resulted in optimal solutions for both Model PAWR and Model PAWOR. To further investigate the computational complexity of Model PAWOR, the optimality gap, which is the relative percentage difference between the upper bound and the lower bound found by the branch and bound algorithm in GUROBI® was plotted against time. The plots for scenario 5 of the 30% dataset and scenario 6 of the 70% dataset are included in figures 6.1 and 6.2 respectively. These scenarios were chosen, since they were most representative of the rest of the scenarios.

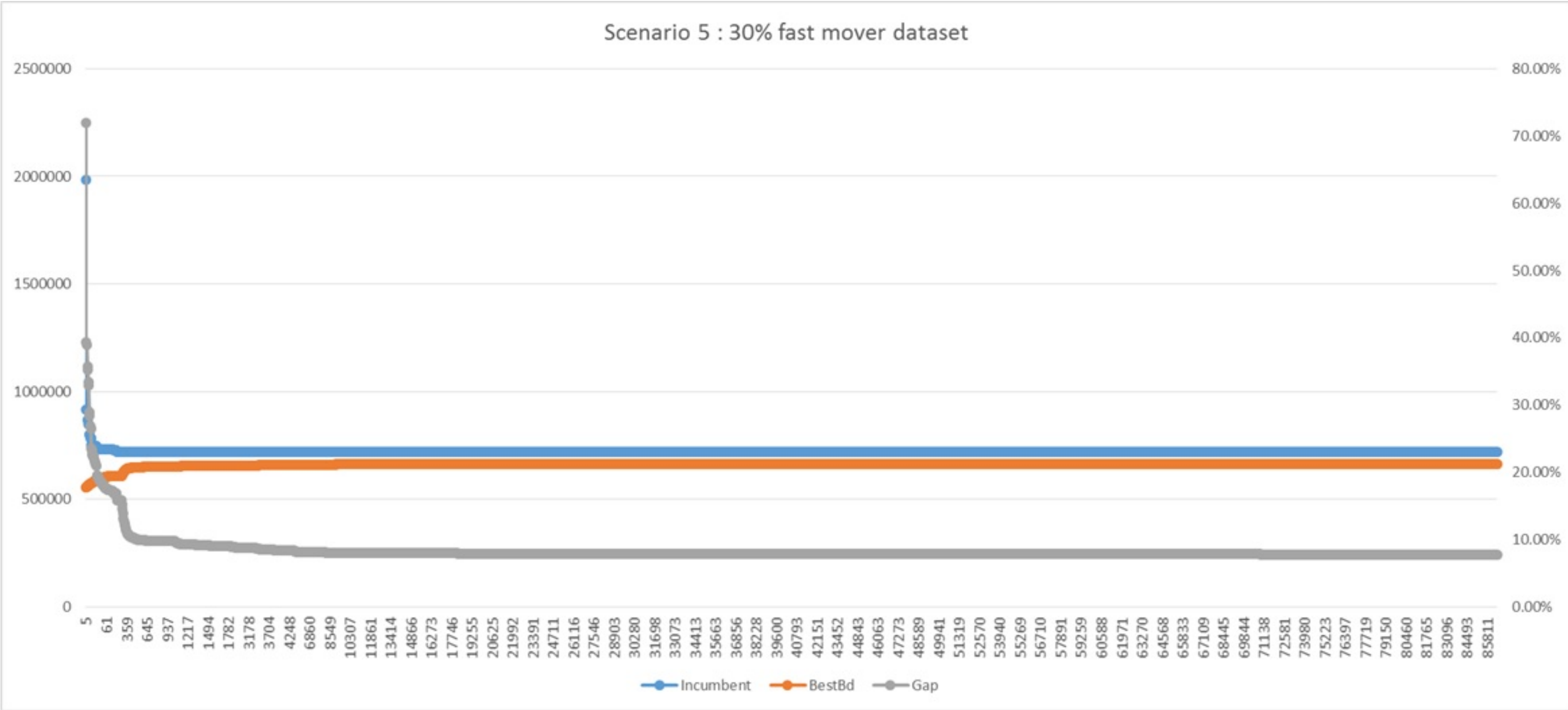

Figure 6.1: Performance of GUROBI® for scenario 5 of 30% fast mover dataset

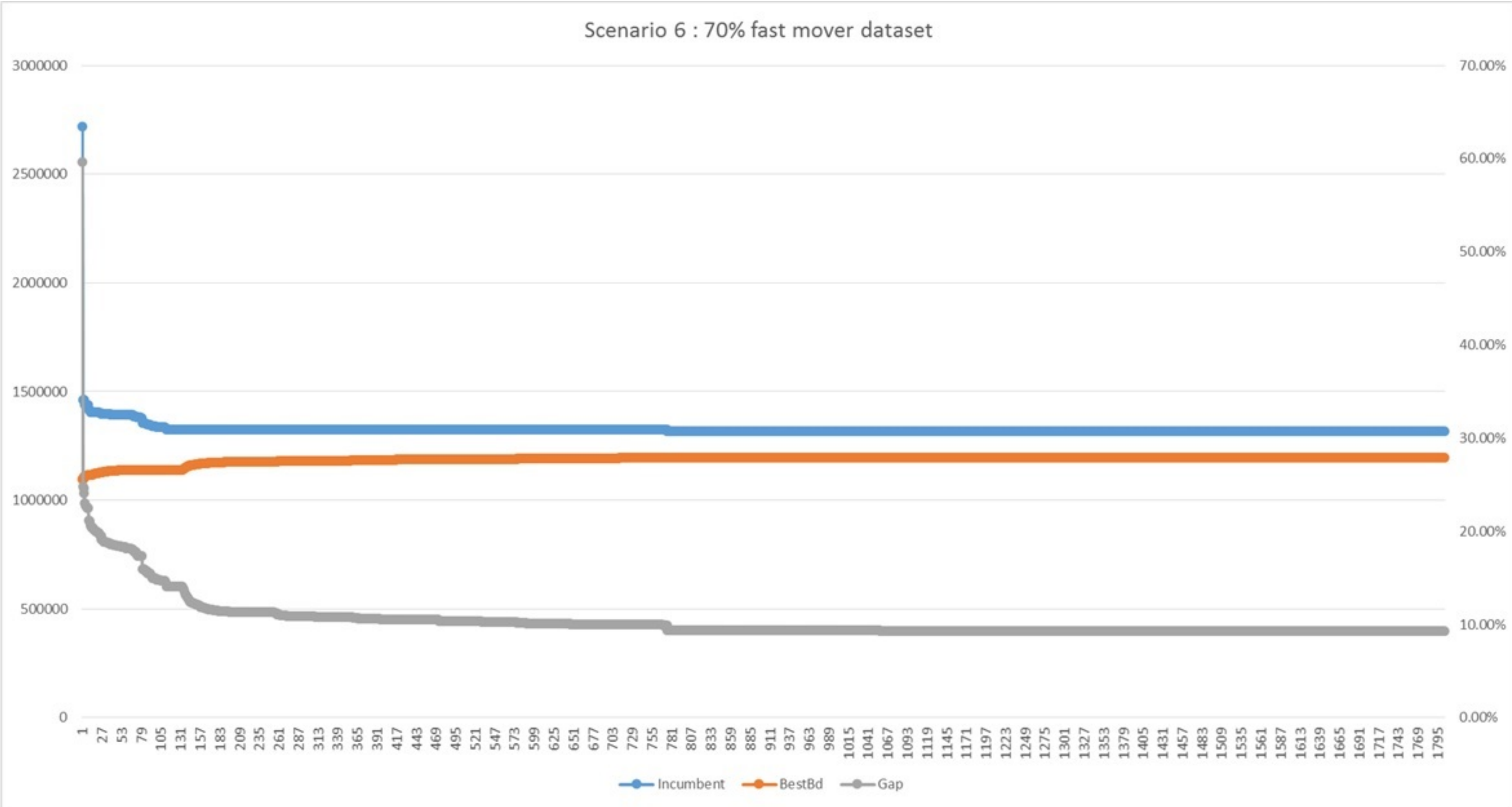

Figure 6.2: Performance of GUROBI® for scenario 6 of 70% fast mover dataset

From the plots we can observe that there is significant improvement in the incumbent solution and the lower bound for the initial time period of the algorithm and as time progresses, we see diminishing improvements. In fact, it can be observed that most of the improvements in the incumbent solution happens within 1.5 hours (5,400 secs) of the start of the model and the remaining 22.5 hours result in negligible improvement in the incumbent solution. This observation has been numerically summarized in Table A.5 in Appendix A.

From Table A.5, it can be concluded that the maximum solution improvement after a runtime of 1.5 hours is approximately 2% for scenario 10 for the 70% fast movers dataset. This suggests that the branch and cut algorithm of GUROBI® finds fewer better solutions after 1.5 hours which suggest that PAWOR is computationally more challenging to solve.

