Truckload Carrier Selection, Routing and Cost Optimization

A Thesis Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Zhixin Han

December 2015

Acknowledgements

I cannot express enough thanks to my committee for their continued support and encouragement: Dr.Rupy Sawhney, my committee chair; Dr. Mingzhou Jin and Dr.John E. Bell. I offer my sincere appreciation for the learning opportunities provided by my committee. My completion of this study could not have been accomplished without the support of my group members. Finally, to my caring, loving and supportive family, my heartfelt thanks.

Abstract

The aim of this thesis was to investigate the routing decision combined with common carrier selection for dedicated contract carriers to reduce full truckload routing cost on pickup and delivery service within time windows in a multiple depots scenario. Mixed Integer Programming and some heuristic algorithms such as the genetic algorithm and annealing algorithm have been successfully used to solve vehicle routing problems for a long time, but researchers seldom simultaneously focus on issues of carrier selection, multiple depots, time window, and the government regulations for a dedicated contract carrier. Therefore, this thesis involved constraints of pickup and delivery with time window, applied exact method to solve this problem and discussed further utilization of equipment, cost variance, and facility location under the influence of the new routing strategy. This thesis used two baseline methods to summarize current popular solutions for this problem. A comprehensive optimization model was proposed to output a better solution comparing to baseline methods, and a greedy algorithm based on this model can reduce solving time significantly. Cost analysis and utilization of equipment were emphasized due to the characteristic of dedicated contract carriers. A case study of Ryder System Inc. was utilized to compare outputs of different methods, as well as a sensitivity analysis on the time window, truck number, and depot locations was conducted. Results indicated that the comprehensive optimization method revealed the lowest cost but the longest running time. The Greedy algorithm was more efficient in solving such a problem but did not reach optimality. Results also recommended that the equipment number should be reviewed once a new routing strategy

is accepted, and that total cost and variable routing cost fluctuated with the change of a limited number of trucks.

Table of Contents

List of Tables

List of Figures

Chapter 1

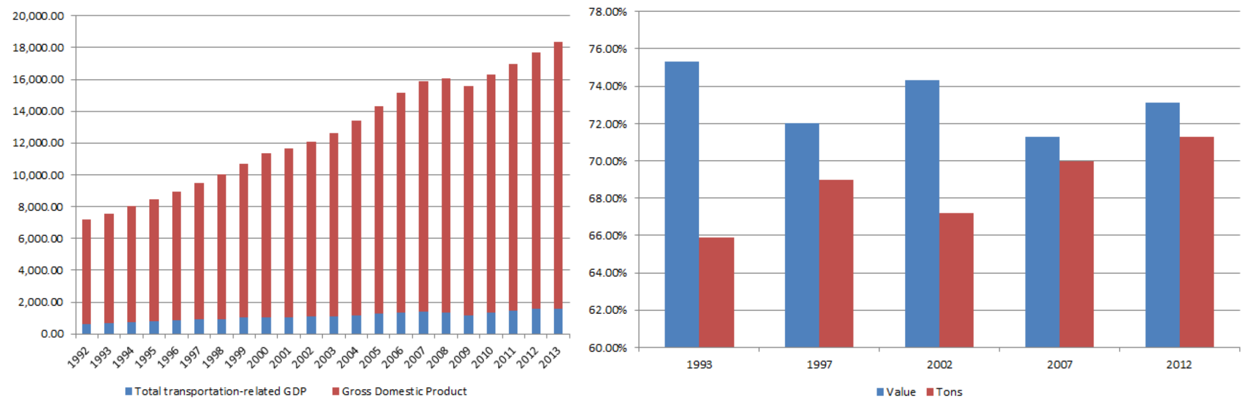
Introduction

1.1 Background

1.1.1 Importance of trucking industry to economy

The trucking industry is an essential part of modern commerce and the economy. It is a cyclical commercial industry, its revenue varying with the state of the economy and the health of businesses, providing shipping services to customers. In the last two decades, this commercial enterprise has constituted approximately 8% of the United States' gross domestic product (GDP) BTS (2014). During an economic upswing's early stages, customers tend to ship more goods in anticipation of stronger business conditions. Conversely, a decrease in trucking demand might signal the beginning of an economic slump, such as the 2008-2009 economic crisis, indicated by the decrease in trucking industry revenue, as shown in Figure 1.1 (a).

