Transportation Resource Scheduling in Food Retail Industry

By

Arzum Akkas
BS. Industrial Engineering (2000)
Istanbul Technical University, Istanbul (Turkey)

Submitted to the Department of Center of Transportation and Logistics in partial fulfillment of the requirements for the degree of

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Signature of the Author..............................
Center for Transportation and Logistics
Engineering Systems Division
May 7, 2004

Certified by...
Jarrod Goentzel
Executive Director, MIT-Zaragoza International Logistics Program
Thesis Advisor

Accepted by...
Yossi Sheffi
Professor, Engineering Systems Division
Professor, Civil & Environmental Engineering Department
Director, MIT Center for Transportation and Logistics

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ABSTRACT

The objective of this thesis is to find an appropriate analytical method for scheduling the daily driver tasks in the grocery industry. The goal is to maximize driver utilization.

A “Bin-packing” approach is employed to solve the problem. A Bin-packing problem concerns packing a list of items into the minimal number of unit capacity bins. In our problem, the drivers correspond to the bins and the daily delivery tasks are equivalent to the items, where we use time units to measure bin capacity.

The model is applied to characterize the operation of a grocery company. Several bin-packing algorithms are implemented on two weeks of delivery data, which represent the company’s transportation demand. The driver requirements are calculated and compared with their actual assets. Driver requirements are assessed on a per-day basis, considering the volatility in transportation demand over the course of the week.

The performance of a given bin-packing algorithm is measured by how well it maximizes driver utilization and balances the workload among the drivers.

The model’s solution generated labor savings and proved that better resource allocation is possible by considering the demands of the various dispatching locations and the days of the week. Extension of the current model to capture the time window constraints of the delivery locations is proposed for future further research.

ACKNOWLEDGEMENTS

First, I would like to thank Jarrod Goentzel, my thesis advisor. I greatly appreciate his guidance and the invaluable insights he provided me into the subject.

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Finally, I would like to thank my father, for providing me the opportunity for my studies at MIT. I am doing my best to be a daughter that you would be proud of if you were alive...

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1. THESIS OVERVIEW AND BACKGROUND OF GROCERY OPERATIONS

1.1. Introduction

As economies grow and companies seek increasing market shares, they must also build the infrastructure within their organization to support that growth. Historically, when a company that owns its private truck fleet expands its business, it often grows the fleet, and acquires additional terminals. As the size of the business and scale of operations increase, the efficient coordination of loads throughout the entire network becomes more difficult. In some companies with multiple truck terminals, an operational decision has been made to centralize the coordination and dispatching of all transportation movements within the network.

In the grocery business in particular, there are many challenges associated with fleet management and the opportunity to centrally manage the entire fleet is viewed as a cost and time-savings opportunity. One of the daily challenges involved in fleet management in the retail grocery business is the efficient management of ordering processes, both of inbound products from vendors and outbound to retail stores. Likewise the transportation managers within the organization must coordinate the daily delivery of products from vendors to their distribution centers, as well as the loads of groceries outbound to stores, from 3 to 7 times per week for each store.

Once loads are created and the demand for truck resources is known, drivers and resources (tractors plus dry and refrigerated trailers) are dispatched to pick up and drop off the loads within the network. For some combinations of location and cost factors, third party carriers are also used for both inbound and outbound transportation and some vendors deliver they own products direct to the grocer's distribution centers. These loads must also be efficiently coordinated within the network.

The grocery business is a high-volume, low-margin industry which can benefit, through economies of scale, from many seemingly small cost reduction opportunities. In the management of a retail grocery fleet, there is much room to look for improvements in processes which would yield greater efficiencies and cost savings. In particular, this research will examine methods to effectively coordinate inbound and outbound loads, as well as the efficient matching of fleet resources to these loads.

1.2. Project Outline

The grocery retail partner for this thesis project currently operates with three terminals, one each at its two DCs and one cross-dock facility. The organization knows it can improve the efficiency and costs associated with transportation and strives to centralize dispatching operations and utilize its transportation assets to realize these savings. To fully investigate the challenges and benefits associated with centralized dispatching and resource management, the project was split into two parts which will be the key components to formulating a central transportation operation.

The first component of the project is to focus on methodologies to generate coordinated loads within the network of the retailer, its suppliers, and its approximately 200 stores. This effort will look at several transportation opportunities within the network, considering the private fleet, the fleet of its wholesale supplier and third party carriers. One of the focuses will be on the coordination of inbound and outbound loads to minimize the number of empty miles driven within the network. This part of the project will be described in detail in the thesis titled Planning

Coordinated Loads to Facilitate Centralized Dispatching in the Grocery Industry, written by Nancy Archambault.

The second half of the project will involve the efficient assignment of resources to the coordinated loads. The focus of the project will be to establish a process which determines the appropriate quantity and scheduling of resources needed to satisfy transportation needs over an entire year (through all seasons). Good fleet management is more than determining the optimal route from point A to point B, it involves managing the daily functions of assigning and dispatching drivers and equipment within constraints such as DOT regulations and customer time windows. The costs of these resources are substantial; driver costs can comprise up to 60% of total transportation costs, so investigation of methods to improve these processes can yield appreciable savings. This part of the project will be described in detail in the thesis titled Transportation Resource Scheduling in the Grocery Industry, written by Arzum Akkas.

1.3. Grocery Operations

Supermarkets have traditionally played the role of consolidating a wide assortment of grocery items and then distributing them conveniently close to consumers. Grocers strive to maintain a clean, well-lit environment for customers to peruse an assortment of products and choose the groceries they need to nourish their families. Retail grocers have the responsibility of procuring produce, meat, dairy, frozen and other dry grocery products from suppliers throughout the country. The retailer must then coordinate the transportation of these groceries from the suppliers to its own distribution centers, and from these distribution centers to retail stores. Within the stores, grocery items must be displayed in an appealing manner, and the quality and freshness of each item must be ensured throughout transportation, storage, and its time on the shelf.[1]

More recently, the dominance of discount retail outlets in the United States, as well as the increasingly wide variety of consumer tastes, have forced retail grocers to stock an increasing number of SKUs. As a result, retail grocer's find themselves in a position where they need to devote tremendous attention to the efficient and cost-effective management of their transportation network and resources.

1.4. Transportation Operations

Transportation is a key decision area within logistics management. If the cost of purchased goods is excluded, transportation costs typically range between one-third and two-thirds of total logistics costs.

Inbound transportation in the grocery industry refers to the movement of merchandise from the source of supply to the distribution centers. Outbound transportation is the process related to the movements of the merchandise from the suppliers or the distribution centers to the supermarkets.

1.4.1. Key Decision Areas in Daily Transportation Operations

Carrier Choice

Companies with products to ship need to determine the appropriate strategy to ship loads within the network. Some organizations choose to operate their own fleet of vehicles to move loads, while others outsource all trucking needs to outside carriers. Between these two extremes, there are many possible mixes of carrier choices which could minimize total transportation costs.

[1] Dr. Edward A. Brand, Modern Supermarket Operation, Fairchild Publications, Inc. New York, 1963

Some of the key factors in choosing a carrier involve: operating lanes, cost per mile, total cost, and quality and reliability of service.

Vehicle routing

Vehicles are routed within the network with the goal of reducing transportation costs and improving the customer service. Routes are created by finding the best paths that a vehicle should follow through a network of roads, rail lines, shipping lanes, or air navigational routes that will minimize time or distance is a frequent vehicle routing decision problem. [2]

Vehicle routing and scheduling

Vehicle routing and scheduling in the grocery industry is an extension of the traditional vehicle routing problem. More realistic restrictions are now included such as:

- Each stop may have loads to be picked up as well as delivered (routing inbound & outbound vehicle movements together)
- Multiple vehicles may be used which have different capacity limitations for both weight and cube (volume)
- A maximum total driving time is allowed on a route before a rest period of at least 8 hours (due to company regulations or U.S. Department of Transportation safety restrictions)
- Stops may permit pickups and/or deliveries only at certain times of the day (called time windows)
- Pickups are permitted on a route only after deliveries are made
- Drivers may be allowed to take short rests or lunch breaks at certain times of the day

[2] Ballou, Business Logistics Management, 1992

Scheduling Driver Assignments

There is a separate problem, one step beyond basic vehicle routing, called a driver assignment and scheduling problem. Driver assignment and scheduling is the matching of the right driver to the right load in a sequence of tasks (deliveries) over time, considering the constraints of labor rules, customer windows, and transportation regulations.

1.4.2. Transportation Metrics

To measure performance within transportation operations, a variety of metrics are used. Some of the most widely used metrics are described below.

- Freight cost per unit shipped: Calculated by dividing total freight costs by number of units shipped per period.
- Cost per mile: Calculated by dividing total freight cost by total mileage made per period.
- Outbound freight costs as percentage of net sales: Calculated by dividing outbound freight costs by net sales. Percentage can vary with sales mix, but it is a very good indicator of the transportation financial performance.
- Inbound freight costs as percentage of purchases. Calculated by dividing inbound freight costs by purchase dollars. The measurement can vary widely, depending on whether raw materials are purchased on a delivered, prepaid, or collect basis.
- Percent of truckload capacity utilized: Calculated by dividing the total pounds or volume shipped by the theoretical maximum. Unused capacity is an opportunity for more efficiency.
- Truck turnaround time: This is calculated by measuring the average time elapsed between a truck's arrival at the facility and its departure. This is an indicator of the

efficiency of the lot and dock door space, receiving processes, and shipping processes. This also directly affects freight carrier profits on the business.

- On-time pickups: Calculated by dividing the number of pick-ups made on time (by the freight carrier) by the total number of shipments in a period. This is an indication of freight carrier performance, and carriers' effect on the shipping operations and customer service. [3]
- Percentage of backhauls: This is calculated by dividing the number of backhaul trips to the total number of trips.

1.4.3. Transportation Management Systems

Transportation Management Systems (TMS) are used to manage freight planning and execution. TMS suites have been extended to include all transportation management functions from strategic planning and strategic sourcing of freight through visibility of freight, payment services and audit capabilities. [4]

The table below represents an evaluation of TMS vendors considering the factors, vendor commitment, vendor viability, operational planning functionality, transportation execution and visibility.

[3] www.supplychainmetric.com
[4] 2003 Gartner Research; Market scope: US TMS Vendors

Vendor	Strong Negative	Caution	Promising	Positive	Strong Positive
Elogex		√			
Global Logistics Technologies			√		
i2 Technologies				√	
LeanLogistics		√			
Logility			√		
Manhattan Associates			√		
Manugistics				√	
Nistevo		√			
Oracle		√			
RedPrairie			√		
SAP		√			
Schneider Logistics		√			

Table 1.1. TMS Vendors

Source: Gartner Research 2003

1.4.4. Operating Costs in Food Industry Transportation Operations

In the food industry, the profit margins are approximately one percent after taxes for both food distributors and self-distributing retail chains. So, it is extremely important to manage costs in transportation, because savings go directly to the total profits of the corporation.

By managing fleet assets more effectively than competitors, grocery companies can seize the opportunity to obtain more business and make more money. In the long term, the most efficient transportation fleet that offers superior customer service will dominate its operating territory. [5]

The expenses in transportation operations can be categorized into five groups:

- **Driver Costs – Direct Labor***:* Wages, benefits, welfare, insurance, travel.
- **Administrative Costs - Indirect Labor***:* Supervision, clerical, benefits, supplies.

[5] 2003 Food Industry Transportation and Fleet Maintenance Report

- **Fixed Costs**: Licences, insurance, depreciation, taxes, loading supplies.
- **Operating Costs**: Maintenance, tires, fuel.
- **Outbound/Inbound Costs:** Services.

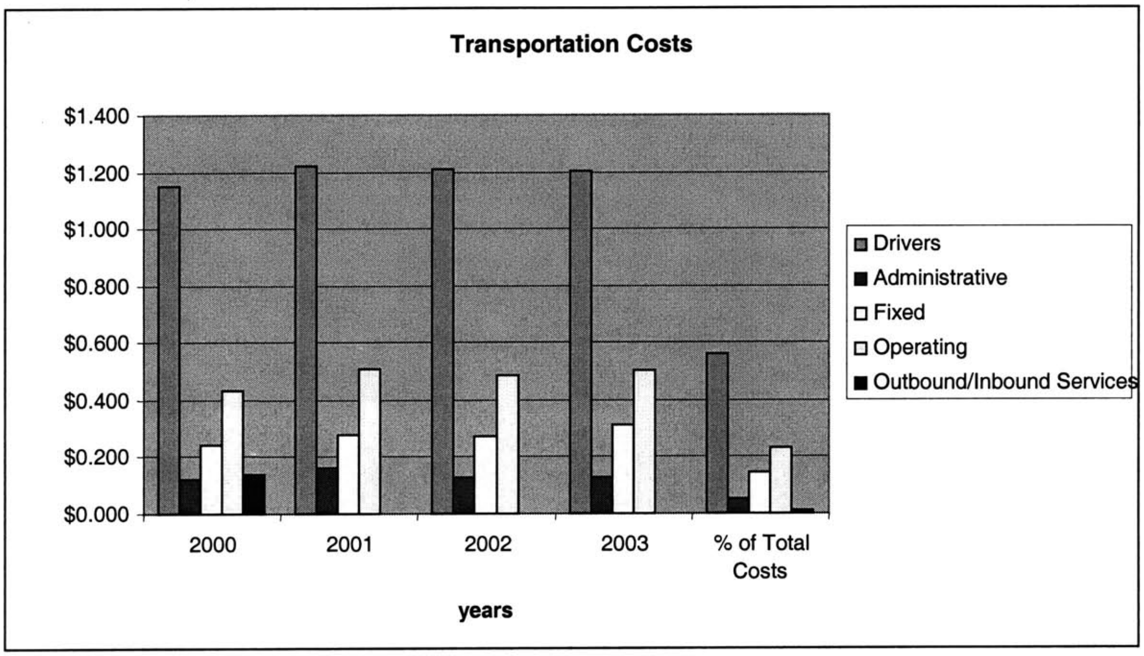

Figure 1.1. Transportation Cost Breakdown

Source: FMI Transportation Benchmarking Report

1.4.5. Trends and Benchmarks in Food Industry Distribution in the US

Several trends in food industry transportation are observed in the 2003 Food Industry Transportation and Fleet Maintenance Report; some of the observations and the data which support them are present in this section.

Outsourcing

More companies continue the move to outsourcing the transportation function, seeking lower operating costs to serve their retail customers while reducing capital investment for rolling stock.

The entire food industry is critically analyzing the transportation function, seeking to find the proper balance between private-fleet ownership and outsourcing the delivery function. Wall Street exerts tremendous pressure to invest capital into resources that yield increased sales and profits. As a result, many firms are minimizing the amount of funds directed to transportation equipment. Many distributors also seek to reduce labor costs by outsourcing the driving function.

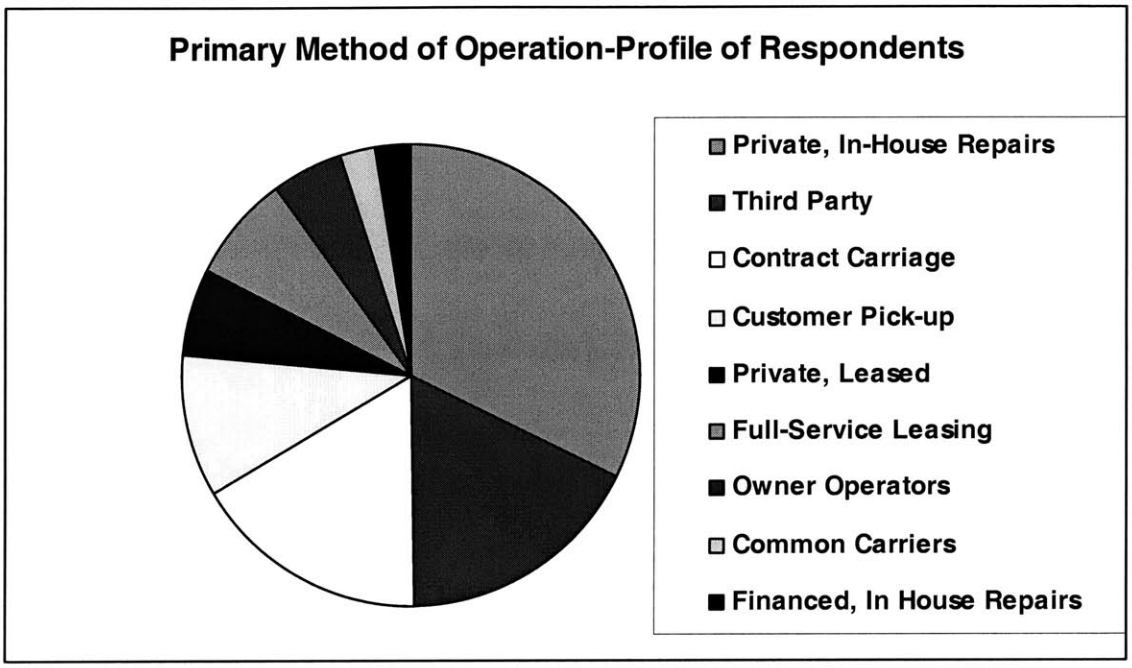

Figure 1.2. Food Industry Trend Report Survey Respondents

Improvements in Key Expense Performance Indicators

Due to the participation of several large food distributors that serve big retail chains and the consolidation of fleets into larger operations, there has been improvements in key performance indicators in the food retail industry.

Key Performance Indicator	Trend	Reason
Cost per Mile	Down	Increase in larger fleets, higher volume operations
Cost per Route	Down	More deliveries to high-volume stores closer to DC
Cost per Case	Down	Larger volume accounts, more cases delivered per stop
Stops per Route	Down	
Cases per Stop	Up	
Cases per Route	Up	Bigger trailer, smaller cube cases
Weight per Route	Up	
Sales per Case	Up	Increase in value-added products, refregirated & frozen
Cost per Stop	Down	Larger order size, to larger volume stores
Miles per Route	Same	More deliveries to stores closer to DC
Weight per Case	Up	Smaller cases for ergonomic improvements

Table 1.2. Key Performance Indicator Trends

Source: FMI Transportation Benchmarking Report

Industry Consolidation

The number of food distributors/retailers continues to shrink as the food industry seeks to achieve economies of scale through consolidation. Several large food retailers in the past year have closed numerous divisions and stores throughout their systems, seeking to eliminate unprofitable stores.

These consolidations reduce the number of fleets in the industry, as the larger companies absorb the new business into their existing supply chain infrastructure.

Wal-Mart Expansion

The rapid growth of Wal-Mart continues to be the biggest influence in the industry. In the short period of 12 years, Wal-Mart has become the largest food retailer in the US and is currently growing sales in food categories at a rate of $8 billion every year. To support its retail environment, Wal-Mart uses its own logistics system.

E-commerce

Many technological developments connected to the internet could have a significant impact on transportation and traffic functions of the food business as auctions, instantaneous bidding on purchases, extranets, and electronic information exchange, RFID, etc., revolutionize the way business conducted.

Changing Consumer Preferences

Customers frequently change their shopping preferences and as a result, retail food distributors struggle to service new channels of distribution, such as Internet home delivery, drug stores and discount stores. The net result of all of this new competition is a reduction in sales for the traditional supermarket segment, which also has a negative impact on many food distributors and self-distributing chains.