For scenarios 6, 7 & 10 in the 30% dataset and scenarios 4, 6 & 7 in the 70% dataset, optimality conditions have not been reached after the maximum runtime of 24 hours. Hence, we can expect that for bigger network configurations, the model will result in suboptimal solutions under the present termination conditions. Hence, strategies to improve the performance of the models need to be investigated. Some of the strategies considered in this study are as follows.

- Change model parameters in the GUROBI® solver to adopt aggressive strategies to find better solutions.
- Develop a heuristic algorithm for the problem which will supply an initial solution to GUROBI® and let the solver improve on the heuristic solution.

6.5 A Greedy First-Fit Heuristic

This section develops a simple greedy heuristic to address the product allocation problem. The inclusion of replenishment frequency will result in the stocking of fast moving goods at distribution centers closer to the respective retail locations so that the associated transportation costs are minimized. The number of replenishments required per year for a product, quantifies the rate of movement of the product and forms a lower bound on the number of trips that need to be taken between the distribution center and the retail store for that product, if an allocation is made. Hence, an effective heuristic approach to the problem could be to prioritize the products in the decreasing order of their respective number of replenishments per year and allocate them to the nearest distribution center. This approach could be seen as an extension of product allocation to storage spaces within a warehouse in the presence of a dedicated storage policy as described in Francis et al. (1974). In a warehouse, allocations are made after the products are prioritized in decreasing order of their throughput-to-storage ratios, where throughput is the number of storage/retrieval operations made per unit time and the storage is the amount of storage slots required by the product.

The following procedure can be used to allocate the various products to the distribution centers:

(a) Set $Z_j = 0 \quad \forall j \in S$

(b) Create an index for the product-retail store combination in the descending order of the number of replenishments per year (F_{ik}) where $i \in P$ and $k \in R$ such that $F_1 \geq F_2 \geq ... \geq F_\lambda$ where $\lambda = n \times l$

(c) Compute TC_{jik} values for all product-retail store combinations where $TC_{jik} = F_{ik}C_{jk}$

(d) Starting from product-retail combination with index 1, set $X_{ij^*k} = 1$ where j^* is the distribution center which has the minimum TC_{j^*ik}, $j \in S_r$ and $Z_{j^*} + 2D_{ik}K_iV_i \leq A_{j^*}$. Set $Z_{j^*} = Z_{j^*} + 2Q_{ik}F_{ik}K_iV_i$. Repeat for all product-retail store combinations in order of increasing indices defined by sorting the replenishment frequency in the decreasing order