From 1993 to 2012, the United States' trucking industry delivered, on average, 73% of cargo in terms of value and 69% in terms of weight, as seen in Figure 1.1 (b). Even other forms of transportation, such as air cargo, railroad, and ocean shipping, significantly rely on trucking to transport cargo from local warehouses to airports, harbors, and rail yards. Because of the complexity and specificity of freight transportation in the United States, the



(a) Trucking Industry related GDP (USD billion) **(b)** Freight Value & Weight

Figure 1.1: Economic Indicator of Trucking Industry

trucking industry has been classified into various types of carriers based on the type of cargo and regulations of individual states.

1.1.2 Classification of carriers in trucking industry

The domestic trucking industry was subjected to government regulations as early as the 1930's Chow (1978). All carriers were regulated by the Interstate Commerce Commission (ICC), tasked with regulating the interstate trucking industry from 1935 until its absolute abolition in 1995. The regulations of motor carriers forced all competitors in the trucking industry to disclose their rates or tariffs. A price regulation regime meant that the carriers did not have the flexibility to change pricing according to the service level provided, offering little competitive freedom. In addition, the laws restricted certain goods to certain prescribed routes. Different carriers had specified regulations for their dedicated routes or regions, making route planning and operations complex and costly. As a result, free competition in the market was restricted and stagnated the transportation services' virtuous development, making it difficult for new carriers to enter the market.

After the government deregulation beginning in 1980, the rates fell due to fair competition, and the service quality improved. Shippers could choose carriers with some freedom. Further, new carriers could enter and compete within the market. Thus, types of carriers' entry intensified competition in the trucking industry. Examples of the various carriers include full truckload and less-than-truckload, for-hire, private, exempt, common, contract, and dedicated contract (Figure 1.2).

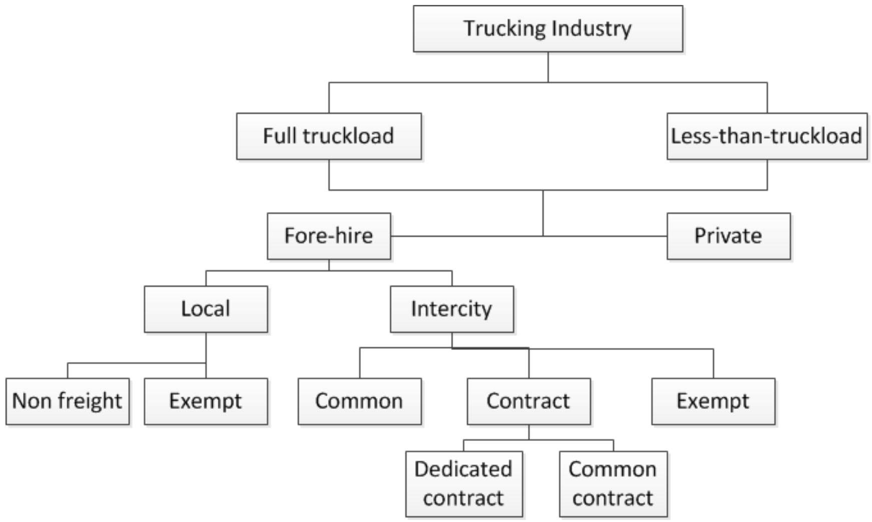


Figure 1.2: Types of Motor Carriers in the Trucking Industry

Full truckload and less-than-truckload carriers: In the trucking industry, almost all carriers depend on full truckload (TL) and less-than-truckload (LTL) carriage modes. Therefore, the industry can be classified based on these two categories. In a full truckload, the cargo from a single customer fills an entire truck. Conversely, in a less-than-truckload, shipments from different customers are transported together. With LTL, the cost of a small shipment is usually lower since customers only pay for the number of products shipped and for the travel distance. However, TL has a fixed rate in terms of distance, regardless of the volume and weight carried. By consolidating smaller shipments and achieving larger volumes, TL rates are usually lower per pound than LTL rates.