All of these challenges affect the transportation function since these new customers and new relationships change previously established delivery patterns. The higher volume stores will seek more full-loads and more frequent drop shipments, while the smaller venues will require smaller shipments with more labor-intensive stocking procedures.

As a result, food distributors are experiencing tremendous volatility in their business. Changing business environments force retailers to continuously review their supply chain strategies to seek efficiency improvements and cost savings. Before examining opportunities for the retail partner in this project, the company's current practices will be described in Chapter 2: Current Operations.

2. CURRENT OPERATIONS

This thesis project was completed in a partnership between two MIT Masters of Engineering candidates and a retail grocery store. The name of the grocer will be omitted from associated thesis documents and selected numerical and financial figures will be disguised. Throughout the thesis documents, the retail grocer who partnered with MIT for this project will be referred to as ABC grocer. The grocer's private will be referred to as RGPF (Retail Grocer's Private Fleet), and the grocer's wholesale supplier will be referred to as wholesaler YZ.

The purpose of the following document is to describe our current understanding of ABC operations, ordering processes, and transportation systems.

2.1. ABC

ABC is a grocery retailer with approximately 200 stores throughout several U.S. states To present a brief snapshot of the scope of ABC sales and transportation network,

As Percentage of Sales:	FY03	FY04*	FY05*
RGPF (ABC) Expenses	0.72%	0.71%	0.65%
YZ Freight	0.23%	0.23%	0.24%
Total ABC Freight Expenses	.96%	.93%	.90%

*projected

Table 2.3. Outbound Transportation-related Expenses (in percentages of total sales) provides some key financial figures. Specific details of the network and carriers will be explained later in this document.

As Percentage of Sales:	FY03	FY04*	FY05*
RGPF (ABC) Expenses	0.72%	0.71%	0.65%
YZ Freight	0.23%	0.23%	0.24%
Total ABC Freight Expenses	.96%	.93%	.90%

*projected

Table 2.3. Outbound Transportation-related Expenses (in percentages of total sales)

ABC overall goal is to provide quality groceries to retail stores so that they are available to customers when the customers need them and at a reasonable price. While providing this service, ABC seeks to minimize operating and administrative costs while maximizing revenue. ABC supply chain network is an essential tool which supports the provision of goods to customers, as described in the next section.

2.2. ABC Supply Chain

2.2.1. ABC Stores & Distribution Centers

To supply its retail stores, ABC owns and operates two distribution centers (DCs) and one cross-dock location. Additionally, four distribution centers owned and operated by YZ Wholesale Grocers directly service ABC retail stores, as described below (and illustrated in Figure 2.2: Distribution Centers). The two distribution centers will be referred to as ABC DC#1 and ABC DC#2; the cross-dock will be refered to as ABC DC#3. ABC DC#2 stocks produce, meat, fish, floral, and deli (i.e.: non-dairy perishables) products for all ABC stores. ABC DC#1 stocks fast-moving grocery (FMG) items (for *118* stores) and frozen food items (for *84* stores). ABC DC #3 serves as a cross-dock location to redistribute products arriving from 12-13 vendors on to ABC trucks for store delivery that same day. No products are stored in ABC DC#3 for any length of time, and items stored at YZ or ABC DCs are not involved in the traffic through this cross-dock.

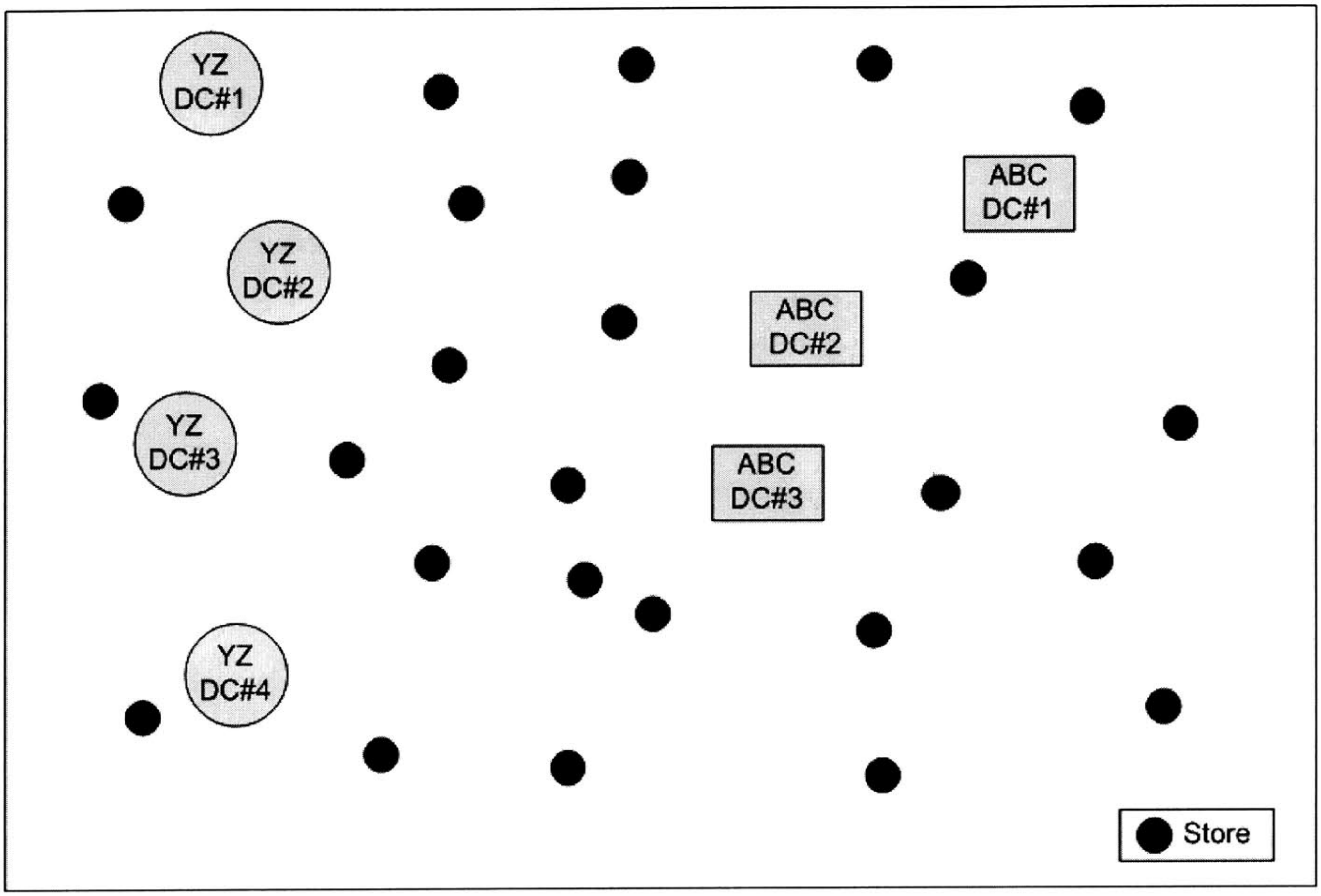

Figure 2.3. Distribution Centers

2.2.2. YZ Distribution Centers

ABC stores which are not serviced directly by an ABC DC or cross-dock for a particular item receive deliveries from YZ Wholesale Grocers. YZ Wholesale Grocers purchases grocery items directly from vendors and then sells them to grocery store chains, including ABC and many of its competitors. YZ provides several different classes of products to a number of different portions of ABC stores. The YZ distribution centers which serve ABC stores will be reffered to as YZ DC#1, YZ DC#2, YZ DC#3 and YZ DC#4. YZ DC#4 provides FMG items to *49* ABC stores and SMG items to all ABC stores. YZ DC#3 provides frozen food products to *117* ABC stores. YZ DC#2 supplies dairy products for all ABC stores. YZ DC#1 supplies FMG items to 34 ABC stores.

2.2.3. Network Clarifications

- Slow moving grocery items are supplied to all ABC stores from YZ DC#4. Those ABC stores which receive FMG products from YZ DC#4 receive their SMG with their FMG deliveries. For ABC stores which receive FMG from YZ DC#1, YZ trucks transport the SMG items for those stores from YZ DC#4 to YZ DC#1 for cross-docking before FMG deliveries are made out of YZ DC#1. Likewise, for ABC stores which receive FMG from ABC DC#1, YZ trucks transport the SMG items for those stores from YZ DC#4 to ABC DC#1 for cross-docking before FMG deliveries are made out of ABC DC#1.
- For some stores, dairy from YZ is picked up at YZ DC#2 and taken to ABC DC#2, to be incorporated with the perishable loads for those stores.
- Currently, besides above bulleted point, all YZ groceries are delivered to ABC via YZ trucks. In the past RGPF (ABC privately owned fleet) has occasionally picked up some of the loads and this option is being considered for re-implementation

	Managed By		Function	
Distribution Center	**ABC**	**YZ**	**Storage**	**Cross-dock**
ABC DC #2	✓		✓	✓
ABC DC #3 (Cross-Dock Facility)	✓		(limited, currently unutilized, storage capacity)	✓
ABC DC#1	✓		✓	✓
YZ DC#1		✓	✓	✓
YZ DC#2		✓	✓	
YZ DC#3		✓	✓	
YZ DC#4		✓	✓	

Table 2.4. Distribution Center Management and Functionality

2.2.4. Transportation

ABC is currently working with two contracted carriers and a number of 3rd party carriers. In the table below, an 'Inbound' trip represents the hauling of products from vendor locations to ABC DCs while an 'Outbound' trip brings mixed pallets of products from a DC direct to retail stores for immediate sale.

	Inbound	**Outbound**
RGPF	✓	✓
YZ		✓
3rd party carriers	✓	x

Table 2.5. Carriers

2.2.4.1. Outbound Transportation

Outbound carrier movements involve the transportation of groceries from DCs (YZ or ABC) and cross-dock locations to individual retail stores. The primary carriers for store delivery are YZ and RGPF; occasionally RGPF contracts the work out to a 3rd party to pick groceries up at an ABC DC and deliver them to stores.

2.2.4.1.1. RGPF

One of the two contracted carriers is ABC's private fleet, RGPF (Retail Grocer's Private Fleet). RGPF is a subsidiary of ABC headquartered near ABC DC#1. RGPF is responsible for outbound transportation from ABC DCs to ABC stores, from certain cross-dock points to ABC DCs, and from ABC ABC DC#3 cross-dock to ABC stores. ABC pays $1.90/mile to RGPF for all transportation services rendered; the miles driven by RGPF are broken down into two categories: store delivery miles and backhaul miles. The cost is actually calculated by determining total RGPF expenditures per period and then dividing by the total miles driven. The figure is always close to $1.90, sometimes varying slightly from $1.85 per mile to $1.95 per mile. The costs are calculated, re-examined and updated every quarter. RGPF serves for both inbound and outbound transportation.

RGPF uses software called Mobius TTS for tracking the mileages. Because the routing software that ABC is using, Manugistics, does not have reliable mileage information, ABC pays RGPF according to the mileage information that Mobius TTS provides. $1.90 is applied to the total distance that RGPF trucks make including line hauls.

RGPF has 3 terminals which are located in ABC DC#1, ABC DC#2, ABC DC#3. The graph below shows the number of assets that are allocated to each of the terminals.

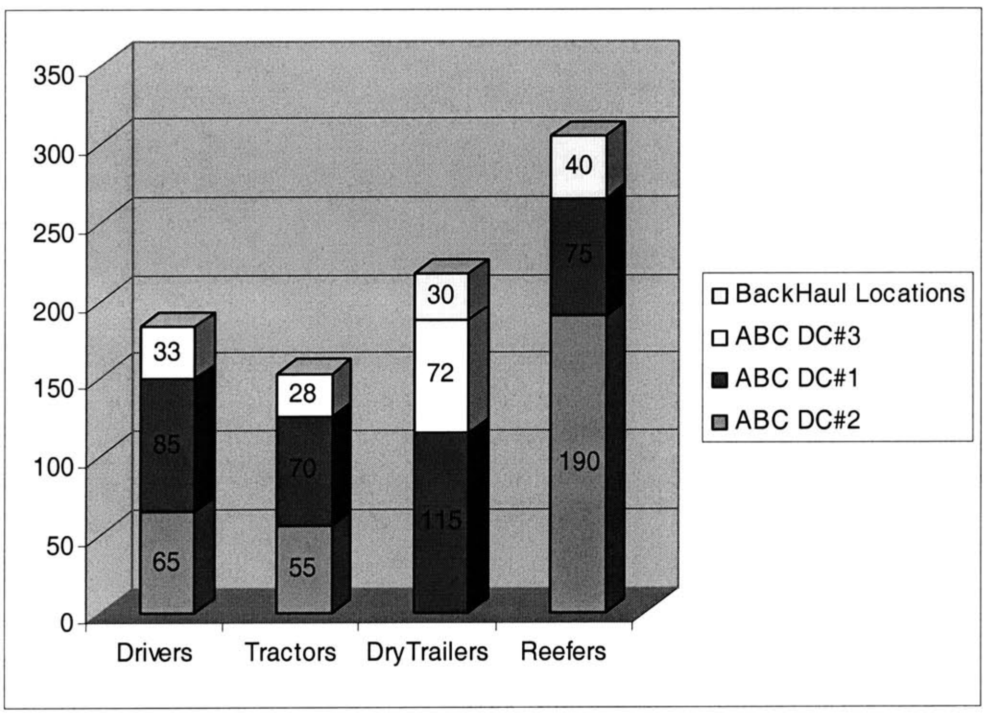

Figure 2.4. RGPF Assets by Location

2.2.4.1.2. YZ

The other carrier that serves ABC is YZ Wholesale Grocers. YZ is one of the suppliers of ABC and responsible for outbound transportation from YZ DCs to ABC stores and certain cross-dock points. (See above description of slow-moving grocery cross-dock.) For outbound transportation, depending on the type of grocery, the area is divided into regions, and each region is assigned to either YZ or RGPF transportation services.

YZ charges ABC based on two price components:

- upcharge rate (based on total value of goods shipped)
- delivery rate (based on total value of goods shipped)

The upcharge rate is the rate that YZ charges ABC for storing and selecting the goods in its DCs. If RGPF delivers YZ stored good, YZ still charges ABC for the upcharge rate. The upcharge rate is multiplied by the value of goods stored and shipped to determine the total warehousing and transportation charges. Rates are negotiated as part of the contract between YZ and ABC; current contract rates were established in October 2003 and will expire in October 2008. The upcharge rates are summarized in the table below.

YZ Distribution Center	Type of grocery item	Destination	Cross-dock (if applicable)	Warehousing Upcharge	Delivery Upcharge	Warehouse picking fee
YZ DC#1	FMG	34 stores		1.94%	1.63%	
YZ DC#2	Dairy	All stores		1.20%	1.68%	
YZ DC#3	Frozen	117 stores		1.19%	1.58%	
	FMG	49 stores		1.99%	0.97%	
	SMG	49 stores		1.97%	1.01%	
YZ DC#4	SMG	118 stores	ABC DC#1	1.99%	1.13%	$0.032/case
	SMG	34 stores	YZ DC#1	2.03%	1.38%	$0.052/case

Table 2.6. YZ Upcharge Rate Detail

The breakdown of movement volume by carrier is depicted in the following table. The figures in Table 5 were calculated based on historical data for weekly load volume outbound from each DC.

Origin/ Carrier	RGPF (fraction of that which is outsourced)*	YZ
ABC DC#1 Grocery	18	--
ABC DC#1 Frozen	4	--
ABC DC#2	31.5	--
ABC DC#3	6	--
YZ DC#1	--	5
YZ DC#2	--	12
YZ DC#3	--	11
YZ DC#4	--	9
YZ Cross-dock – DC#4 to ABC DC#1	--	2
YZ Cross-dock – DC#4 to YZ DC#1	--	1
YZ DC#4 Slow	--	.5

Table 2.7. Outbound Movements by Carrier (% of Total Outbound)

Note: Overall, within RGPF miles, approximately 10% are outsourced.

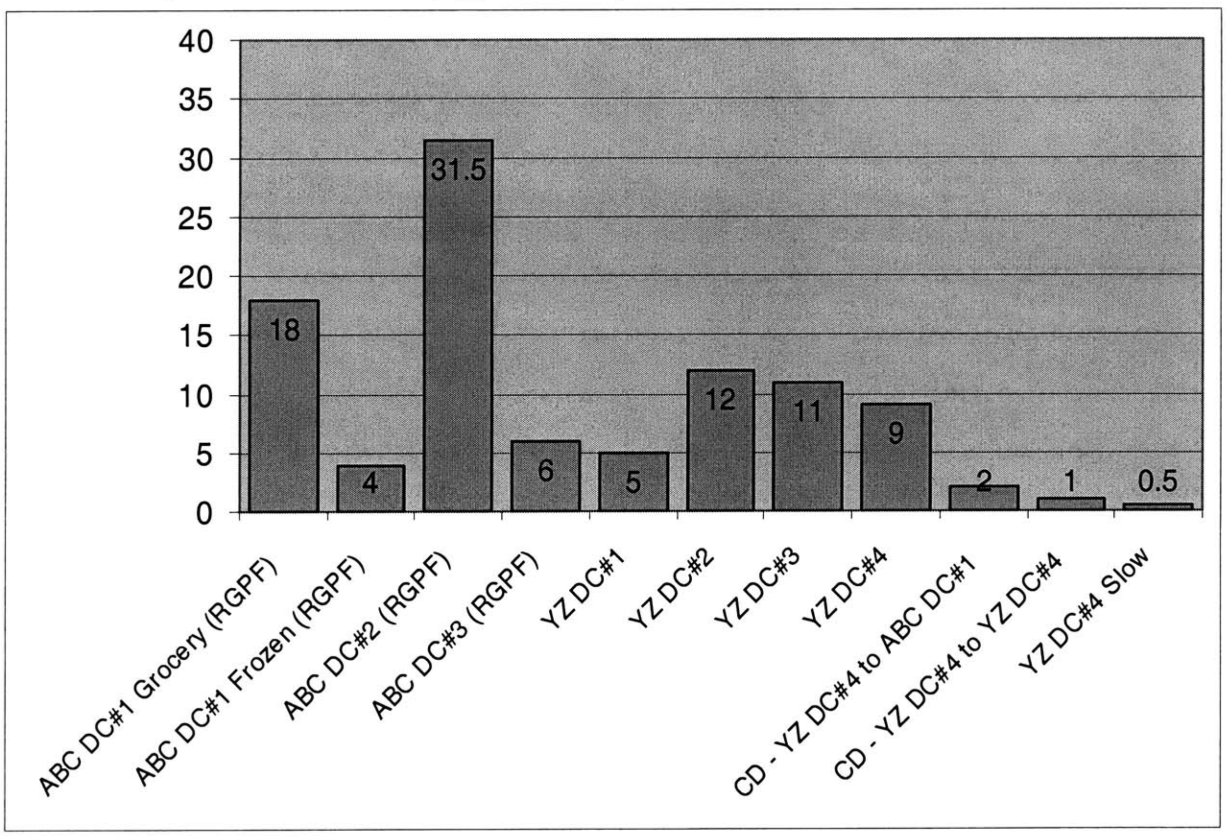

Figure 2. 5. Outbound Carrier Movements (% of Total Outbound)

2.2.4.2. Inbound Transportation

ABC currently works with 37 3rd party carriers for inbound transportation. This number can vary year to year. These carriers are mostly preferred for the deliveries from the vendors which are located outside of the states where ABC stores are located, but occasionally 3rd party carriers are used within the region as well. Third party carriers are utilized within the region if the RGPF fleet does not have the appropriate equipment to transport the product (i.e. a paper supplier requiring 53 foot, high-cube trailers) or if RGPF cannot transport the goods as cheaply as a third party carrier could. There are a total 481 (city-to-city) lanes defined as inbound routes within ABC supplier network. Annually, ABC gives expected volumes per lanes to the carriers, and the carriers declare their prices based on this given information. Then, ABC decides whether to work with any particular carrier for the given lane.