Step 1 sets Z_j which is the current space occupied at distribution center $j \in S$. In step 2, all the product-retail store combinations are ordered in the descending order of the number of replenishments per year. This is because the number of replenishments per year forms a lower bound on the number of trips between a distribution center and a retail store if an allocation is made and also it quantifies the rate of movement of a product. Hence the indexing is a prioritization step. In step 3, we compute the total transportation cost TC_{jik} for each product-retail-distribution center combination. In step 4, starting from the product-retail store combination which has the lowest index meaning the highest number of replenishments per year we make an allocation decision to the distribution center which can service the retail store, which has necessary storage capacity and which has the minimum transportation cost for the product-retail store combination. Then, the Z_j value for the distribution center to which the allocation is made is augmented by a value that will equal the maximum possible volume that will be occupied by the product. Finally in step 5, the decision variable y_{jkl} is calculated as the maximum of the number of trips required by a product during a week, G_{ikl}, the trips required to transport the aggregate volumes and weights constrained by the truck volume and the truck weight limits. The above heuristic is designed primarily for obtaining a solution to Model PAWR as the replenishment frequency is explicitly taken into account.

6.6 Performance of the Heuristic

To test the performance of the heuristic, it was run for the scenarios of the 30% fastmover dataset. The resultant heuristic cost and the solution obtained from GUROBI® were compared using the percentage difference in the resultant costs using the solutions from Model 1 and the heuristic. The percentage difference was calculated as the ratio of the difference in costs of the solutions from the heuristic and Model PAWR to the cost of Model PAWR. The results are summarized in Table 6.1.

Table 6.1: Heuristic Performance: 30% Fastmover Dataset

Scenario	DC	Retail	Products	Heuristic	Gurobi	% Diff
1	2	20	50	2211060	1880269	18%
2	2	20	100	2561527	1989466	29%
3	2	20	150	2437385	1949517	25%
4	2	20	200	2467960	1952460	26%
5	3	30	50	2796178	2515242	11%
6	3	30	100	2899454	2527893	15%
7	3	30	150	2915652	2533052	15%
8	3	30	200	2921990	2521654	16%
9	4	40	50	3305153	2994029	10%
10	4	40	100	3272623	2940061	11%
11	4	40	150	3428405	3028844	13%
12	4	40	200	3235615	2958474	9%

From Table 6.1 it can be observed that the heuristic gives solutions that are atleast 9% higher and as high as 29% higher than the solution obtained by solving Model PAWR using GUROBI®. The heuristic performance suggests that it provides solutions that result in as much as 30% higher costs than the optimal solutions.

6.7 GUROBI® Performance Tuning

For the performance improvement of Model PAWR, various strategies were used which were combinations of parameter settings in GUROBI® coupled with injecting solutions from the heuristic described in Section 6.6. The test case considered was scenario 6 in the 30% fast mover dataset since it gave 0.25% gap for Model

PAWR and 8.01% gap for Model PAWOR. The base case performance using default parameter settings in GUROBI® is shown in Table A.6 in the Appendix section.

Strategy 1 was to first solve the heuristic for the respective scenario and inject the solution to GUROBI®. The resulting performance from this strategy is given in Table A.7 in Appendix A. It can be observed that Strategy 1 does not result in any improvement.

This resulted in pursuing a more aggressive Strategy 2 which involved injecting the solution of the heuristic as well as changing the value of the parameter called *MIPFocus* to "1" in GUROBI®. This forces GUROBI® to increase the emphasis on finding better feasible solutions. The performance of this strategy is given in Table A.8 in Appendix A. Strategy 2 causes GUROBI® to find a solution with the same objective function value but the gap is slightly higher, due to weaker overall bound.

Strategy 3 involves changing the *MIPFocus* parameter to 3 which causes GUROBI® to focus on improving the bounds that might cause a reduction in the gap and may cause the branch and cut algorithm to meet optimality conditions. The performance resulting from this strategy is given in Table A.9 in the Appendix section. Strategy 3 also results in no improvement in the model performance.

Finally, Strategy 4 involved injecting the heuristic solution along with changing a parameter called *ImproveStartGap* which causes GUROBI® to change into a more aggressive heuristic strategy once the gap reaches the predetermined limit. This limit was set to 10%. This meant that once the gap less than or equal to 10%, GUROBI® will change to a more aggressive heuristic strategy. The performance of this strategy is given in Table A.10 in the Appendix section. Strategy 4 results in better model performance.