For-hire carriers: A for-hire carrier provides freight services to the general public and charges a fee for a given service. For-hire carriers can be further categorized as local and intercity operators. Local carriers pick up and deliver freight within a city's commercial zone. Intercity carriers operate between specifically defined commercial zones. The two types of carriers often work in tandem.

Private carriers: Private carriers refer to vehicles owned and used by a company to transport its own goods. A private carrier does not transport goods as its primary business, but owns a private fleet, including vehicles, trailers, drivers, and maintenance equipment. Private carriers provide fast and highly reliable delivery. A long-term and stable transportation volume benefits the private carrier by reducing the average operating cost.

Exempt carriers: An exempt carrier is exempt from economic regulations. The type of commodity hauled determines exemption. Exempt commodities usually include unprocessed or unmanufactured goods according to the Interstate Commerce Act (fruits and vegetables; ordinary livestock; wood chips; natural crushed, vesicular rock to be used for decorative purposes; and other items of little or no value) or by the nature of transportation operation (air transportation and empty shipping containers including intermodal cargo containers and farm goods transportation).

Common carriers: A common carrier provides freight-transportation services to the general public upon demand; at reasonable rates; and without discrimination, treating every customer equally. Examples of common carriers include FedEx and UPS.

Contract carriers: A contract carrier's primary business is to provide transportation services to certain shippers under the specific contract-of-carriage. For example, a contract carrier that flies organs, transplant tissues, or sensitive medications has specified staff or equipment in such transportation situations. A contract carrier also has the right to choose a customer or refuse to convey freight for payment. For example, one contract carrier can negotiate a higher price for a particular service by providing some specific service.

Dedicated contract carriers: A dedicated contract carrier (DCC) leases vehicles and drivers to shippers under continuous contracts. It operates as a private fleet for shippers, enabling them to avoid the burden of owning trucks; maintaining equipment; hiring and retaining drivers; and dealing with safety, compliance, and liability issues.

Full truckload and less-than-truckload are the trucking industry's two main transportation modes. TL provides services to shippers who tender sufficient volume to meet the minimum weights required for a full truckload shipment and truckload rate. LTL provides services to shippers who tender shipments lower than minimum truckload quantities: 50 lbs. to 10,000 lbs. LTL consolidates numerous smaller shipments into TL quantities for intercity transportation and disaggregates TL shipments at the destination for delivery in smaller quantities.

Some companies that own their own transportation fleets may use contract carriers or common carriers in certain situations, such as when many goods need to be shipped but all the company's vehicles are in use. These outsourced contract or common carriers are called third-party logistics (3PL) companies, which provide all of a complex supply chain's necessary logistics services, including storage, transshipment, and other value-added services. The for-hire carriers can be considered 3PL as a flexible alternative method for private carriers facing a shortage of warehouses or vehicles. However, owning a private fleet is capital intensive for companies whose demand is unstable and whose revenue is seasonality sensitive. For example, some shopping malls replenish stock associated with seasonal or holiday sales.

As a type of 3PL supplier, the dedicated contract carrier provides a solution by offering the hybrid advantages of private and contract carriers, thus enabling management of fleet and drivers. Some of them also support warehousing, inventory management, and cross-docking solutions, which result in greater cost and time savings. Although DCCs provide flexible and economic solutions to shippers, they still face many challenges. Especially in TL transportation, empty running cost accounts for a large proportion of the travelling cost. Furthermore, in daily transportation planning, selecting a common carrier is seldom considered from a cost perspective.