The carrier selection for truck movement is made daily. The dispatcher looks at the price information at ABC Transportation Management System (TMS) and decides which carrier to assign to a group of orders.

The volume of movements for each carrier is represented in the following two tables.

Destination/ Carrier	**RGPF (fraction of that which is outsourced)***	**Contracted Third Party Carriers**	**Vendor Delivery**	**Percent of total inbound volume**
ABC DC#1 Grocery	5% (10%)*	5%	21%	31%
ABC DC#1 Frozen	1% (10%)*	2%	7%	10%
ABC DC#2	9% (10%)*	21%	27%	57%
Total	15%	28%	55%	98%

Table 2.8. Inbound Movements by Carrier (% of Total Inbound)
Note: Overall, within RGPF miles, approximately 10% are outsourced; values add to 98% due to rounding errors

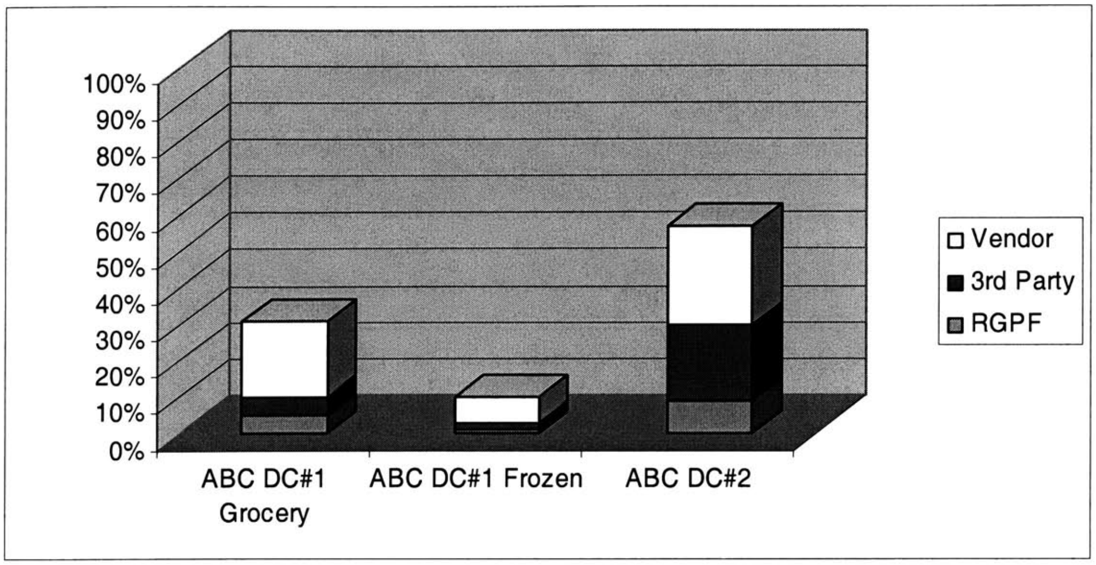

Figure 2.6. Inbound Carrier Movements (% of Total Inbound)

Weekly Total Movements (Low/High)	Jan – Apr	May - July	Aug - Oct	Nov - Dec
Inbound	1150			
Outbound RGPF				
ABC DC#3	119/164	101/150	123/154	128/167
ABC DC#1 Grocery	375/445	395/476	418/505	261/500
ABC DC#1 Frozen	75/102	88/111	85/98	79/127
ABC DC#2	602/862	735/1054	661/800	564/912
Outbound YZ	860			

Table 2.9. Approximate Average Weekly Total Carrier Movements

2.2.5. Carrier Utilization

The current utilization of RGPF trailers for outbound movements (deliveries to stores) is outlined in the table below. The term 'cube' refers to volume of product shipped,measured in cubic feet.

	Maximum Cube	Expected Cube	Actual Cube	Cube Utilization
ABC DC#2	1540	1350	1143	74.2%
ABC DC#1 Grocery	1800	1750	1447	80.4%
ABC DC#1 Frozen	1540	1350	1105	71.8%
ABC DC#3	1800	1550	938	53.2%

Table 2.10. RGPF Outbound Cube Utilization

	Cube Utilization
ABC DC#2	61%
ABC DC#1 Grocery	50%
ABC DC#1 Frozen	75%
ABC DC#3	95%

Table 2.11. RGPF Inbound Cube Utilization

2.3. Operational Processes & Information Systems

2.3.1. Ordering – Non-Perishables

To replenish stock of non-perishable items to the stores, ABC uses an in-house IT system called Supervised Re-Order (SRO). Orders are created via automated processes for most stores and by hand for some stores. Orders for non-perishable items are run on a daily basis. Quantities are based on previously established forecasts, knowledge of sales and promotion, and current inventory levels.

2.3.2. Ordering – Perishables

For the ordering of perishable items ABC is using an internally developed system called Perishable-Re-Order (PRO). The ordering process covers a 3 week cycle. In the 1st week, buyers finalize product recommendations for the 3rd week, and stores review these recommendations. In the 2nd week, stores begin keying in store amendments, and then they are transferred to the PRO system. Buyers can view amendments in the PRO system. In the 3rd week the deliveries to the stores are made, and stores have a chance to make adjustment 2 days in advance of the delivery.

2.3.3. Ordering Process - Inbound

ABC purchases grocery items directly from vendors to supply its two DCs and one cross-dock facility; these vendors are located all over the United States. Every Monday, orders are downloaded from POM to LIMS, new orders are created, and carriers are assigned to the transportation of each order from supplier location to ABC DC. The orders are coordinated so that deliveries arrive over the course of a week, in volumes that can be handled by the staff on hand at the DC on the day and time of arrival.

In the procurement of each product, there are different costs associated with each of the possible transportation options. ABC reviews the costs of each option annually and updates the information in TMS so that transportation decisions can be made based on current data. The three possible transportation options associated with delivery of groceries to distribution centers are outlined below:

- Delivery: The vendor delivers the product to one of ABC distribution centers and ABC is charged the cost of delivery
- Pickup via RGPF: A RGPF truck travels to the vendor pick-up point for the ordered item, retrieves the product, and delivers it to the appropriate ABC facility.
- Pickup via Third party carrier: ABC hires third party transportation provider to pick up the product at the vendor's pick-up point and then deliver it to the appropriate ABC facility.

ABC utilizes several IT systems to store the data relevant to these decisions and to facilitate the ordering and carrier choice processes. Below is a representation of those systems.

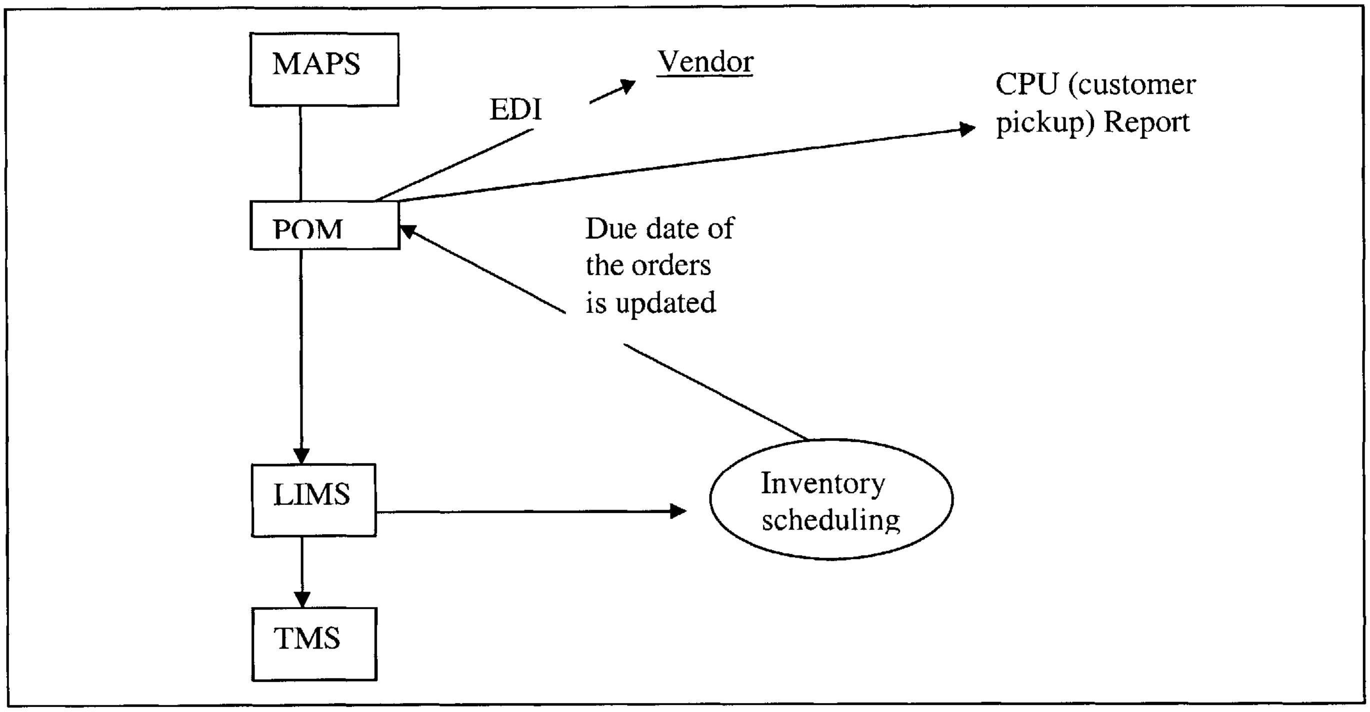

Figure 2.7. Inbound Order Process Information Flow

2.3.4. Ordering Process - Outbound

The information flow between the systems is illustrated below.

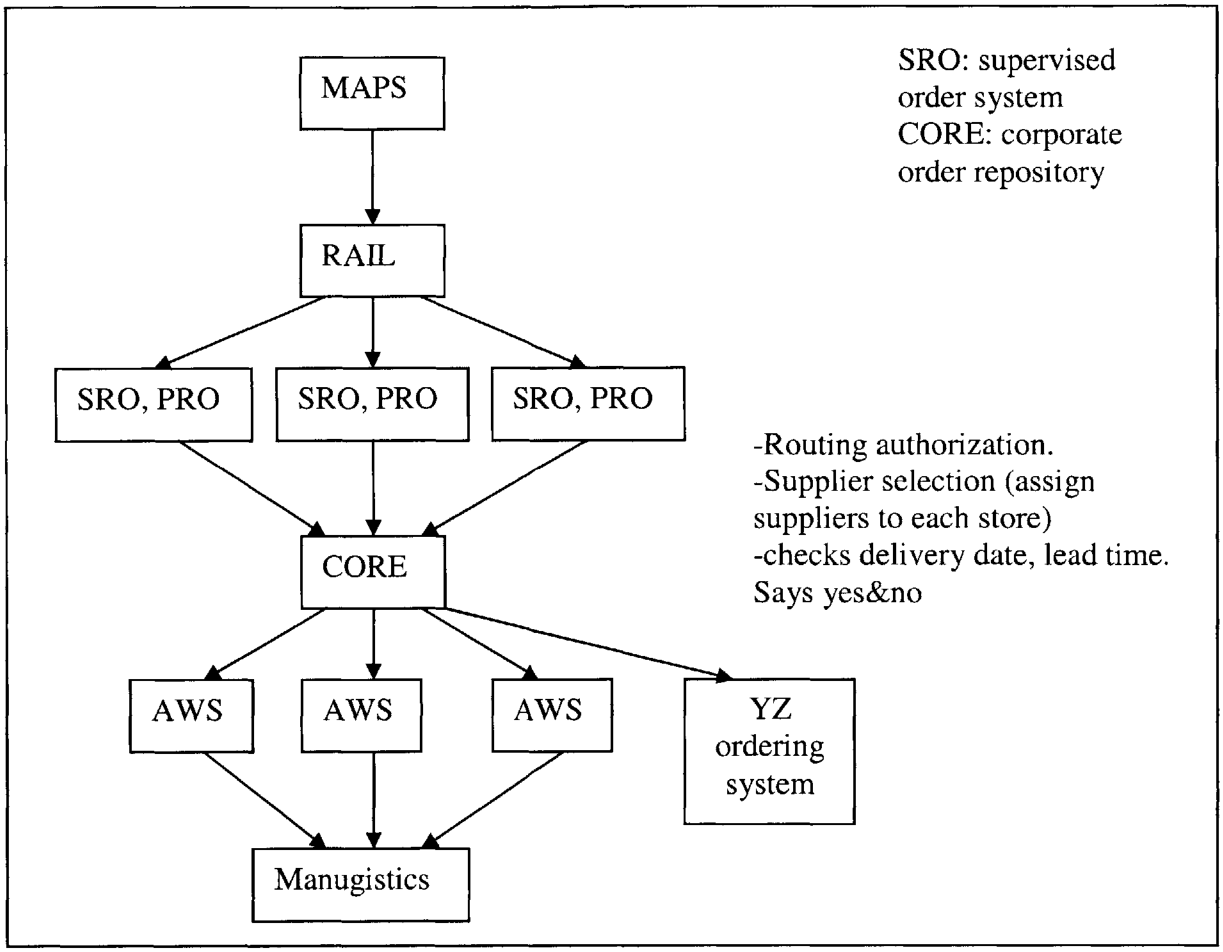

Figure 2.8. Outbound Order Process Information Flow

The following figure depicts the flow of information and decision making processes throughout the transportation function, from order placement to product delivery.

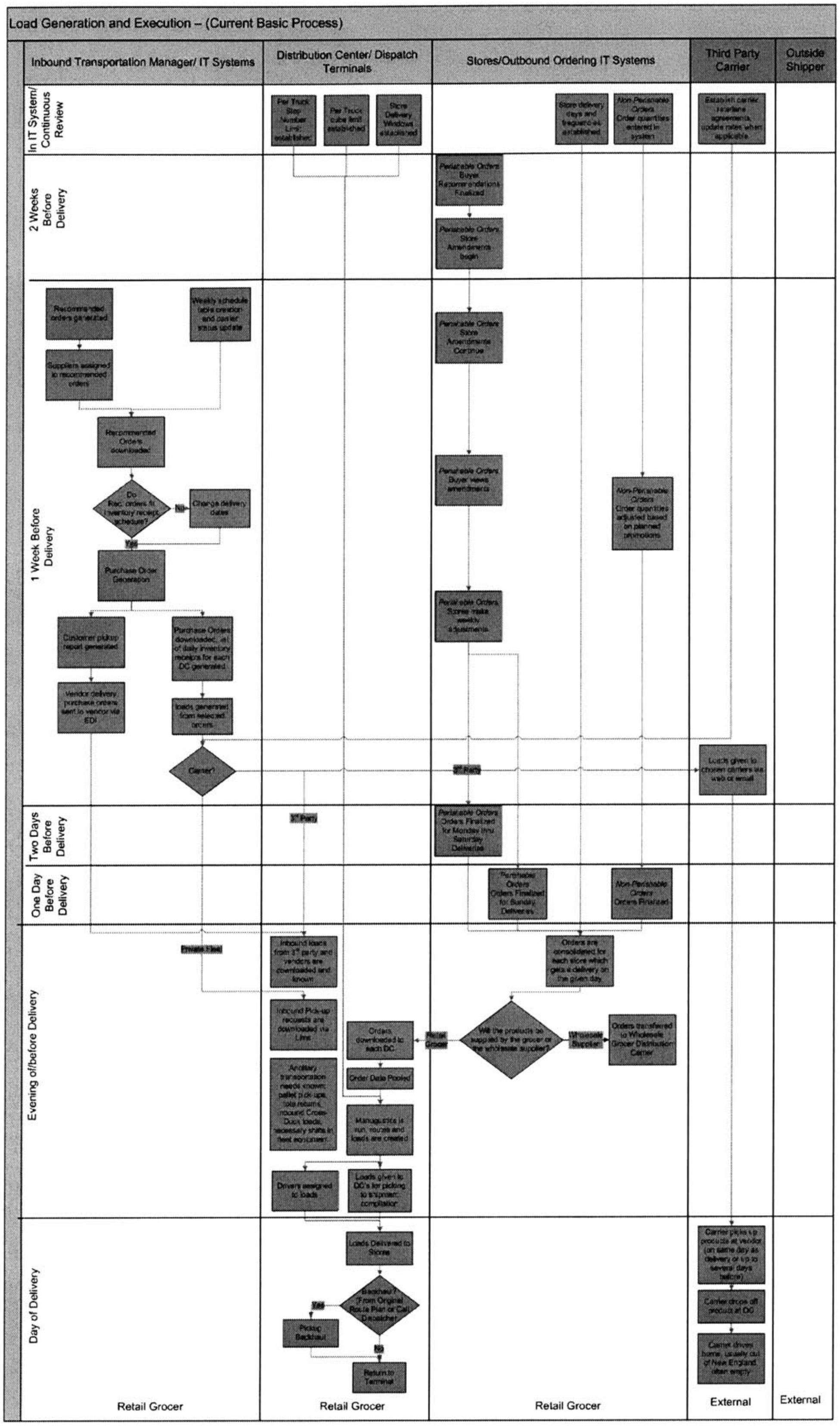

Figure 2.9. Information Flows Through the Transportation System

3. TRANSPORTATION RESOURCE SCHEDULING

3.1. Transportation Resource Scheduling Problem

The scheduling problem can be described as the assignment of the tasks (jobs) to resources in a scheduled manner where constraints, such as the time windows of the tasks and resources, are met.

The transportation resource scheduling problem is the assignment of the loads to drivers, considering the driver rules, such as maximum working hours, and the time windows of the load's orders.

3.1.1. Review of Literature

Scheduling problems in transportation are mostly studied for public transportation, the rail industry, and the airline industry, since scheduling greatly affects cost in the transportation operations in these industries.

We can approach the problem in several ways. Task scheduling is one of the methods that could be applied to transportation resource scheduling problems.

Rafaeli and Mahalel (2002) studied a heuristic approach to task scheduling which concerned delivery fleet scheduling, maintenance crew, machine scheduling, and personnel scheduling. [6] The work deals with scheduling a group of tasks to a predetermined number of resources. The tasks are characterized by fixed starting times and known durations. A task cannot be performed simultaneously on more than one resource, each resource having a capacity of one task at a time. The algorithms that were developed have been implemented on a microcomputer and were used to solve transportation-resource problems.

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[6] Rafaeli Dolev, Heuristic Approach to Task Scheduling: 'weight' and 'improve' algorithms

Raymond and Daren investigate (2003) a stochastic optimization framework for driver task assignment. [7] The tasks must be started within certain time windows and their servicing times are uncertain while the decisions are made over time. The problem is formulated in a stochastic optimization structure with the objective of minimizing the costs of current driver-task assignment and the expected future costs. A time-window sliding solution procedure is developed to estimate the expected future costs by solving the minimum cost flow problems iteratively.