Though the objective function value remains the same, the run time is considerably less at 18.2 hours as compared to 24 hours and the optimality conditions are met as well. Therefore, this particular strategy was used for all the scenarios in the 30%

and the 70% datasets for which Model 1 did not solve to optimality. The results of strategy 4 on these scenarios is given in Table A.11 in Appendix A.

It can be observed for almost all scenarios, we see a modest performance improvement resulting due to Strategy 4 as opposed to using the default settings. Most notably for the last scenario in the 70% dataset, the default setting in GUROBI® caused the computer to run out of memory but the parameter settings in Strategy 4 resulted in an optimal solution within 9 hours of runtime. It should be noted that for the 2 DCs, 20 Retail stores and 200 products scenario, there is an increase in the optimality gap from 0.62% to 1.34% but the incumbent solution value did not increase.

It can be inferred that Strategy 4 does result in modest performance improvement of Model PAWR in most of the scenarios and resulted in a slightly decreased performance for one scenario. This suggests that alternative strategies like developing more efficient heuristics/algorithms in tandem with the tuning of GUROBI® will facilitate large problem instances to be solved to optimality.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

The objective of this research was to explore the advantages of adopting a replenishment frequency based product allocation strategy in a retail supply chain. Two optimization models were developed, one explicitly considering replenishment frequency in product allocation decisions (Model PAWR) and the other considering freight consolidation factors to form full truckloads only (Model PAWOR). Realistic datasets were constructed to provide input to the models so as to obtain realistic estimates of potential cost savings due to consideration of replenishment frequency driven requirements during product allocation decisions. A set of scenarios were defined for numerical experimentation purposes which differed in the supply chain network configuration for two separate datasets which had 30% fast movers and 70% fast movers respectively. For the numerical study, the models were programmed in GUROBI® using the python programming language and were run using the Cimmaron cluster of the Oklahoma State University High Performance Computing Center (OSUHPCC). A cost comparison methodology was developed as a post processing step to facilitate proper comparison of costs from considering and not considering replenishment frequency requirements explicitly. The numerical experiments yielded insights into potential cost savings and also threw light upon the computational complexity of the models. A greedy first-fit heuristic was developed to solve the problem for large instances. Finally, several strategies to improve model performance in GUROBI® were tested and the best strategy was further tested on scenarios that yielded sub-optimal solutions.

7.1 Results

The results of the research are as follows:

- Out of 24 scenarios tested, only 4 scenarios yielded optimal solutions for both the models. The cost comparison methodology when exercised on these scenarios indicated cost savings between the range of 10% to 27%.
- The heuristic developed was tested on all the scenarios in the 30% fast movers dataset. It yielded solutions with cost difference in the range of 9% to 30% more than the optimal solution, indicating a high variability in the performance. Hence, it was concluded that it would be prudent to use the heuristic solution in combination with GUROBI® to explore the possibility of enhanced performance.
- A set of 4 strategies was explored which included injecting the heuristic solution into GUROBI® and tuning certain MIP parameters in GUROBI® to study the effect on performance. It was observed that changing the *ImproveStartGap* parameter to 10% along with injecting the heuristic solution at the start yielded the best improvement in performance.
- The best performance strategy was tested on the scenarios which originally resulted in sub-optimal solutions of Model PAWR in both the 30% and the 70% dataset. Out of 7 scenarios, 6 scenarios resulted in performance improvements. Most notably, the optimal solution was found for a scenario in the 70% dataset which otherwise would have caused the computer to run out of memory when the default settings in GUROBI® were used.

7.2 Directions for Future Research

This study was aimed at estimating potential cost savings due to explicit consideration of replenishment frequency driven requirements during product allocation decisions in a retail supply chain. This research was limited by the non-availability of industry data. If real-world data was available, the cost of the models could be compared to actual transportation costs to derive more accurate cost savings. Some of the avenues of future research are discussed below.