1.2 Problem introduction

1.2.1 Problem statement

The main problem DCCs face is managing fleets for shippers. In increasingly fierce market competition, most trucking companies compress costs to capture the market share, and DCCs are no exception. TL service is widely used in some industries, such as dry food, temperature-controlled service, cross-dock, and just-in-time (JIT) inventory maintenance. Despite having less flexibility than LTL due to its transportation service's specific characteristics, TL service can provide faster delivery and lower transportation costs.

When a DCC is required to provide full truckload transportation, it usually resorts to a traditional operation method: between two requests, vehicles must return to the depot, resulting in a high routing cost. Since cost is critical to a trucking business's survivability and profitability, this thesis focuses on minimizing the cost of TL transportation for DCCs. The overall cost involves variable and fixed costs. Variable cost is proportionate to the distance the fleet travels. Therefore, minimizing travel distance would reduce transportation's overall variable cost. Fixed cost depends on long-term capital and overhead costs. This study focuses on minimizing cost by minimizing travel for DCCs in terms of multiple depots; time window; pickup and delivery services; selection of outsourced common carriers; and the relationship among routing strategy, cost, and equipment utilization.

1.2.2 Objective and hypothesis

This work's objective is twofold: to develop a mathematical model optimizing transportation cost while outsourcing some requests to common carriers, and to compare this model with baseline methods. The greedy algorithm will prove helpful in reducing the solving time. The conclusion of this thesis discusses which the DCC fleet routing strategy is more appropriate for optimizing costs as described above by answering the following questions:

- How can empty miles be reduced?
- How can common carriers in transportation operations be assigned to reduce costs?

- How does routing strategy affect equipment utilization?
- How do facility locations and time-window constraints affect transportation costs?

This study's hypothesis is that by comparing output results, the comprehensive optimization model has the highest cost-saving performance; meanwhile, the greedy algorithm has the shortest solving time and relatively good optimality Kontoravdis and Bard (1995) and Yuan and Fügenschuh (2007). In addition, fleet size would largely impact vehicle utilization, and the new routing strategy would reduce this size. However, variable and total costs can fluctuate with the fleet number, and the lowest variable cost does not necessarily indicate the lowest mean total cost Smith et al. (2007)

1.3 Approaches

Approaches introduced in this study are data transformation and clustering, vehicle routing, mixed-integer programming, greedy algorithm and sensitivity analysis. Data transformation and clustering was used to analyze raw data; vehicle routing and mixed- integer programming was used to formulate mathematical models for the traditional, two-stage optimization, and comprehensive optimization models, while greedy algorithm was used to reduce the solving time in obtaining a relative optimal solution. Sensitivity analysis was useful in understanding how model parameters affected the objective function.

1.3.1 Data transformation and clustering

The purpose of data transformation is to convert a set of data values or format from one or several systems' databases to fit the destination system. Three data sources were used in this study: customer's orders, DCC fleet information, and common carrier information. Before employing the models introduced in this thesis, all of the data was formatted in a temporary file using R studio software, helping import eligible data into optimization models. Data clustering is a method used to classify patterns (observations, data items, or feature vectors) into groups (clusters). Clustering is useful in several exploratory pattern-analyses, pattern classification, grouping, and decision-making. One simple clustering process is shown in Figure 1.3. This procedure is used to reduce problem complexity and solve the problem in the polynomial time. In computational complexity theory, the polynomial time is how fast an algorithm can optimally solve a model or problem.