Crew scheduling could be another approach for transportation resource scheduling problems. Crew scheduling is the problem of assigning crews to basic tasks under several legality constraints while attempting to minimize the company's operational cost. [8] It is widely used for large transportation companies such as airlines and railways.

Crew scheduling uses set partitioning models. The problem of choosing the best tours to cover the loads is a classical example of a set partitioning problem, where we have a set of tours, and we wish to choose the best tours from his set to maximize profits or minimize costs, subject to the constraint that we cannot choose two tours to cover the same load. This problem can be covered as a classical linear programming problem. We can use very general rules to determine which tours should be considered, i.e., if we want to get a driver home, then we can require that only tours that return a driver home be considered.

In a set of surveys, Goumopoulos and Housos (2003) focused on trip generation process, the most time consuming phase in the solution process of crew scheduling problems. They explore an efficient trip generation method that utilizes a rule modeling system in order to reduce the corresponding search space. Special pruning rules are defined using a high-level rule

[7] Raymond Cheunng, A Time-window sliding procedure for driver task assignment with random service times, 2003
[8] Goumopoulos Christos, Efficient trip generation with a rule modeling system for crew scheduling problems, 2002

language, and the legality checking mechanism is used to cope with the vast amount of legality checks required by the trip generator.

Cynthia Barnhart and Brian Rexing, from Massachusetts Institute of Technology, investigate airline fleet assignment considering time windows constraints (2000). They present a generalized fleet assignment model for simultaneously assigning aircraft types to flights and scheduling flight departures. The model assigns a time window to each flight and then discretizes each window, allowing flight departure times to be optimized. Two algorithmic approaches are developed to solve large scale problems, and they are tested using data from a major U.S. airline. In every test scenario, the model produces a fleet assignment with significantly lower costs than the basic model, and, in a separate analysis, the model is used to tighten the schedule, potentially saving aircraft.

Even though crew scheduling could be an option, it does not apply well to truck fleet scheduling. Crew scheduling employs hard and complicated algorithms concerning to cover every network of links by crews focusing on origins and destinations. On the other hand, truck fleet scheduling problem is relatively simple, planning the schedules across discrete sets of trips with the same origins and destinations. Thus, the truck fleet scheduling problem is more like a task scheduling problem.

3.1.2. Driver Scheduling Software Solutions

The tremendous complexity of this type of scheduling makes it very difficult to master without decision-support solutions. Some of the benefits of such decision support system are:

- Improve a transport operation's reactivity and service quality
- Increase driver utilization and, as a result, keep the labor costs down
- Improve both customer and employee satisfaction

The transportation management systems market is mostly focused on route planning solutions, where orders are scheduled into routes/loads. Typically drivers are not assigned in these systems and are instead left for dispatchers. Advanced decision support systems for transportation resource scheduling is yet an emerging idea in the software industry. However, there are a few software vendors in the market, offering driver scheduling solutions for the trucking operations:

ILOG Company develops enterprise software components and services for business rule management, optimization and visualization. As a part of their solutions for transportation and travel industry, crew and driver scheduling is a component in the planning and scheduling tool. This software focuses on optimization, offering various methods and robust performance. However, there is not a user interface for easily modeling truck operations.

Manugistics is one of the two biggest supply chain management software solution providers in the market. Networks Resourcing is the name of their tool for the management of drivers, tractors, and trailers as a part of the fleet management solutions. It generates optimum resource schedules within the constraints of labor rules, customer windows and transportation regulations. It is a recent addition to their transportation software suite.

InterGis creates routing, scheduling and dispatching solutions for the assignment of workers or pick-up/delivery operations to customer locations. Their core product is Visual Control Room, a software system that provides users with optimal schedules and routes, based on miles, costs, customer needs, and work rules.

3.2. Why Driver Scheduling is Important for Grocery Industry?

According to a recent transportation benchmarking report conducted by Food Marketing Institute (FMI), driver costs comprise almost 60% of the total transportation costs in the food retail industry.

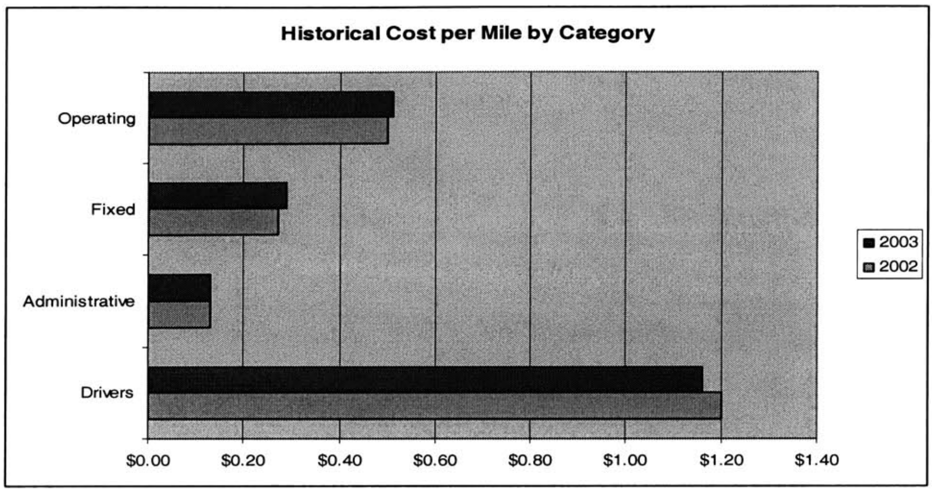


Figure 3. 1. Transportation cost per mile per category

The above graph illustrates the changes in transportation cost per driven mile over the years 2002 and 2003. The costs are categorized into 4 main groups: operating, fixed, administrative, and drivers. As reflected in the graph, driver costs is the biggest cost center in the transportation operations, which is consecutively followed by operating costs (maintenance, tires, fuel), fixed costs (licenses, insurance, depreciation, taxes), and administrative costs.

Since driver costs generate about 60% of the total costs, any improvement in the driver operations will have a big impact in the total transportation costs. There is opportunity to reduce the number of drivers, since they typically take multiple loads per day, each of which varies in length. Proper assignment of loads to drivers could reduce the number of drivers required. Therefore, it becomes very important to efficiently manage the scheduling of the driver activities in order to utilize the drivers and consequently to drive down the overall transportation costs.

However, in the grocery industry, more technology and effort is used in the routing activities (turning store orders into loads) than in resource scheduling (assigning trucks, trailers, and drivers to the loads). Typically resource scheduling is performed by individuals at each depot in an ad hoc and dynamic manner. Currently at ABC, driver schedules are generated manually without the help of an analytical tool.

3.3. Current Scheduling Practice at ABC

Bidding on the working schedules

At the beginning of each year, the drivers bid according to their seniority for the daily start times and the weekly days off. Every driver works five days in a week. Most drivers start working early in the morning around 6am, while few of them start at later hours such as 18:00 or 22:00. Once it is set up, these schedules are followed by the drivers until the end of the year. According to the 2004 bidding results, the driver availability at each dispatching location is as below:

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ABC DC#1	51	52	66	61	64	50	21
ABC DC#2	51	55	51	58	52	54	40
ABC DC#3	20	22	23	25	23	16	11

Table3. 1. Driver availability in the three dispatching locations

The highest number of drivers was assigned to Wednesday in ABC DC#1, to Thursday in ABC DC#2 and ABC DC#3.

The load density for year 2003 -in number of loads- throughout the week at each dispatching locations is as follow:

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
ABC DC#1	76.4	67.8	90.7	81.9	71.5	79.4	72.0
ABC DC#2	114.3	87.8	99.7	124.9	129.7	117.9	84.9
ABC DC#3	14.7	26.8	28.5	26.7	19.5	20.9	NONE

Table3. 2. Load density in the three dispatching locations

The transportation demand shows different patterns in three different dispatching locations. The busiest day of the week in ABC DC#1 is Wednesday, where it is Friday in ABC DC#2 and Wednesday in ABC DC#3.

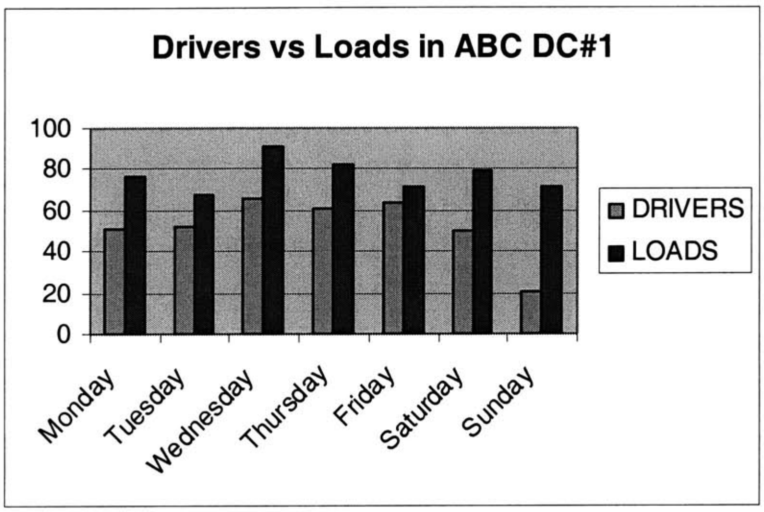


Figure 3. 2. Available drivers versus load density in ABC DC#1 facility

The above graph shows us the number of available drivers and average number of loads in the year 2003 at ABC DC#1 facility. The data is broken into the days of the week. The graph helps us to comprehend the volatility of the transportation demand over the course of the week and compare it with the current driver resources. We can clearly observe here that even though Sunday is a busy day, few drivers were allocated for this day which might cause a problem in covering all the delivery tasks with the current available full time drivers. Moreover, Wednesdays, Thursdays, and Saturdays are relatively busy, however the driver availability does not exactly match to these peaks in demand.

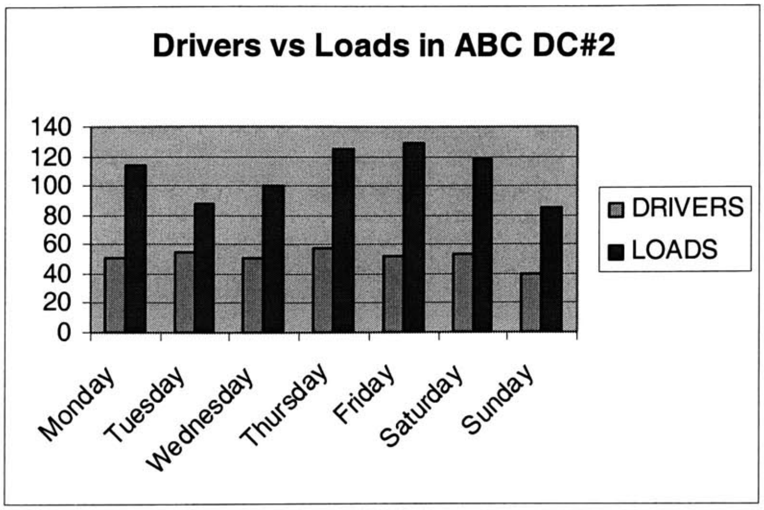


Figure 3. 3. Available drivers versus load density in ABC DC#2 facility

It can be clearly seen from the above graph that in facility ABC DC#2 the drivers were distributed quite evenly throughout the week. However, the load density does not follow a constant pattern over the week. For example, on Tuesdays and Sundays, the workload is relatively less when compared to the other days of the week. This pattern seems interesting to contrast with DC#1. Driver to load ratio is much lower in DC#2 than in DC#1. This may be due to the distant position of DC#1 to the region that it is serving. So, the loads may take longer time to deliver, which would require more driver per load for DC#1 than for DC#2.

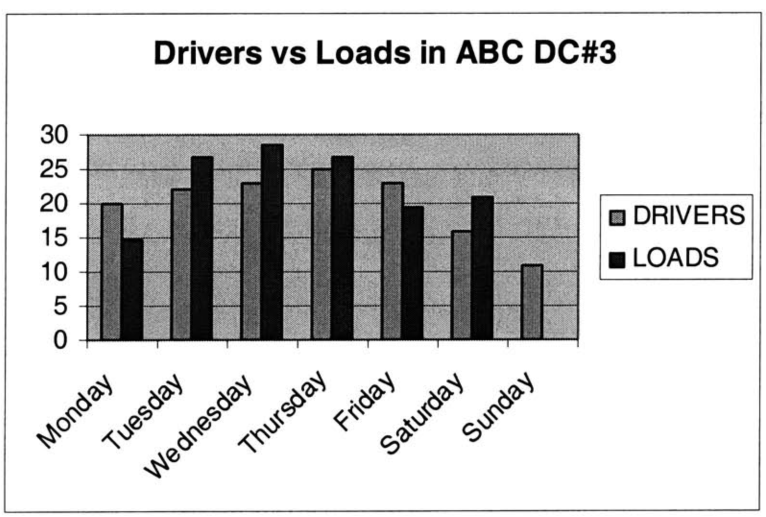


Figure 3. 4. Available drivers versus load density in ABC DC#3 facility

This graph is quite different than the first two ones. As seen, for some days such as Monday and Friday, the number of drivers is higher than the number of loads. This is because DC#3 is used as a cross-docking center, and drivers deliver backhaul loads as well as outbound loads. The numbers in the graph only represent the outbound deliveries, since the outbound truck operations are the focus of our studies. Moreover, the drivers assigned in DC#3 often deliver loads for DC#2. On Sundays, there are very few deliveries, which are neglected in the report.

If there are clear variations in transportation demand over the course of the week, it is important to allocate the labor resources for each day according to these variations in order to achieve better resource utilization. Another important, maybe the most important, challenge is the matching loads of varying length into a minimal number of 8, 10, or 11 hour workdays on any given day.

The daily routing and scheduling practice

The daily orders are pooled in the central transportation routing system. The routing system generates the daily loads from these orders. A load corresponds to a truck movement where the truck leaves the distribution center, stops at several locations for either for pick-up or delivery purposes, and then comes back to the original location. One load serves multiple orders.

The next step after route generation is the assignment of drivers to the loads. At ABC, this assignment is performed dynamically by dispatchers without the help of an analytical tool or decision support software. The dispatchers must consider the capacity and the availability of the drivers when performing this assignment. The Department for Transportation mandates that a driver can drive a maximum of 11 hours a day. In addition, drivers cannot exceed the weekly capacity. For example, a driver can drive 13 hours today and 9 hours tomorrow as long as he/she does not exceed his/her weekly capacity.

The company does not have any problem of too few drivers to accomplish the daily deliveries. They also do not know whether their driver workforce is sized appropriately or how much they are utilizing their resources. There is always plenty of labor to meet the daily delivery requirements, even if it is a peak demand season in the year.

3.3.1. Problem Definition

ABC needs to determine the potential of an analytical tool to create the daily schedules for their drivers. To do that, a model of the dispatching environment must be created. These scheduling constraints need to be considered:

1. <u>Driver capacities:</u> The Department of Transportation mandates that a driver can drive maximum 11 hours a day. Weekly capacities can handled by adjusting the daily driver capacity according to the previous week's log.
2. <u>Time windows of the locations:</u> The company make deliveries to about 200 stores. 57 of these stores have time restrictions for receiving loads while the rest can operate 24 hours a day. Table 3 shows an sample of the time windows that must be followed.

store number	time window
1	2000 to 0700 hours
2	2000 to 0700 hours
3	2000 to 0700 hours
4	2100 to 0400 hours
5	2100 to 0500 hours
6	2100 to 0600 hours
7	2100 to 0600 hours
...	.....
...	.....

Table3. 3. Time window restrictions of the stores

The chart below shows the different time windows for the restricted locations. The numbers at the bottom represents the hours of a day, and each color represents a different time window. Each bar has a label showing how many stores belong to that particular time window.

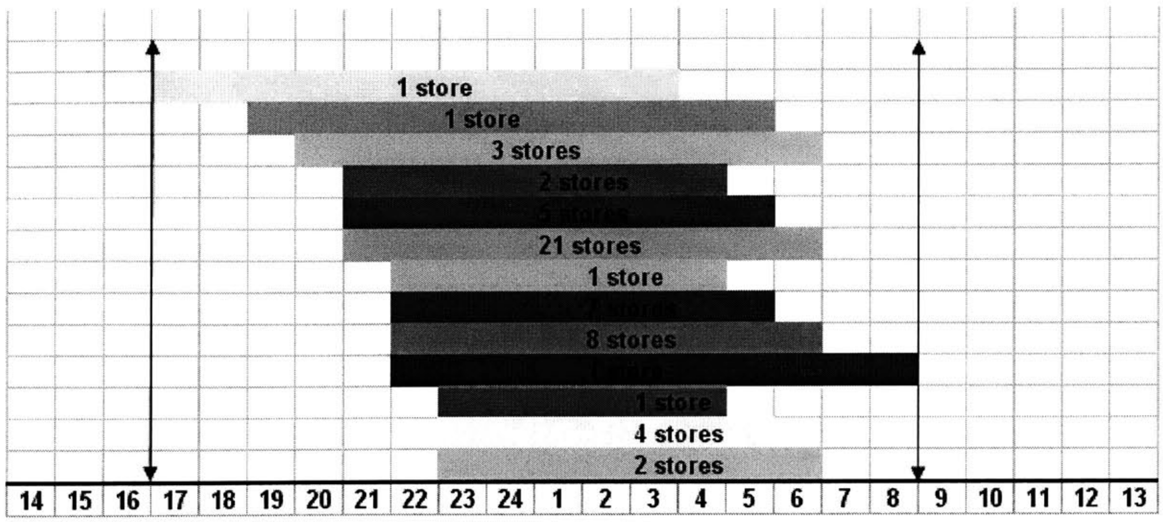


Figure 3. 5. Time windows and the number of related stores

3. Driver availability: It is pre-determined for each driver at what time of the day they will start working and what days of the week they take off. (see the table below) So, the driver availability changes according to the day of a week and the time of a day.

DRIVER	BID TIME	DAYS OFF
1	0600-0900	SUN & SAT
2	0600-0900	SUN & SAT
3	0600-0900	SUN & SAT
4	0700-1000	SUN & SAT
5	0700-1000	SUN & SAT
6	0800-1100	SUN & SAT
7	0600-0900	SUN &MON
...	....	....
...	....	....

Table3. 4. Driver bid times and work off days

"Bid Time" represents the time of the day that one driver can start working.

The problem here is not just scheduling the driver tasks feasibly, but doing this using the minimum number of drivers possible. In order to achieve the maximum utilization of the resources, first we need know how much resources we need.

3.3.2. Approach to the Problem

The objective of this research is to analyze the labor resource requirements of the company's delivery operations and to find an appropriate analytical method for the assignment of the daily loads to the drivers.

3.3.2.1. Bin-Packing Problem

Bin-Packing approach is proposed for modeling the transportation resource scheduling problem. This section gives a brief introduction of the bin-packing problem and then describes the methods that are used in our case.

Definition

Bin-packing is a fundamental problem in combinatorial optimization, that the goal is to pack a list L of items $<a_1, a_2, \ldots a_n>$ of size $a_i \in (0,1)$ into minimal number of unit capacity bins. Although it seems that the problem is simple, it turns out to be NP-Hard, which means that you cannot reliably obtain an optimal solution in a reasonable amount of time.[9] Therefore we try methods that will be as close to the optimal solution as possible, though we cannot guarantee the solution is the best.