(a) The current work includes a greedy first-fit heuristic that yielded optimal solutions for 2 scenarios out of the 12 scenarios it was tested on and also generated solutions that were as high as 30% more than the optimal solution. Hence, development of more sophisticated metaheuristic algorithms will facilitate solving of large problem instances more efficiently.

(b) Vehicle routing can be combined with product allocation decisions to allow for milk run routes from distribution centers to retail stores to better represent real-world operations.

(c) During freight consolidation, it is important to take into account compatibility constraints between products. An example of non compatible products are dangerous chemicals and food products. The compatibility factor when taken into account may increase the number of truckloads required resulting in an increase in overall transportation costs.

(d) Transportation costs have alone been considered during development of the models. Inclusion of more cost components like inventory holding costs and material handling costs like cross docking costs could change product allocation decisions based on various cost structures.

As retail supply chains become larger and more complex due to a broad product portfolio of present day retailers, it is clear that it would be advantageous to incorporate a replenishment frequency based strategy for product allocation to realize cost savings as opposed to imposing the replenishment frequency requirements post product allocation decisions. We believe this study is a first step in this direction.

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APPENDIX A

This section contains the computational results of the 30% and 70% fast mover dataset in tables A.1 and A.2 respectively. Also, cost comparion statistics of the true costs of Model PAWOR and Model PAWR for the 30% and 70% datasets are included in tables A.3 and A.4 respectively. Table A.5 reports the optimality gap improvement for Model PAWOR between 1.5 hours and 24 hours of running time in GUROBI®. Tables A.6 through A.10 report performance of GUROBI® due to performance improvement strategies tested. Finally, Table A.11 includes performance improvement of GUROBI® due to adoption of Strategy 4 for a set of scenarios as discussed in Section 6.7.

Table A.1: 30% Fast Movers Dataset: Computational Results

				PAWR			PAWOR		
Scenario	DC	Retailstores	Products	OFV	Running time (secs)	Optimality gap	OFV	Running time (secs)	Optimality gap
1	2	20	50	1880269	72	0.00%	533536	256	0.00%
2	2	20	100	1989466	866	0.00%	985211	86400	2.27%
3	2	20	150	1949517	1020	0.00%	1362194	41718	0.00%
4	2	20	200	1952460	2328	0.00%	1751002	86400	1.31%
5	3	30	50	2515242	24627	0.01%	720117	86400	7.82%
6	3	30	100	2527893	86401	0.25%	1302076	86400	8.01%
7	3	30	150	2533052	86401	0.25%	1813460	86400	3.11%
8	3	30	200	2521654	1833	0.01%	2356421	86400	3.99%
9	4	40	50	2994029	29911	0.01%	855527	86400	5.79%
10	4	40	100	2940061	86405	0.09%	1520247	86400	7.13%
11	4	40	150	3028844	64466	0.01%	2163348	86401	2.49%
12	4	40	200	2915894	86401	0.21%	2756130	86401	3.17%

Table A.2: 70% Fast Movers Dataset: Computational Results

				PAWR			PAWOR		
Scenario	DC	Retailstores	Products	OFV	Running time (secs)	Optimality gap	OFV	Running time (secs)	Optimality gap
1	2	20	50	1892465	58	0.00%	530265	200	0.00%
2	2	20	100	1990559	541	0.00%	990230	86400	1.95%
3	2	20	150	1991037	1583	0.00%	1355366	4220	0.00%
4	2	20	200	1984646	86400	0.62%	1744591	86400	1.43%
5	3	30	50	2517115	8527	0.01%	716056	86401	8.67%
6	3	30	100	2529703	86401	0.04%	1318403	86400	9.25%
7	3	30	150	2535861	86401	0.01%	1803770	86400	3.06%
8	3	30	200	2520158	725	0.01%	2351976	86400	3.90%
9	4	40	50	3006984	8238	0.00%	850021	86400	5.93%
10	4	40	100	*	*	*	1543607	86400	9.18%
11	4	40	150	3047976	86401	0.30%	2144035	86401	2.32%
12	4	40	200	2956814	86401	0.20%	2765527	86401	3.73%