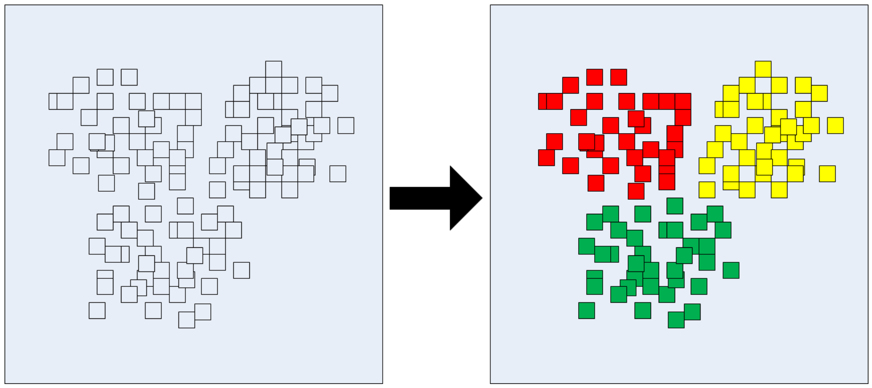


Figure 1.3: Data Clustering

1.3.2 Vehicle routing

Dantzig and Ramser (1959) proposed the vehicle routing problem (VRP), proposed by based on another optimization problem called the traveling salesman problem (TSP). Given a number of cities (n) in this problem, the traveling salesman has to visit every city once and return to the original city; the objective is to minimize the total traveling cost, time, or distance. As the number of cities increases, computation becomes more and more complex. This problem is, defined as NP-hard, meaning the problem is hard to solve or its solution's accuracy is difficult to verify in polynomial time using known methods. Differing from TSP, VRP uses one fleet of vehicles instead of one salesman, which is a combinatorial optimization and integer programming problem seeking to service many customers in order to minimize the total traveling cost. Much of the current literature uses customers on nodes, which do not include cost to optimize edges among different nodes in a graph. Three typical VRP models were used in this study: vehicle routing problem with time window, vehicle routing problem with pickup and delivery, and multi-depots vehicle routing problem.

- **Vehicle routing problem with time window (VRPTW)**

  VRPTW is an extension of VRP, which requires that the service at each customer or location must be commenced and completed in the time interval or time window consisting of the earliest and latest arrival time $[e_i, l_i]$, where i is customer index. Time window is one of the services standards. Soft time window terms may be violated by paying a penalty; but for hard time window, customers must be visited and served during the time window. Even if arriving at the location before the earliest allowable serving time, a vehicle must wait until the customer is ready to begin service.

- **Vehicle routing problem with pick up and delivery (VRPDP)**

  As an extension of capacitated vehicle routing problem (CVRP), which stipulates the quantity of carried loads must fall within the vehicle's capacity, VRPPD determines some loads must be picked up at one or more locations and delivered to others, while multiple pickups or deliveries are allowed and follow the rule of first-in last-out (FILO).

- **Multi-depots vehicle routing problem (MDVRP)**

  As a branch of classical VRP, MDVRP is used to serve customers in a region and decides which depot is the best to serve one group of customers. A vehicle from one of the depots should return to the corresponding depot, although repositioning a vehicle is allowed under some circumstances.

These three VRP concepts were combined to formulate the mathematical model in the mixed-integer programming.

1.3.3 Mixed-integer programming

Used for decades to describe and solve VRPs, mathematical or exact methods, usually provide an optimal solution when the calculation complexity is in the acceptable range. With mixed-integer programming (MIP), some of the variables in linear programming are continuous and some are discrete; therefore, the corresponding optimization problem is called a mixed integer linear program (or mixed-integer programming). The constraints are all linear equations or inequalities, and the objective is a linear function to be minimized (or maximized).

$$\begin{aligned} min \quad & c^T x \\ s.t. \quad & Ax = b \\ & x \in \mathbb{Z}^+ \end{aligned}$$

Where c, b are vectors and A is a matrix that has integer values, x could be binary, integer, or continuous variables.

MIP is widely and often used to solve VRP. Although many heuristic algorithms have been developed to solve this kind of problem, MIP is the most accurate method to provide the optimization solution in benchmark problems. Meanwhile, linear relaxation, branch and bound as well as cutting plane techniques can be applied to solve MIP. GUROBI solver, which is an optimization software, has powerful capabilities to solve MIP. Preprocess in GUROBI uses a decomposition technique to reduce variable size and lower redundant constraints. A heuristic algorithm could help find bounds very quickly in the solution process Padberg and Rinaldi (1991).