Applications

Bin-Packing approach can be applied to many areas including job scheduling and resource assignments. Below are some of the practical applications of the problem:

-Assigning newspaper articles into newspaper pages

-Finding the allocation scheme that minimizes fragmentation of memory usage in the operating systems

[9] Po Lun, Report on Simple One-Dimensional On-Line Bin Packing Algorithms,

-Finding the minimum number of trucks to be sent to the end customer having products less than the size of the truck.

Dimensions of Bin-Packing Problems

Different dimensional of items in Bin-Packing require different algorithms. For example, assignment of articles into the newspaper pages is a two dimensional bin-packing problem. Minimization of the number of trucks required is a three dimensional problem.

One-dimensional bin packing is a problem related to minimization of space or time. In this research, we are going to use the one-dimensional bin packing approach to find the minimum number of drivers that are needed for the delivery of a list of loads with different length of times.

3.3.2.2. Modeling Transportation Resource Scheduling as Bin-Packing Problem

In current practice at the company, the routing software generates the optimum routes for each truck movement (load). It also calculates how long the delivery of each of these loads takes. The calculation also considers the total driving time and loading and unloading times at each stop. Our goal is to assign these loads to the minimum number drivers possible, while minimizing each driver's spare time under the daily capacity of 11 hours.

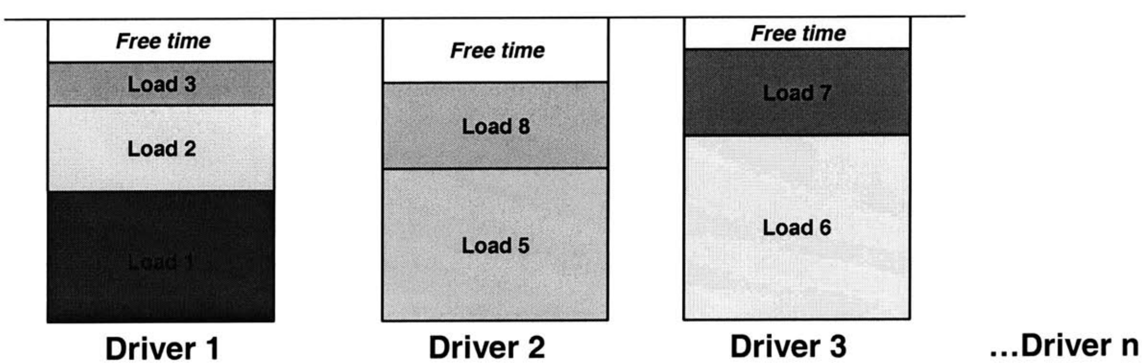


Figure 3. 6. Driver assignment as a bick-packing problem

The above figure simply depicts the problem. Using time as the dimension, we are trying to fit all of the loads – which vary in length of time - into bins - which are equivalent to the drivers, with size in hours according to their log capacity - using the minimum number of bins (drivers) possible.

Bin-Packing Algorithms

We consider algorithms for the one-dimensional bin packing problems that fall into two categories: *Next Fit (NF) Algorithm* and *Any Fit (NF) Algorithms.* The main classification between these algorithms is the space requirement, where the next fit algorithm only needs to examine the current bin (named the active bin), the algorithm that belongs to the class Any Fit has to examine all the bins accessed before.

<u>Next Fit (NF) Algorithm</u>: This is the simplest algorithm in the family. It starts from the first bin and defines it as the active bin. If the next coming item fit the bin, it will place that item in the bin, otherwise, it will create a new bin, and the new bin becomes the active bin, and packs the item into the new bin. In this method, during the process, there is only one active bin.

<u>Any Fit (AF) Algorithm</u>: It examines all the bins opened before and fit if there is any suitable bin to fill in. The rules in AF algorithms are First Fit (FF), Best Fit (BF), Worst Fit (WF).

1. First Fit (FF): It tries to fit the items as soon as possible by scanning the list of bins in increasing time of open order to find the first suitable bin and fit into it.

2. Best Fit (BF): Same as FF, but it will find a bin which will fit a new item with the smallest gap left over.

3. Worst Fit (WF): Opposite to BF, it will find a bin which will fit a new item with the largest gap left over.

4. Almost Worst Fit (AWF): Similar to WF, but it is going to find a bin which will fit a new item with the second largest gap over.

4. COMPUTATIONAL ANALYSIS AND RESULTS

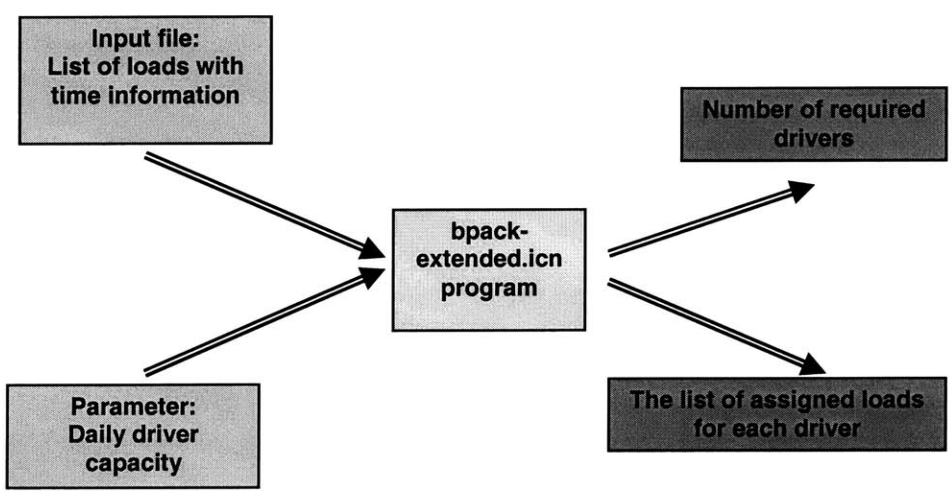
In order to solve the problem of assignment of daily tasks to the drivers, we utilized a software program that implements different bin-packing algorithms. In the following sections, the methodology is described, and it is applied to the case. The section also includes some analysis of the results for ABC and examines the performances of different algorithms.

4.1. Methodology

The **bpack-extended.icn** program is designed for this research for the implementation of the bin-packing problem. This program is an extended version of **bpack.icn** which is developed at the Department of Computer Science in University of Arizona for the Icon Programming Language practices. [10]

Bpack-extended.icn :

As simply depicted in the below figure, the program uses a list of loads as input, while the driver capacity is the parameter that can be changed at each run.



[10] Townsend, 1997, http://www.cs.arizona.edu/icon/oddsends/bpack/bpack.htm

Figure4. 1. Information flow of the bpack-extended.icn program

When the program is run, it assigns each of the loads to a particular driver and generates the minimum number of required drivers.

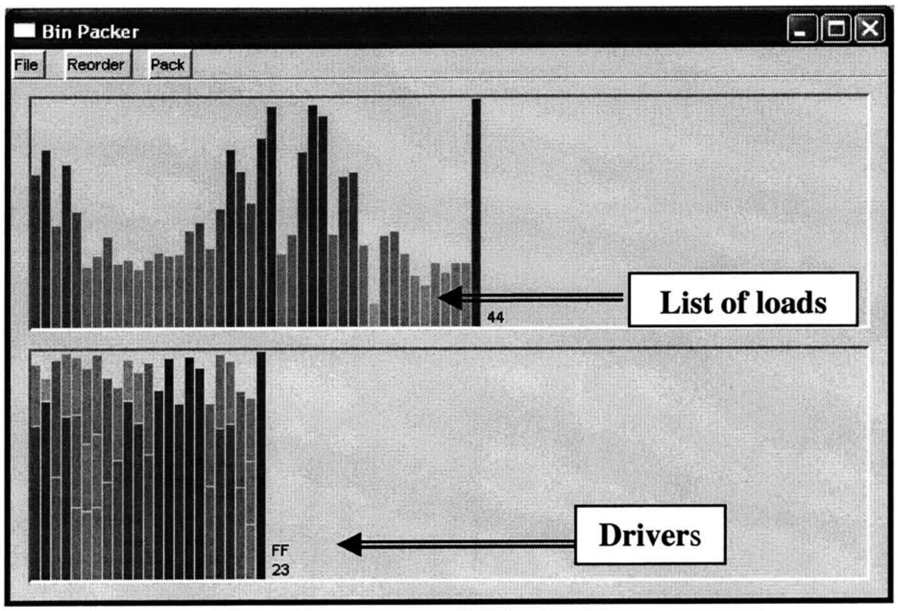
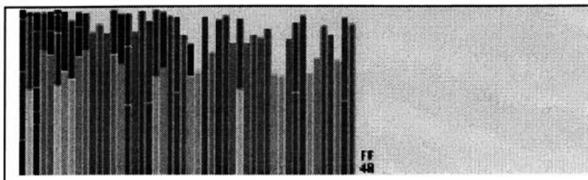
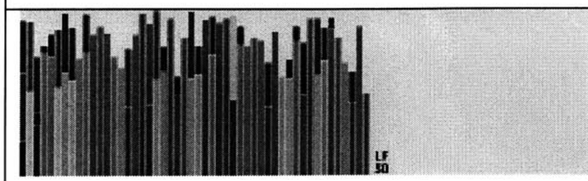
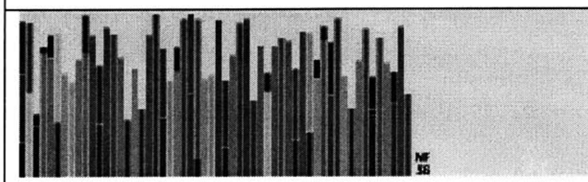
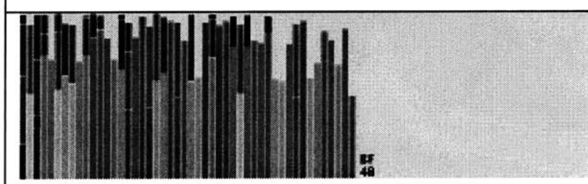
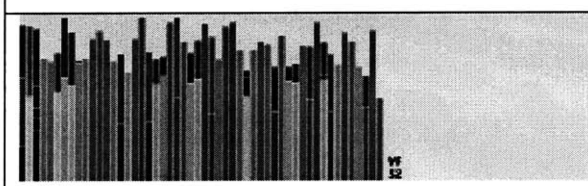
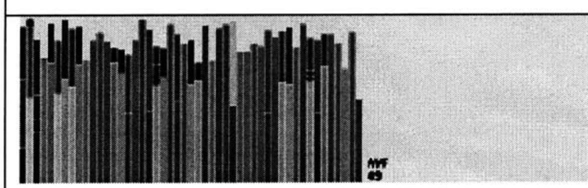


Figure4. 2. A screen shot from the bpack-extended.icn program

The program also provides some graphical features. As seen above, two shelves of objects appear in the program display. The top shelf shows the candidate loads to be packed. The bottom shelf shows the results of packing, each object representing a driver. The **Reorder** menu rearranges the candidate loads on the top shelf. The **Pack** menu selects an algorithm and packs the loads onto the bottom shelf using the selected algorithm. The resulting display notes the packing algorithm used by its initials, and also indicates the number of drivers required.

All algorithms take the loads from the top shelf in order and place them one at a time. A new driver (bin) is created whenever the algorithm cannot use an existing driver (bin).

The behaviors of the different bin-packing algorithms are described below:

	The **First Fit** algorithm places a new load in the leftmost driver that still has room.
	The **Last Fit** algorithm places a new load in the rightmost driver that still has room.
	The **Next Fit** algorithm places a new load in the rightmost driver, starting a new driver if necessary.
	The **Best Fit** algorithm places a new load in the fullest driver that still has room.
	The **Worst Fit** algorithm places a new load in the emptiest existing driver.
	The **Almost Worst Fit** algorithm places a new load in the second-emptiest driver.

4.2. Driver Task Assignment and Implementation

4.2.1. Introduction

This section is a short summary about ABC's total driver assets and the transportation demand at the dispatching facilities. It also describes how the input information, which is going to be used in the application of our methodology, is generated at ABC's current IT systems.

The company employs a total of 183 drivers. The allocation of these drivers to the three dispatching locations is as below:

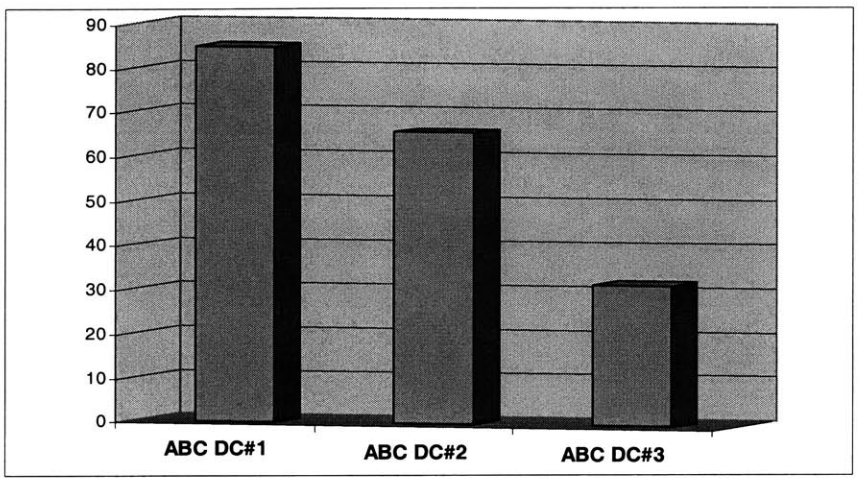


Figure4. 3. Allcocation of the drivers throughout the dispatching locations

As seen in the above graph, majority of the drivers are allocated for the ABC DC#1 facility, whereas the ABC DC#3 facility was assigned the smallest number of the total drivers.

The below graph shows the average number of outbound deliveries in year 2003 at three dispatching locations:

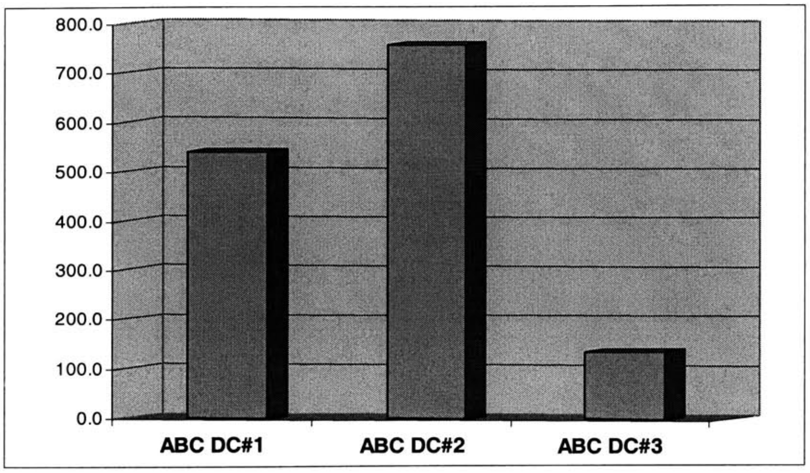


Figure4. 4. Average number of outbound deliveries in 2003

As shown in the graph, ABC DC#3 facility is significantly less busy than the other dispatching locations, whereas ABC DC#2 has the highest transportation demand.

Looking at these two graphs it seems that the driver resources were not allocated among the locations considering the transportation demand. Otherwise, ABC DC#2 facility would be allocated more drivers than ABC DC#1 facility, because of the higher demand. This may result in frequent driver resource switches between the locations which would make it more difficult to manage and plan driver operations.

As mentioned above, the routing system generates loads and calculates the time required for each of the loads. Below is a sample of the data that we will be using which is taken out from the routing system:

load number	total hours
P001	3.10
P002	4.10
P003	2.32
P004	2.70
P005	3.12
P006	3.02
P007	3.63
P008	3.35
...	...
...	...

"total hours" is the sum of the total driving time and the loading/unloading time at each location.

Table 4. 1.Sample output from the routing system

4.2.2. Driver Requirements Assessment

This section aims to assess the company's driver requirements by implementing the bin-packing approach. Bin-packing algorithms were designed to assign the daily tasks (loads) to the drivers. Since, the objective is to do so with the minimum number of drivers possible, the algorithm also gives us the driver requirement for that day.

DC#2 was chosen for the analyses, since it is the primary dispatching point with the highest number of outbound deliveries per year. In order to calculate the driver requirements of the company, two weeks of data for DC#2 was selected. These two weeks best represent ABC's transportation demand at that DC. The data consist of a list of loads, having each load with time information in hours.

Each day's load data is run in the **bpack-extended.icn** program, with maximum driver capacity set to 11 hours and utilizing the 6 different bin-packing algorithms: First Fit (FF), Last Fit (LF), Next Fit (NF), Best Fit (BF), Worst Fit (WF), and Almost Worst Fit (AWF). The driver requirement is the minimum of all the algorithm results. (refer to Appendix D for further details)

For each day, there are 2 runs for 2 groups of loads. This is because there are two shifts of delivery in each of the dispatching locations everyday, one starting after 6pm, and the other the next morning around 7am. So, the driver assignments and requirements are made separately for the night and the morning deliveries.

The summary over all of the program runs is shown below:

minimum:	39
maximum:	61
average:	51.1
standard deviation :	8.9

Figure 4.5 illustrates the total driver requirements for each day over the two week period using the best result of the six algorithms on each day. The dashed line in the bottom shows the minimum requirement and the dashed line on the top shows the maximum requirement for this period. Looking at the graph, day 7 has the minimum requirement with 39 drivers, where day 1 and day 4 have the maximum with 61 drivers. The average requirement is calculated as 51.

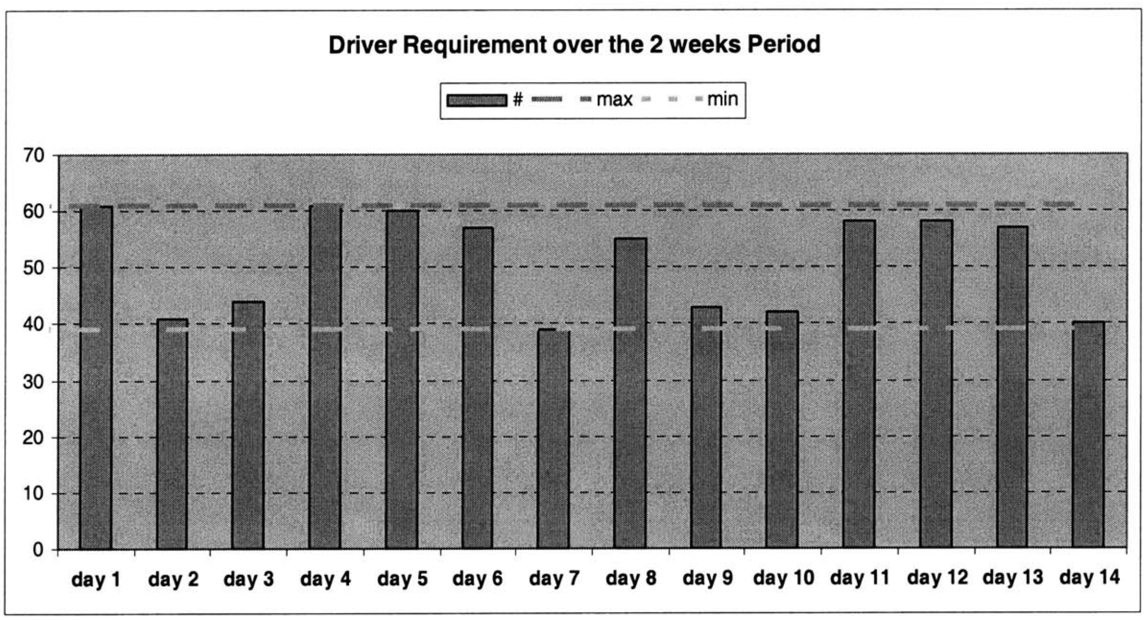


Figure4. 5.Driver requirements over the two weeks

As seen in the graph, there is weekly seasonality in the driver demand. For example, Tuesday (days 2 and 9), Wednesday (days 3 and 10), and Sunday (days 7 and 14) have relatively low demand. This would suggest that demand variability could be incorporated into driver resource allocation for each day of the week. Since the demand is not distributed uniformly throughout the week, the driver resources could be positioned accordingly. This is a tactical level planning decision that should be made during the annual driver bidding process, setting up the daily task scheduling of the driver resources.