Table A.3: Cost Savings for 30% Fast Mover Dataset

Scenario	DC	Retailstores	Products	Model PAWOR true cost	Model PAWR Cost	% Savings
1*	2	20	50	2085432	1880269	10%
2	2	20	100	2856249	1989466	30%
3*	2	20	150	2650872	1949517	26%
4	2	20	200	2912293	1952460	33%
5	3	30	50	2965898	2515242	15%
6	3	30	100	3255852	2527893	22%
7	3	30	150	3303472	2533052	23%
8	3	30	200	3522627	2521654	28%
9	4	40	50	3536361	2994029	15%
10	4	40	100	3492014	2940061	16%
11	4	40	150	4169902	3028844	38%
12	4	40	200	3235615	2958474	9%

Table A.4: Cost Savings for 70% Fast Mover Dataset

Scenario	DC	Retailstores	Products	Model PAWOR true cost	Model PAWR Cost	% Savings
1*	2	20	50	2178547	1892465	13%
2	2	20	100	2950671	1990559	33%
3*	2	20	150	2739036	1991037	27%
4	2	20	200	2954345	1984646	33%
5	3	30	50	3062186	2517115	18%
6	3	30	100	3393760	2529703	25%
7	3	30	150	3410523	2535861	26%
8	3	30	200	3499175	2520158	28%
9	4	40	50	3584024	3006984	16%
10	4	40	100	-	-	-
11	4	40	150	3442428	3047976	13%
12	4	40	200	3345896	2956814	13%

Table A.5: Optimality Gap Improvement Between 1.5 hours and 24 hours

				30% fastmovers dataset			70% fastmovers dataset		
Scenario	DC	Retail	Products	Optimality gap at 1.5 hours	Optimality gap at 24 hours	Improvement	Optimality gap at 1.5 hours	Optimality gap at 24 hours	Improvement
5	3	30	50	8.22%	7.82%	0.40%	8.99%	8.67%	0.32%
6	3	30	100	8.58%	8.01%	0.57%	10.40%	9.25%	1.15%
9	4	40	50	6.47%	5.79%	0.68%	6.59%	5.93%	0.66%
10	4	40	100	8.72%	7.13%	1.59%	11.10%	9.18%	1.92%

Table A.6: Base Performance: Scenario 6 of 30% Fastmover Dataset

OFV	Runtime (secs)	Gap
2527893	86401	0.25%

Table A.7: Strategy 1 Performance: Scenario 6 of 30% Fastmover Dataset

OFV	Runtime (secs)	Gap
2527893	86402	0.25%

Table A.8: Strategy 2 Performance: Scenario 6 of 30% Fastmover Dataset

OFV	Runtime (secs)	Gap
2527893	86401	0.32%

Table A.9: Strategy 3 Performance: Scenario 6 of 30% Fastmover Dataset

OFV	Runtime (secs)	Gap
2527893	86401	0.27%

Table A.10: Strategy 4 Performance: Scenario 6 of 30% Fastmover Dataset

OFV	Runtime (secs)	Gap
2527893	65583	0.00%

Table A.11: Strategy 4 Performance Comparison

				Default Setting			Strategy 4		
Dataset	DC	Retailstores	Products	OFV	Runtime (secs)	Gap	OFV	Runtime (secs)	Gap
30%	3	30	100	2527893	86401	0.25%	2527893	65583	0.00%
30%	3	30	150	2533052	86401	0.25%	2532764	86402	0.02%
30%	4	40	100	2940061	86405	0.09%	2940061	20732	0.01%
70%	2	20	200	1984646	86400	0.62%	1984646	86403	1.34%
70%	3	30	100	2529703	86401	0.04%	2529703	29404	0.00%
70%	3	30	150	2535861	86401	0.01%	2535861	21086	0.01%
70%	4	40	100	*	*	*	2945079	31049	0.01%

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