1.3.4 Greedy algorithm

A greedy algorithm, like the heuristic algorithms, is a mathematical process that looks for simple, easy-to-implement solutions to complex, multi-step problems by deciding which next step will provide the most obvious benefit. Greedy algorithms help make the best decisions given the immediate context and the lowest effort. In other words, they help make decisions that are locally optimal with a possibility that such decisions will lead to globally optimal solutions. As an approximation algorithm, the greedy method does not consider the larger problem but reaches the best possible decision at an algorithmic stage based on the current local optimum and the best decision made in a previous stage. Once a decision is reached, it is never reconsidered. It is not exhaustive and does not give the best answer to many problems like other heuristic methods do; but when it works, it is the fastest method.

1.3.5 Sensitivity analysis

Sensitivity analysis is a method used to investigate the potential changes of parameter values, or some assumptions, and their impacts on conclusions to be drawn from mathematical models, such as linear programming and integer programming. Sensitivity analysis not only identifies critical values, thresholds or break-even values where the optimal strategy changes, but also helps modelers understand and estimate relationships between input and output variables. This study used an experimental method to test how constraint slacking affected the objective function's value.

1.4 Thesis organization

Chapter 2 discusses literature relating to the vehicle routing problem, carrier selection, and cost structure. In Chapter 3, the comprehensive optimization model is formulated by using mixed integer programming and applied in greedy algorithm. A clustering method is also addressed for allocating customer requests to relative depots in baseline methods 1 and 2. The trucks' variable cost is considered the standard in determining a routing strategy's performance. The case study and sensitivity analysis of Ryder System Inc. is conducted to compare results among different scenarios in Chapter 4. The decision of truck numbers and facility locations is also discussed Chapter 4; these two factors are very significant in the cost structure and in market-rate reduction. Chapter 5 includes a conclusion and proposes future work.

Chapter 2

Literature Review

2.1 Vehicle routing problem

The classical vehicle routing problem (VRP) has been used in a wide range of applications in the trucking industry. In addition, numerous modifications have been made to the classical VRP that broaden its application. Examples of modifications to the VRP include a sensitive time-window, pickup and delivery service, and multiple trips. The core problem in this thesis is pickup and delivery problem with time window (PDPTW). This problem was derived from vehicle routing problem with pickup and delivery (VRPPD) and vehicle routing problem with time window (VRPTW). The time window is associated with customers' requests; one request has the earliest and latest arrival time a_i and b_i; both times could be hard or soft. A hard time window forces the vehicle to visit the request between a_i and b_i; in contrast, a soft time window allows the vehicle to visit the request out of this range, but a penalty is applied for any such time relaxation. Pickup and delivery service indicates the vehicle could pick up cargo in one place and deliver it to a single location or multiple locations, and vice versa.

After Dantzig and Ramser (1959) proposed VRP, it developed rapidly and had many variations. Goetschalckx and Jacobs-Blecha (1989) also summarized five methods to solve VRP: (a) cluster-first/route-second, (b) route-first/cluster-second, (c) savings/insertion, (d) improvement/exchange, and (e) exact method with some relaxed constraints. Many heuristic methods have been widely used in this area in the last 30 years since Christofides (1979) summarized this method. Lahyani et al. (2015) and Eksioglu et al. (2009) summarized all the literature relating to VRP under various conditions in taxonomy reviews.

2.1.1 Exact solution method

Several PDPTW surveys have been presented by Savelsbergh and Sol (1995), Mitrovic-Minic (1998) and Desaulniers et al. (2002). Using dynamic programming, Desrosiers et al. (1986) introduced the first pure PDPTW exact method for the pure PDPTW. Ford Jr and Fulkerson (1958) found that using a mathematical structure could reduce a problem's complexity. Dantzig and Wolfe (1960) decomposed the exact method's special structure to a smaller problem, which hastened the solving process. Both studies brought new ideas to solve a mathematical model called column generation.