The below graph summarizes the performance of the bin-packing method. The x axis corresponds to the days that the method was applied to, and the y axis shows the driver utilization at the given day. Utilization was calculated based on the average work hour of the drivers as a percent of the 11 hour capacity. Driver utilization changes between 84% and 91% over the 14 days. This utilization is fairly high, showing that the bin-packing approach has potential for the driver-load assignment problem.

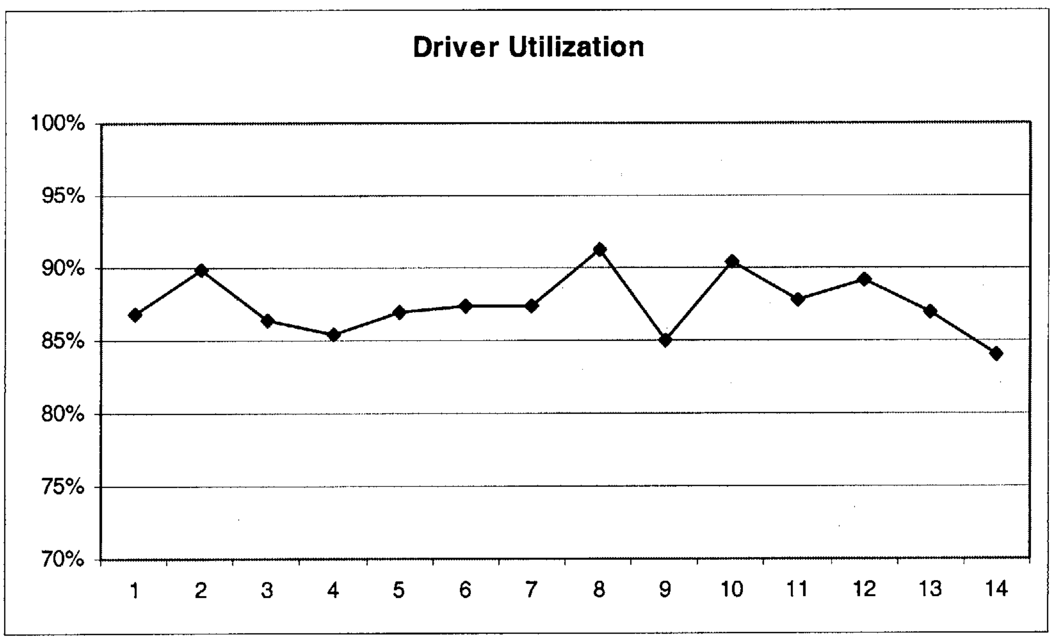


Figure4. 6. Driver utilization

It is expected that as the loads are longer and more variable, the driver utilization is not as good, since in this case it is harder for the algorithm to optimally pack the loads into the fixed driver schedules. The table below shows the average load duration and the standard deviation of the load time compared to the driver utilization for each of these days. It can be observed here that in most cases the conjecture holds. For example in day 14, the average load time is 5.1 hours with the standard deviation of 2.1, and the corresponding driver utilization is 84%. At the other extreme, on day 10 the average load is 4.8 hours with standard deviation of 2.1, and the related utilization is 90%. However, some counter examples exist, such as the 91% utilization on day 8 in spite of a high average load duration (5.2) and standard deviation (2.3). More research is needed to evaluate the impact of load length and variability on driver utilization.

	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	day 11	day 12	day 13	day 14
Percent of 11 hour shift	87%	90%	86%	85%	87%	87%	87%	91%	85%	90%	88%	89%	87%	84%
Average load duration	5.2	5.0	4.8	5.2	5.2	5.3	5.0	5.2	5.0	4.8	5.0	4.8	5.1	5.1
Std. dev. in load duration	2.2	2.3	2.1	2.1	2.1	2.2	2.0	2.3	2.2	2.1	2.2	2.2	2.3	2.1

Table 4. 2. Load statistics and driver utilization

Another way to determine how well the bin packing solution performs is to compare it with current driver staffing. The dark colored columns on the right correspond to the current driver availability in the given days, and the light columns on the left are the required number of drivers that were calculated by the help of the bin-packing method. On Tuesdays and Wednesdays there are far more drivers available than actually needed. For example, day 2 only requires 41 drivers, whereas there are 55 full time drivers available for this day. However, on most other days, the driver demand exceeds the driver supply. Some of the driver resources could be transferred from Tuesday and Wednesday to the other days in order to balance the supply and demand.

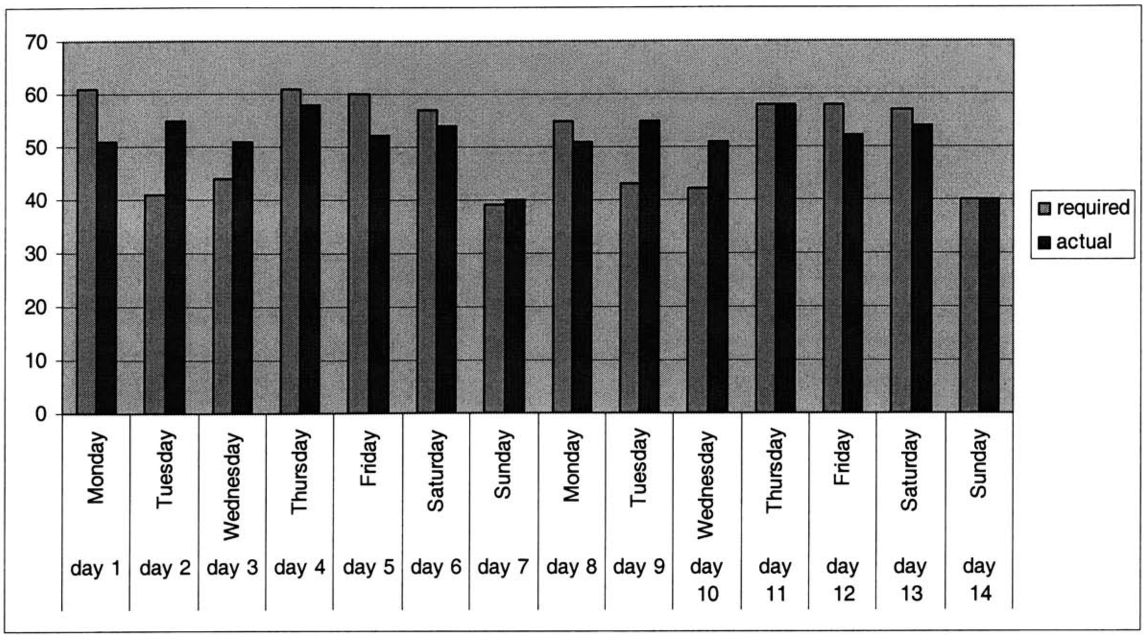


Figure4. 7. Required drivers versus actual numbers

It is surprising that even though the bin-packing method generated task assignments to the drivers with about 90% utilization, the above graph shows that for the majority of the days, the actual driver staff is far less than the bin packing method required. This brings into question how the company manages to cover all these tasks with so few resources. One reason could be that they often borrow drivers from other dispatching locations. It is true that DC3# drivers often do deliveries for DC#2.

Another option is that there are accuracy problems with the data. In order to test this, we added all the load durations for each day to determine the absolute minimum requirements. We observed that for some of the days, this value was bigger than the corresponding day's number of available drivers multiplied by the 11 hours capacity. So, there were more tasks to be accomplished than the total resource capacity. This indicates that there may be data issues. .

One data issue may be the estimation of the load duration. ABC uses routing software to estimate this load duration for the dispatchers. ABC claims that the mileage information from their routing software differs from the GPS system does not match, and the data in the GPS system is more reliable. The routing system determines driving time based on the distance information and the pre-defined truck speeds. So, the reliability of the load durations is also questionable. Accurate data is very important in order to create correct and dependable driver schedules.

4.2.3. Driver Capacity Simulation

In this section we analyze how the driver workforce requirements vary according to the workday length. The driver capacity is simulated between 8 and 11 hours, and accordingly the driver requirements are calculated by the bin-packing method. One week of data were used for the analyses. The details of the program runs could be found in Appendix D.

The total driver requirements for each day (sum of the results of the 2 runs) and the statistics summary are as in the below table:

	8-hours	**9-hours**	**10-hours**	**11-hours**
day 1	81	73	67	61
day 2	56	50	46	41
day 3	58	54	48	44
day 4	78	73	67	61
day 5	80	72	66	60
day 6	77	70	63	57
day 7	53	48	45	39
average	**69**	**62.86**	**57.43**	**51.86**
min	**53**	**48**	**45**	**39**
max	**81**	**73**	**67**	**61**

Table 4. 3. Simulation results of the driver capacity

The driver requirement is almost linearly proportional with the driver capacity as clearly seen in the below graph.

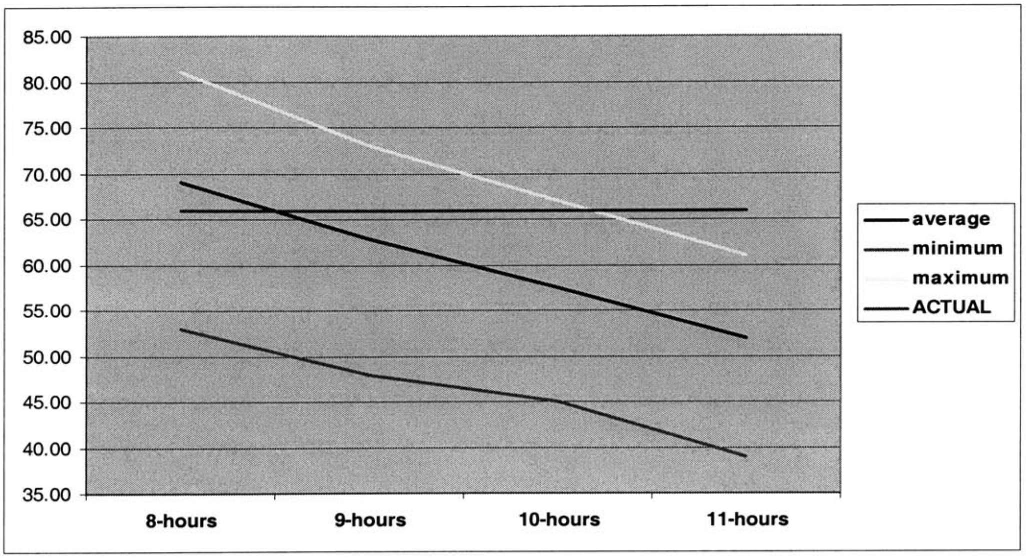


Figure4. 8. Driver capacity simulation results

The red line in the graph represents the actual number of full-time drivers which were assigned to this location. The graph tells us that if the drivers work on average less than 9 hours everyday, the current number of available drivers would not be enough. In the worse case, when the transportation demand reaches the highest point, a driver workday of 10 hours does not quite cover all the transportation demand with the current labor resource reserves. Hence, 11 hour days are required on occasion.

It was thought that the relationship between drivers' daily working capacity and the total driver requirement would not be directly proportional, revealing an optimal workday length. However, the analyses showed that there is linear relationship between them. As the drivers work longer days, the company requires proportionally fewer drivers.

4.2.4. Algorithm Performances

This section evaluates performances of the bin-packing algorithms. Two criteria were considered in the evaluations:

- The ability of the algorithm to find the minimum number drivers
- How well the algorithm balances the workload among the drivers

We made a total of 28 runs for 14 days of data, 2 runs for each day. For each run, 6 different algorithms assigned the loads to the drivers and calculated the minimum number of required drivers. The results of the algorithms in terms of the required number of drivers were sometimes different from each other, since each of them has its unique computation procedure. However, we consider the one which had the smallest value as the base, which we refer to as "best", and compare the others if their result is equal to this minimum. For the details of the procedure, please refer to Appendix D.

At the end, these values are added up to find how many times an algorithm found the "best" value over the 28 program runs. Bellow is the graphical representation of the result:

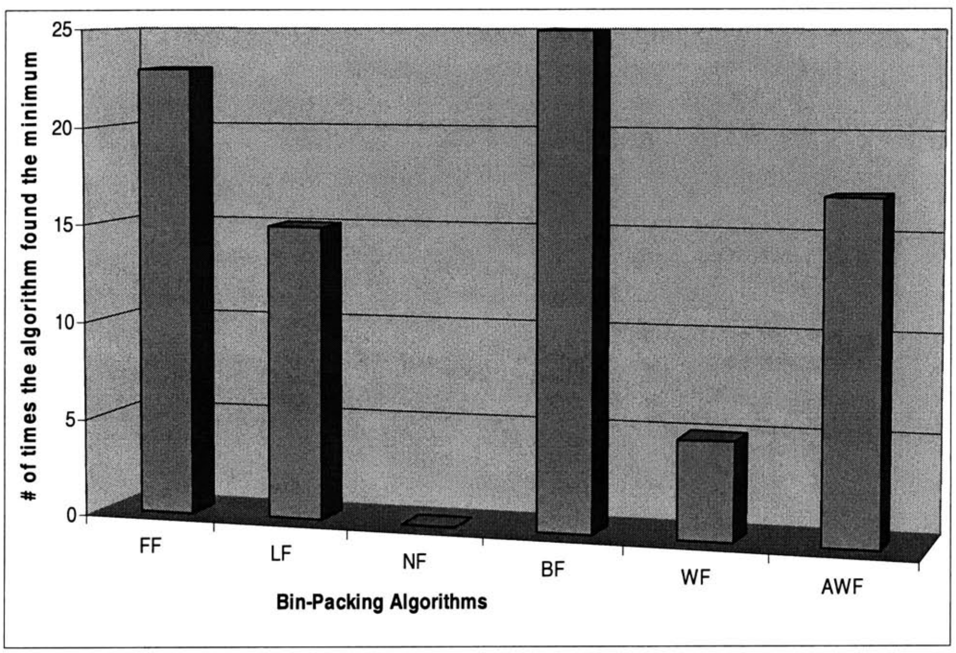


Figure4. 9. Algorithm performances in finding the minimum requirement

Looking at the above graph, "Any Fit" group of algorithms (First Fit, Last Fit, Best Fit, Worst Fit, and Almost Worst Fit) performed well, whereas "Next Fit" algorithm failed. In particular, Best Fit and the First Fit algorithms performed outstandingly better than the other members of the "Any Fit" family. As we could remember, "Next Fit" algorithms only examine the current bin (active bin), whereas the algorithms that belong to class "Any Fit" examines all the bins accessed before.

The other way in assessing the algorithm performance is to measure how well it balances the workload among the drivers. In order to measure the workload balance of an algorithm, the variations of the workload among the drivers are calculated. The methodology is as follow:

Step 1 - Total working hours of each driver is computed.

driver	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
working hours	10.07	7.87	7.88	6.68	8.85	8.47	11.85	8.96	8.68	9.2	7.13	9.42	6.52	6.95	10.78	10.13	4.67	8.17	7.57

Step 2 - The standard deviation of these working hours is calculated.

Standard deviation (10.07, 7.87, 7.88, 6.68, ..., 7.57) = 1.683901

Step 3 - The algorithm with the least standard deviation balances the workload best. The reason for this is least standard deviation means least variation of working hours among the drivers, which eventually means a good work balance.

The above methodology is applied to 3 different runs from the days 3, 6, and 10. The program outcomes for these runs are as follow:

	# of loads	FF	LF	NF	BF	WF	AWF	min
day 3-run 2	31	19	19	21	19	19	19	19
day 6- run 2	43	29	29	33	29	29	29	29
day 10 -run 2	31	17	17	19	17	17	17	17

In all of these runs, 4 out of 5 algorithms were able to find the "best" value. The above methodology was applied only to these 4 algorithms. The below table demonstrates the standard deviations of the work hours of the drivers for each algorithm at each run, the red color pointing out the minimum. As seen in the table, Worst Fit algorithm has the smallest standard deviation in each of the three runs. Then, it can be concluded that Worst Fit algorithm performed the best in balancing the workload among the drivers, although it has performed poor in finding the minimum number of required drivers.

	FF	LF	BF	WF	AWF
day 3-run2	168.82	130.10	169.65	**122.61**	156.82
day 6-run2	152.42	**145.66**	158.17	**145.66**	152.42
day 10-run2	**106.72**	106.81	106.81	**106.72**	133.23

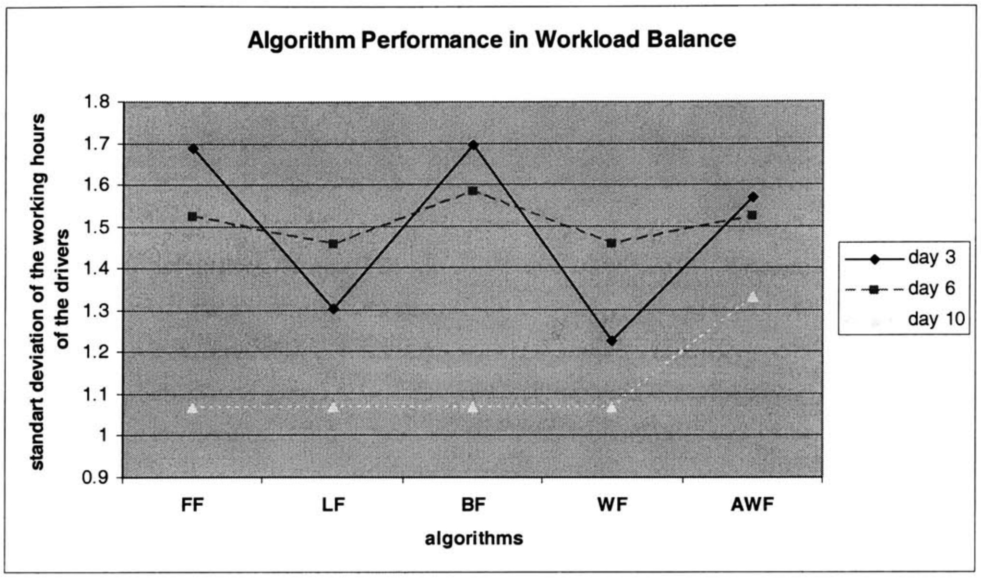


Figure4. 10. Algorithm performance in work balance

The above graph summarizes the performances of the algorithms in how well they balance the workloads. The y-axis shows the standard deviation of the work hours of the drivers, and the x-axis represents the bin-packing algorithms. Three days' performances are demonstrated in the graph, the solid line representing day 3, the dashed line on the top day 6, and the dashed line on the bottom day 10. For day 3 and day 6, there is a clear pattern that Last Fit and Worst Fit algorithms worked better, since the driver work hours have the lowest standard deviation for these algorithms. For day 10, almost the same standard deviation was found for all of the algorithms, except for the Almost Worst algorithm, which had the highest one. A completely similar observation can not be made for day 10, but Last Fit and Worst Fit algorithms still have the smallest standard deviation for this day.

It is very interesting that the algorithms which performed well in finding the minimum number of required drivers did not perform well in balancing the workload among the drivers. However, First Fit and Last Fit algorithms have the best combined performance, finding minimum while balancing well. In a practical application one could run all algorithms and select the assignment plan of an algorithm that found the minimum driver requirement but at the same time balanced the workload best .

5. CONCLUSION

5.1. Introduction

This thesis is the second piece of a two component research project which is completed in a partnership between two MIT Masters of Engineering candidates and a retail grocery store, Company ABC. The project investigates methods for efficient load generation and transportation resource scheduling for grocery industry. To fully investigate all the aspects of the subject, the project was split into two pieces. The first component of the project is focuses on methodologies to generate coordinated loads within the network of the retailer. This part of the project is described in detail in the thesis titled *Planning Coordinated Loads to Facilitate Centralized Dispatching in the Grocery Industry*, written by Nancy Archambault. The second half of the project involves the efficient assignment of coordinated loads to the resources. This part of the project is studied in this thesis under the heading *Transportation Resource Scheduling in the Grocery Industry.*

5.2. Summary and Conclusion

The first chapter of the thesis is an introduction to the grocery operations. The transportation operations in the grocery industry are elaborated, emphasizing routing and scheduling operations. The transportation cost components across different categories is described. The motivation for this research and how it could make improvements on the transportation costs are explained. At the end of the chapter, the new trends in the grocery industry are illustrated.

The second chapter of the thesis is a system analysis report which was conducted in Company ABC in order to understand their overall supply chain and transportation operations. The current operations of the company, its supply chain network, and supply chain operations are explained in detail. The business systems in planning and execution of the transportation operations are described. The information flow between these systems is demonstrated. At the end of the section, there are process maps of the company illustrating each of the steps in the transportation and ordering operations processes.

The third chapter generally discusses the transportation resource scheduling problem. The transportation resource scheduling problem is the sequencing of the loads between the drivers, considering the driver rules, such as maximum working hours, and the time windows of the locations. In the beginning of the chapter, there is a literature review providing further information for readers interested in this topic, followed by a section giving brief information about the transportation resource scheduling software solutions in the market. Following this, the motivations for solving the problem in the grocery industry are explained.

The chapter continues with the explanation of the current scheduling processes at ABC. The transportation scheduling problem at the company is defined, and the main issues in the processes are articulated. ABC wishes to be able to schedule the daily driver activities while having the lowest number of drivers possible in the team. Following the problem description, the approach of this research to the problem is introduced. The bin-packing method is proposed to solve the problem of the assignment of tasks to the drivers. The bin-packing problem can be simply defined as packing a list of items into minimal number of unit capacity bins. In this case, the bins are equivalent to the drivers and loads are equivalent to tasks. A load is the name of a truck movement, in which a truck makes a whole delivery trip starting from and coming back to the same location. The end of the chapter describes different bin-packing algorithms that were used in the analyses section. This chapter also includes an analysis comparing the transportation demand with the driver availability for each day of the week. The analysis is done for each of the three dispatching locations. It is observed that the driver resources are not well allocated among the dispatching locations and throughout the week. For example, in some days of the week there is relatively low demand, whereas the number of available drivers is stable over the week.

The fourth chapter is the computational analyses part. The model is applied to a two weeks of data of Company ABC from one dispatching location. The data consists of the list of loads and their time information. These two weeks were carefully selected to represent ABC's transportation demand capturing the highs and lows. In this chapter, the methodology is described in detail including how each individual algorithm works.

A program was developed in *Icon Programming Language* for the execution of the bin-packing algorithms. The program reads the input file, which consists of the list of the loads with their time lengths, and processes this information giving the assignment plan of loads to drivers according to 6 different bin-packing algorithms. The program provides a graphical interface showing the list of the loads and the assignment plan with the number of required drivers on a chart.

The results of the two week data run were evaluated. It was observed that there is weekly seasonality in the driver demand. This suggests us that demand variability could be incorporated into driver resource allocation for each day of the week. Since the demand is not distributed uniformly throughout the week, the driver resources could be positioned accordingly. This is a tactical level planning decision that should be made during the annual driver bidding process, setting up the daily task scheduling of the driver resources.

It was found that the driver utilization varies between 84% and 91% for two weeks period, which is a fairly good achievement, verifying that bin-packing algorithm applies well to the driver task assignment problem. Also, a comparison between the required drivers and the driver availability for each day of the week is made. The drivers decide which days they will take off in an annual bidding process, and accordingly the driver availability for each day of the week is known. It was observed that in some days of the week, the number of available drivers exceeds the requirement.

This analysis also pointed out a very important issue, that the company may have data accuracy problems. Despite the driver utilization levels of 90% from the bin-packing approach, data showed that ABC is able to cover the loads with fewer resources. However, we observed that on some days the number of available drivers multiplied by the 11 hours capacity was less than the total load hours. So, there were more tasks to be accomplished than the total resource capacity. In order to generate reliable resource schedules, it is very important to work with accurate data.

To see how the driver requirements are related to the length of workday, the daily driver capacity is simulated between 8 hours and 11 hours. We observe a linear relationship between the capacity and the requirement. It was thought that a certain driver workday length may be best given the typical load lengths. However, reduction in workday hours gives a commensurate increase in drivers required.

The chapter concludes with a performance assessment of the 6 different bin-packing algorithms. The algorithms are evaluated according to their ability in finding the minimum driver requirement and how well they balance the workload between the drivers. It is found that "Best Fit" and "First Fit" bin-packing algorithms tend to work best in finding the minimum driver requirements. "Last Fit" and "Worst Fit" algorithms balance the driver workload better, where they by contrast performed the worst in finding the minimum driver requirement. However, First Fit and Last Fit algorithms have the best combined performance, finding minimum while balancing well. The best way for selecting the best assignment plan could be to run all the algorithms everyday and select the one that balances the workload among the ones which found the minimum requirements.

5.3. Benefits of the Model

Good fleet management is more than determining the optimal route from point A to point B, it also involves managing daily functions of scheduling the driver tasks. Drivers are the most valuable fleet resources, comprising the 60% of overall transportation costs in the food retail industry. Therefore, it is very crucial to efficiently manage the scheduling of the driver activities in order to utilize the drivers and consequently to drive down the overall transportation costs.

The complexity and the scale of the problem make it almost impossible to supervise without the use of advanced analytical methods and software programs. In ABC, there are about 300 loads generated from three dispatching locations everyday. It is very difficult and time consuming to capture all the opportunities in the scheduling process in an efficient manner with manual procedures.

The scheduling model that is proposed in this research, the bin-packing approach, seems to be a suitable method for driver utilization. The application of the model in this case showed that ABC could reach 85-90% driver utilization, if such an analytical method is employed in the daily assignment processes. The method could also be used to better allocate the driver resources among the dispatching locations and throughout the days of the week. The past transportation demand data could be evaluated using the model to determine the labor requirements per day and per location.

In the current daily operations of ABC, the optimal routes are generated at the central routing system, and then at the dispatch terminal the dispatchers assign the drivers to the loads manually (see Appendix D for details). The bin-packing tool could be incorporated to the transportation process at this last step where the driver schedules are created. The bin-packing software works very quickly, generating driver assignments in seconds, which could enable the dispatchers save significant planning time.

5.4. Further Research

Time window constraints of the locations are not taken into account in the bin-packing approach. The reason is that time windows are not very constraining for this scheduling problem. Most windows are very similar and are very wide. For the companies with shorter or more varied time windows, the bin-packing approach may not work as well. In that case, a detailed scheduling optimization tool should be investigated.

Another important issue that needs to be explored at ABC in the further research is to improve the estimates of load duration. Time studies could verify the typical duration at a store. GPS could be utilized to evaluate distance and speed parameters. In order to create trustworthy transportation resource schedules, it is important to employ accurate data in the optimization and planning processes.

Appendix A – Glossary of Terms

Inbound: Flow of the goods from suppliers to the DCs

Outbound: Flow of the goods from DCs to the stores

Distribution Center (DC): The warehousing facility that holds products purchased from the vendors, waiting to be distributed to the stores. Every day cases of products are selected from shelves in the DC and packed onto pallets for delivery to individual stores.

Backhaul: The process of a truck returning from the original destination point to the point of origin, carrying an inbound load

Backhaul Location: Location (other than a DC/terminal) where a trailer may be dropped to be picked up a later time.

ABC Stores Product Groups

Frozen: 3,125 frozen food SKUs

Dairy: 1,220 dairy product SKUs (All stores supplied by YZ DC#2)

Non-Dairy Perishable: Produce, meat, fish, floral & deli, 4,000 SKUs (All stores supplied by ABC DC#2)

Fast-moving Grocery: full-line non-perishable grocery products, approximately 5,000 of the fastest moving SKUs, example: popular name brand peanut butter

Slow-moving Grocery: full-line non-perishable grocery products with slower movement than FMG items, these represent approximately 7,100 SKUs, example: organic peanut butter

Appendix B – Glossary of Systems

MAPS: This is the basic information system that stores item information.

Inbound operations related systems

POM: Purchase Order Manager

LIMS: Logistics Inbound Management System

TMS: Transportation Management System

Outbound operations related systems

RAIL: Rail contains delivery attributes for each item such as delivery frequency, lead time, processing time, ship-from information.

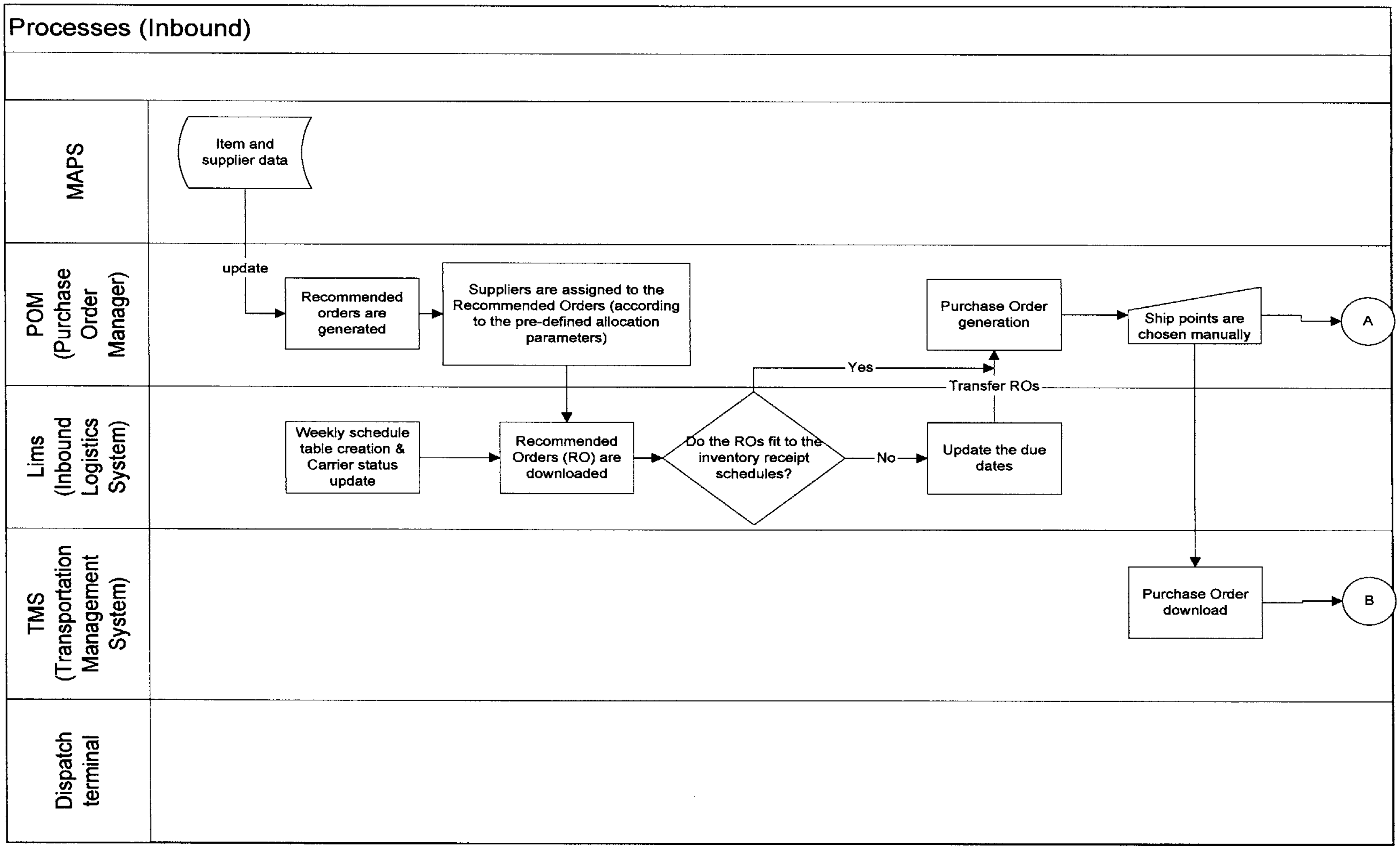
SRO & PRO: These are ordering systems located separately at each store. PRO (Perishable Re-Order) system is used for perishable items, where SRO (Supervised Order System) is used for the rest of the items.

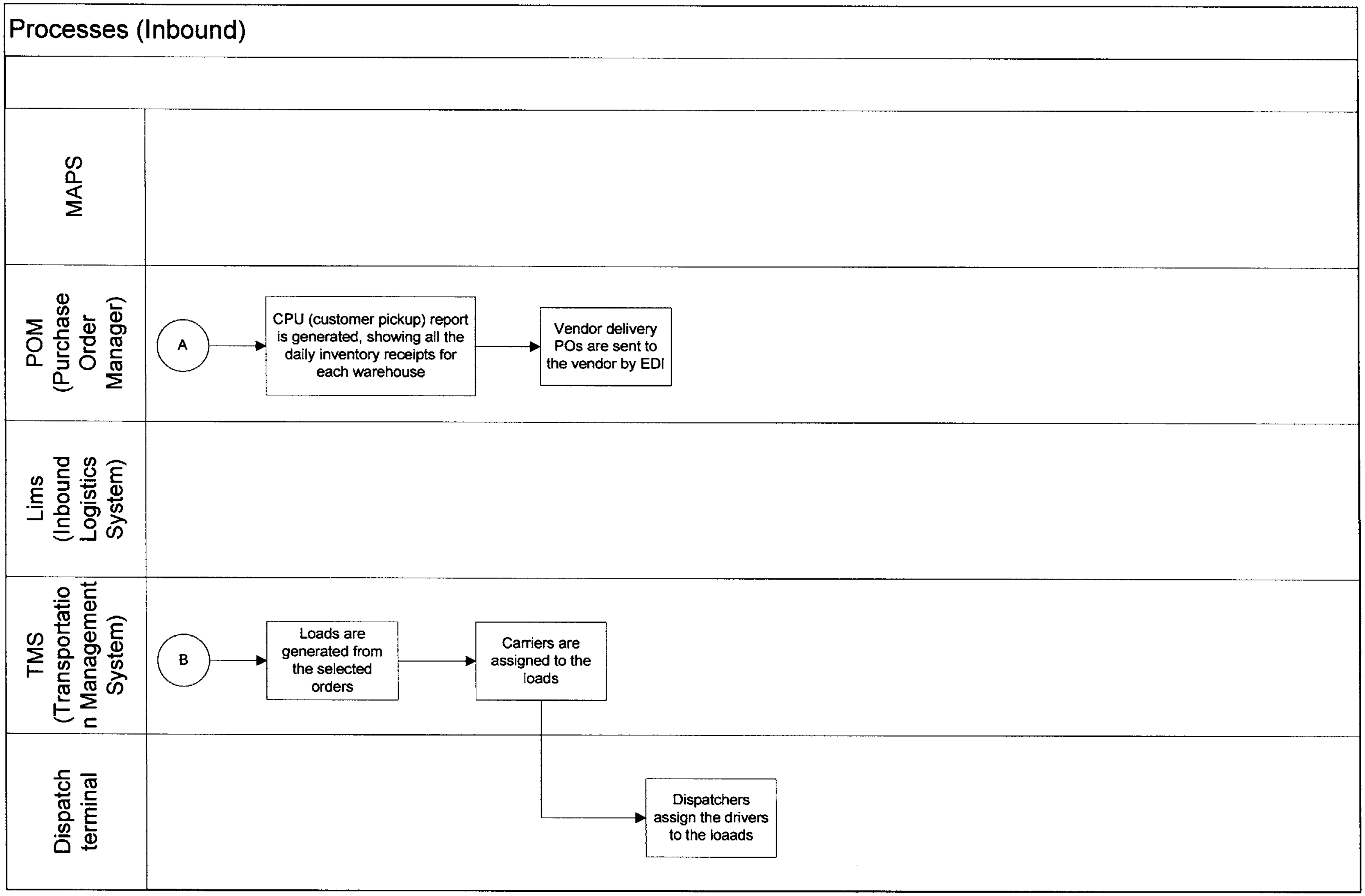
CORE: This is the system for pooling all the orders from all of the stores. From CORE (Corporate Order Repository), the order information is distributed to ABC DCs and to YZ.

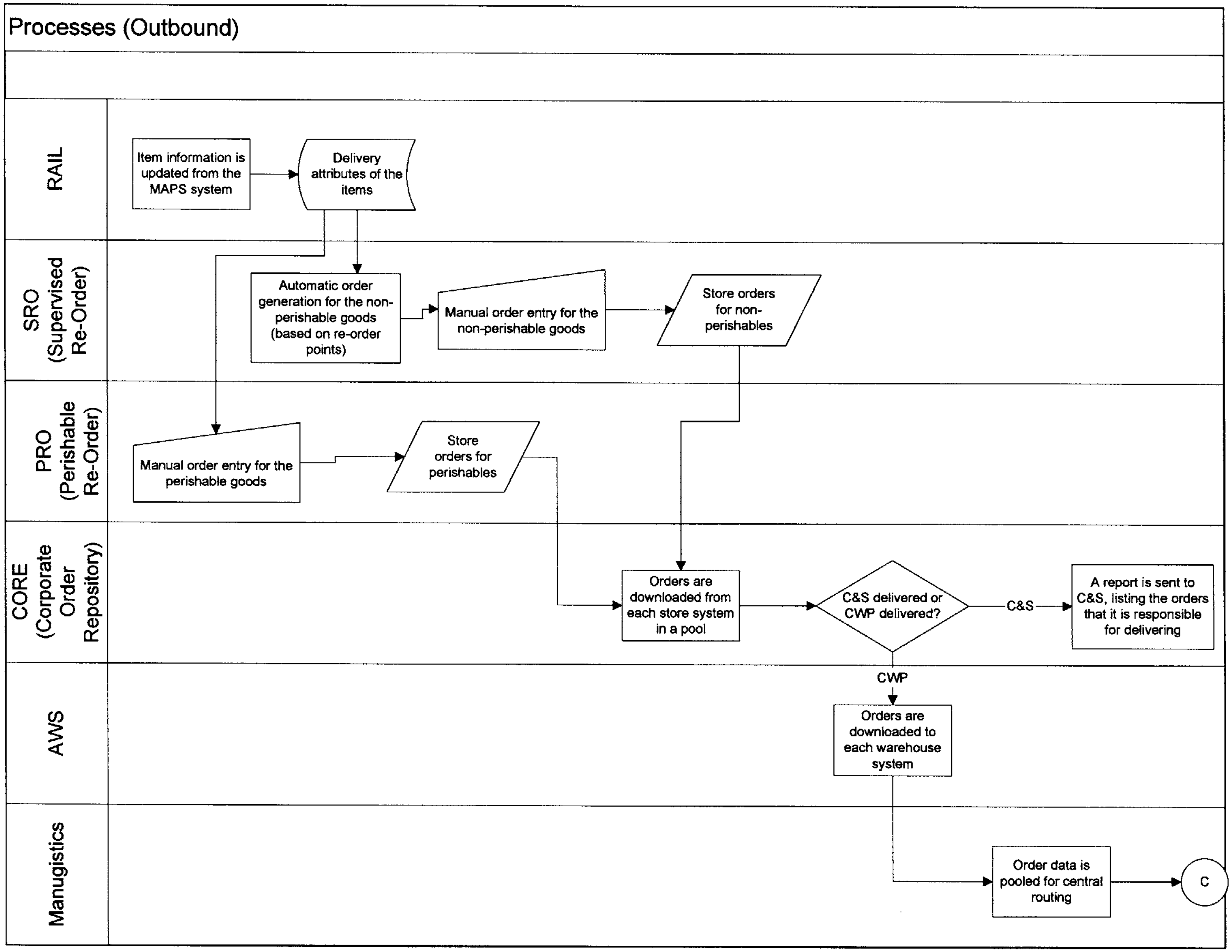
AWS: This is the warehouse management system that is established in each of ABC distribution centers and cross-dock facilities.

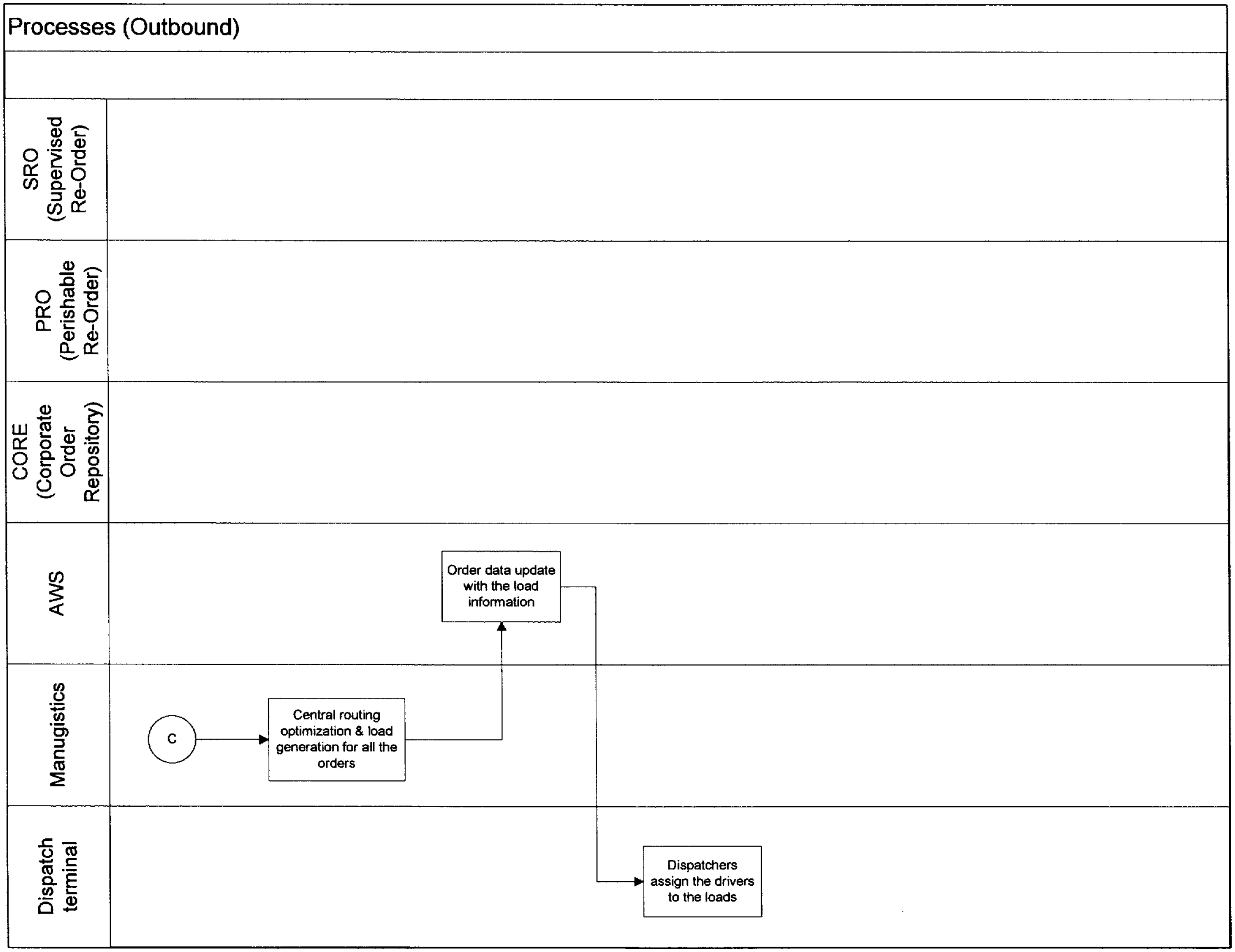
Manugistics: This is the routing software that plans daily routes of the trucks according to the daily order information.

Appendix C – Process Maps




Processes (Inbound)
MAPS
POM (Purchase Order Manager)
A
CPU (customer pickup) report is generated, showing all the daily inventory receipts for each warehouse
Vendor delivery POs are sent to the vendor by EDI
Lims (Inbound Logistics System)
TMS (Transportation Management System)
B
Loads are generated from the selected orders
Carriers are assigned to the loads
Dispatch terminal
Dispatchers assign the drivers to the loaads


Processes (Outbound)
RAIL
SRO (Supervised Re-Order)
PRO (Perishable Re-Order)
CORE (Corporate Order Repository)
AWS
Manugistics
Item information is updated from the MAPS system
Delivery attributes of the items
Automatic order generation for the non-perishable goods (based on re-order points)
Manual order entry for the non-perishable goods
Store orders for non-perishables
Manual order entry for the perishable goods
Store orders for perishables
Orders are downloaded from each store system in a pool
C&S delivered or CWP delivered?
C&S
A report is sent to C&S, listing the orders that it is responsible for delivering
CWP
Orders are downloaded to each warehouse system
Order data is pooled for central routing
C


Processes (Outbound)
SRO (Supervised Re-Order)
PRO (Perishable Re-Order)
CORE (Corporate Order Repository)
AWS
Manugistics
Dispatch terminal
Order data update with the load information
C
Central routing optimization & load generation for all the orders
Dispatchers assign the drivers to the loads

Appendix D – Analyses

	# of loads	FF	LF	NF	BF	WF	AWF	min
	67	31	31	38	30	32	31	30
day 1	44	31	31	34	31	31	31	31
	42	18	19	20	18	19	18	18
day 2	39	24	23	25	23	24	24	23
	56	25	25	31	25	27	26	25
day 3	31	19	19	21	19	19	19	19
	67	31	32	38	31	32	31	31
day 4	44	30	30	34	30	30	30	30
	69	32	32	38	32	33	32	32
day 5	42	28	29	31	28	29	28	28
	60	28	29	34	28	30	28	28
day 6	43	29	29	33	29	29	29	29
	51	23	25	25	26	25	23	23
day 7	24	16	16	17	16	17	16	16
	66	29	30	35	29	31	30	29
day 8	40	27	26	29	26	27	27	26
	44	19	18	22	19	19	19	18
day 9	37	25	25	27	25	26	25	25
	57	25	25	29	25	26	25	25
day 10	31	17	17	19	17	17	17	17
	70	30	31	35	30	32	31	30
day 11	45	28	29	30	28	29	28	28
	70	30	30	35	30	31	31	30
day 12	48	29	30	34	28	30	29	28
	63	27	28	34	27	29	28	27
day 13	46	30	30	32	30	31	30	30
	49	23	24	27	23	24	23	23
day 14	25	17	18	21	18	19	18	17

a. The outcomes of the bin-packing algorithm runs for driver requirement calculation for 14 days

The numbers associated with each of the algorithms are the minimum number of drivers required. The "min" column on the right is the smallest value of the related row, which is equal to the minimum of all algorithms' results.

	# of loads	# of required drivers			
		8-hours	9-hours	10-hours	11-hours
day 1	67	42	37	33	30
	44	39	36	34	31
day 2	42	26	22	20	18
	39	30	28	26	23
day 3	56	34	31	28	25
	31	24	23	20	19
day 4	67	42	38	35	31
	44	36	35	32	30
day 5	69	44	39	36	32
	42	36	33	30	28
day 6	60	39	35	31	28
	43	38	35	32	29
day 7	51	33	29	27	23
	24	20	19	18	16

b. Driver capacity simulation results

		FF	LF	NF	BF	WF	AWF
day 1	run 1	0	0	0	1	0	0
	run 2	1	1	0	1	1	1
day 2	run 1	1	0	0	1	0	1
	run 2	0	1	0	1	0	0
day 3	run 1	1	1	0	1	0	0
	run 2	1	1	0	1	1	1
day 4	run 1	1	0	0	1	0	1
	run 2	1	1	0	1	1	1
day 5	run 1	1	1	0	1	0	1
	run 2	1	0	0	1	0	1
day 6	run 1	1	0	0	1	0	1
	run 2	1	1	0	1	1	1
day 7	run 1	1	0	0	0	0	1
	run 2	1	1	0	1	0	1
day 8	run 1	1	0	0	1	0	0
	run 2	0	1	0	1	0	0
day 9	run 1	0	1	0	0	0	0
	run 2	1	1	0	1	0	1
day 10	run 1	1	1	0	1	0	1
	run 2	1	1	0	1	1	1
day 11	run 1	1	0	0	1	0	0
	run 2	1	0	0	1	0	1
day 12	run 1	1	1	0	1	0	0
	run 2	0	0	0	1	0	0
day 13	run 1	1	0	0	1	0	0
	run 2	1	1	0	1	0	1
day 14	run 1	1	0	0	1	0	1
	run 2	1	0	0	0	0	0
		FF	LF	NF	BF	WF	AWF
	total	23	15	0	25	5	17

c. Algorithm performances in finding the "best" value

The table below reflects the ability of the algorithms in finding the "best" value. Each data point, corresponding to a run and an algorithm, takes a binary value, where it is 1 if the algorithm's minimum is equal to the minimum of the 6 algorithm outcomes, 0 otherwise.

Appendix E – Source Code for the bpack-extended.icn Program

```
############################################################################
#        File:   bpack-extended.icn
#        Subject:  Program to demonstrate some bin packing algorithms
############################################################################
# Usage:  bpack [window options]
# Bpack illustrates several approximation algorithms for solving the
# one-dimensional bin packing problem.
############################################################################
# Requires:  Version 9 graphics
############################################################################
# Links: numbers, graphics, random, vsetup
############################################################################link numbers
link graphics
link random
link vsetup
$define Version "Binpack Lite (November, 1997)"
$define FULL 1100          # value representing a full bin
                           # (least common multiple of {1 to 18, 20, and 25})
$define PieceWidth 6       # width of one piece
$define BinWidth 7         # width of one bin
# pieces
global pieces              # list of piece sizes
# current output parameters
global xll, yll            # display origin
global bin                 # list of current bin sizes
global nfilled             # number of bins (partially) filled
# colors
global color               # array of GCs of different colors
global cscale              # conversion from piece size to color index
# display regions
global shelf1              # input segments
global shelf2              # packed bins
########################## main program ##########################
procedure main(args)
  local v, r, c, gc
  v := ui(args)                      # open window, set up vib-built vidgets
  r := v["root"]
  shelf1 := v["shelf1"]
  shelf2 := v["shelf2"]
  if shelf1.uw ~= shelf2.uw | shelf1.uw ~= shelf2.uw then
    runerr(500, "inconsistent layout")
  # make a set of colors for different bin heights
  # note that exactly half are reds/yellows and half are blues & darker
  color := []
  every c := Blend(
      "black", 1, "deep purple-magenta", 10, "cyan-blue",
      1, "reddish-yellow", 1100, "orange-red") do {
    gc := Clone(&window)
    Fg(gc, c)
    put(color, gc)
    }
```

```
  color := copy(color)                    # ensure contiguous array
  cscale := *color / real(FULL + 1)
  reload()                                # initialize random bins
  GetEvents(r)                            # enter event loop
end
######################## bin packing primitives ########################
# prepare(v) -- prepare shelf v for placing pieces
procedure prepare(v)
  xll := v.ux
  yll := v.uy + v.uh
  bin := list(*pieces, 0)
  nfilled := 0
  EraseArea(v.ux, v.uy, v.uw, v.uh)
  return
end
# place(p, b) -- add a piece of size p to bin b
procedure place(p, b)
  local o, t, x, y0, y1
  static m
  initial m := shelf1.uh / real(FULL)
  o := bin[b] | fail
  if (t := o + p) > FULL then
    fail
  bin[b] := t
  nfilled <:= b
  x := xll + (b - 1) * (PieceWidth + 1)
  y0 := integer(yll - m * o)
  y1 := integer(yll - m * t) + 1
  FillRectangle(color[cscale * p + 1], x, y1, PieceWidth, 0 < (y0 - y1))
  writetofile(p,x)
  return
end
# status(s) -- write string s and shelf population at end of output shelf
procedure status(s)
  local x
  x := xll + nfilled * BinWidth + 4
  x >:= xll + shelf1.uw - TextWidth("000 ")
  GotoXY(x, yll - WAttrib("leading") - WAttrib("descent"))
  WWrites(s)
  GotoXY(x, yll - WAttrib("descent"))
  WWrites(nfilled)
  return
end
######################## source set manipulation ########################
# reload() -- reload first shelf with random-sized pieces.
procedure reload()
  local i, j, z, p,f,temp
  temp :=list(1,"1100")
  f := open("jr.txt","r")
  pieces := temp
  while line:=read(f) do
          push(pieces,line)
  prepare(shelf1)
  every place(pieces[i := 1 to *pieces],i)
  status("")
  return
```

```
end
#  mix() -- randomly reorder the first shelf.
procedure mix()
  local i
  every i := *pieces to 2 by -1 do
    pieces[?i] :=: pieces[i]
  prepare(shelf1)
  every place(pieces[i := 1 to *pieces], i)
  status("")
  return
end
#  regular() -- place equally-spaced using golden ratio
procedure regular()
  local i, n, p
  n := integer(*pieces / &phi + 1)
  while gcd(*pieces, n) > 1 do
    n -:= 1
  i := 0
  every p := !sort(pieces) do {
    i := (i + n) % *pieces
    pieces[i + 1] := p
    }
  prepare(shelf1)
  every place(pieces[i := 1 to *pieces], i)
  status("")
  return
end
#  ascending() -- sort the first shelf in ascending order
procedure ascending()
  local i
  pieces := sort(pieces)
  prepare(shelf1)
  every place(pieces[i := 1 to *pieces], i)
  status("")
  return
end
#  descending() -- sort the first shelf in descending order
procedure descending()
  local i
  pieces := sort(pieces)
  every i := 1 to *pieces / 2 do        # change from ascending to descending
    pieces[i] :=: pieces[-i]
  prepare(shelf1)
  every place(pieces[i := 1 to *pieces], i)
  status("")
  return
end
# read from file
procedure writetofile(p,b)
        local f
        f := open("output.txt","at")
        every write(f,p," ",b)
        close(f)
end
#########################  packing algorithms  #########################
#  nextfit(l) -- pack using next-fit algorithm
```

```
procedure nextfit(l)
  local p
  every p := !l do
    place(p, nfilled | nfilled + 1)
  return
end
#  firstfit(l) -- pack using first-fit algorithm
procedure firstfit(l)
  local p
  every p := !l do
    place(p, 1 to nfilled + 1)
  return
end
#  lastfit(l) -- pack using last-fit algorithm
procedure lastfit(l)
  local p
  every p := !l do
    place(p, (nfilled to 1 by -1) | (nfilled + 1))
  return
end
#  bestfit(l) -- pack using best-fit algorithm
procedure bestfit(l)
  local p, b, i, max, found
  every p := !l do {
    max := FULL - p                    # fullest acceptable bin size
    found := 0                 # size of best bin found so far
    b := nfilled + 1                   # index of where found
    every i := 1 to nfilled do
      if found <:= (max >= bin[i]) then
        b := i
    place(p, b)                # place in best bin found
    }
  return
end
#  worstfit(l, n) -- pack using worst-fit algorithm
procedure worstfit(l, n)
  local p, b, i, found
  every p := !l do {
    found := FULL - p                  # size of best bin found so far
    b := nfilled + 1                   # index of where found
    every i := 1 to nfilled do
      if found >:= bin[i] then
        b := i
    place(p, b)                # place in best bin found
    }
  return
end
#  nearworst(l, n) -- pack using almost-worst-fit algorithm
procedure nearworst(l, n)
  local p, a, b, i, found
  every p := !l do {
    found := FULL - p                  # size of best bin found so far
    a := b := &null
    every i := 1 to nfilled do
      if found >:= bin[i] then {
        a := b
```

```
        b := i
        }
    place(p, \a | \b | (nfilled + 1))     # place in second-best bin found
    }
  return
end
########################## event handling ##########################
# menu_cb(v, a) -- File and Reorder menu callback
procedure menu_cb(v, a)
  case a[1] of {
    "About":                about()
    "New":                  reload()
    "Quit":                 exit()
    "Random":               mix()
    "Regular":    regular()
    "Ascending": ascending()
    "Descending":           descending()
    }
end
# pack_cb(v, a) -- Pack menu callback
procedure pack_cb(v, a)
  local s, p
  a[1] ? {
    s := tab(upto(' '))                 # get 2- or 3-letter name
    }
  prepare(shelf2)                       # clear the shelf
  p := copy(pieces)
  case s of {
    "FF":         firstfit(p)
    "LF":         lastfit(p)
    "NF":         nextfit(p)
    "BF":         bestfit(p)
    "WF":         worstfit(p)
    "AWF":        nearworst(p)
  }
  status(s)
  return
end
#===<<vib:begin>>===   modify using vib; do not remove this marker line
procedure ui_atts()
  return ["size=600,400", "bg=pale gray", "label=Bin Packer"]
end
procedure ui(win, cbk)
return vsetup(win, cbk,
  [":Sizer:::0,0,600,400:Bin Packer",],
  ["file:Menu:pull::0,0,36,21:File",menu_cb,
    ["About","New","Quit"]],
  ["line:Line:::0,22,599,22:",],
  ["pack:Menu:pull::93,0,36,21:Pack",pack_cb,
    ["FF   first fit","LF   last fit","NF   next fit","BF   best fit","WF   worst fit",
    "AWF  almost worst"]],
  ["reorder:Menu:pull::36,0,57,21:Reorder",menu_cb,
    ["Random","Regular","Ascending","Descending"]],
  ["shelf1:Rect:sunken::12,34,576,170:",],
  ["shelf2:Rect:sunken::12,217,576,170:",],
  )
```

```
end
#===<<vib:end>>===      end of section maintained by vib
```

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