Column generation is used frequently to solve a large linear program. The master problem is reorganized and decomposed to a subset of problems; every sub-problem is created to identify a new variable. The sub-problem's objective function is the new variable's reduced cost corresponding to the current dual variable. If one sub-problem's objective value is negative, the variable is added to the master problem, which is resolved. Next, a new set of dual variables is generated by resolving the master problem. The process is repeated until there is no negative reduced cost, with the master problem being considered optimal. The method decomposes the original problem's computational complexity.

Xu et al. (2003) proposed a heuristic method based on column generation to solve a PDPTW. The problem considers that pickup and delivery must be nested in such a way that the last order loaded is the first unloaded (LIFO) on the route. The model also considers drivers' legal working hours, but strict time windows of pickup and delivery services are not considered. Furthermore, every order has multiple pickup and delivery times. Parragh et al. (2012) introduced a Dial-a-ride Problem, which is similar to PDPTW but more suitable for passenger pickup and delivery transportation. Based on an exact mathematical model, column generation was used to solve a real-world problem for a non-profit organization in this study; drivers' regulations and time windows were constrained in the problem. However, this problem only considered one depot Ileri et al. (2006) used column generation to solve daily drayage transportation problems in terms of an exact method, in which trucks picked up and delivered a loaded or empty container, or trailer, between customers and rail ramps. Time windows and drivers' maximum working hours were considered in the exact method; stops were allowed in the model, and trucks departed only from prescribed depots.

2.1.2 Heuristic method

Heuristic methods' characteristics and algorithms for the VRP were introduced by Cordeau et al. (2002) and Cordeau et al. (2005). In these two studies, different heuristic methods were compared with benchmark problems, and accuracy and speed were key factors to evaluate. Generally speaking, heuristic methods could be summarized by several algorithms: tabu search, genetic algorithm, simulated annealing, ant colony, neural network, etc. Minocha and Tripathi (2013) proposed a two-phase method to solve VRPTW, which first using a genetic search to find a local optimal solution and then applying a simulated annealing random search to find a better solution. Adelzadeh et al. (2014) used mathematical methods and a simulated annealing heuristic algorithm to solve VRPTW under multiple depots; the time window in this work is fuzzy, similar to the soft window method.

Nagy and Salhi (2005) used a heuristic algorithm to solve the PDPTW, in which trucks must deliver all goods after one pickup. These researchers' methodology is capable of solving the multiple depot problem as well. Nanry and Barnes (2000) used tabu search and neighborhood selection to solve a benchmark problem's classical PDPTW. However, multiple depots and drivers' regulations were not Nanry and Barnes' concerns. Pisinger et al. (2004) applied PDPTW to transport livestock from one location to another. To prevent the spread of diseases, extra constraints on the route were enforced so that one truck transporting ill livestock could not be re-used in the transportation fleet before being disinfected.

2.1.3 Summary of VRP

In summary, the studies described above and other studies by Desrosiers et al. (1986), Derigs and Döhmer (2008), Tarantilis and Kiranoudis (2002) only considered a few of the multiple depots' constraints, including regulations of working time, strict time windows, and fixed numbers of trucks. Furthermore, because DCCs were not their research focus, TL utilization was not their concern. This thesis not only focuses on exact methods to solve real-life, full-truckload pickup and delivery vehicle routing problems within strict time windows with multiple depots but also considers truck utilization.

In addition, several factors are brought into focus in this work, as identified below. By comparing 18 classical studies in the taxonomy review in Table 2.1, none of these researches focuses on the following factors simultaneously:

a. Driver scheduling

b. Multiple depots

c. Pickup and delivery

d. Multi-trip

e. Fixed number trucks

f. Driver regulations

g. Strict time window on customer

h. Carrier selection or outsourcing

i. TL service

j. Descriptive mathematical formulation (exact method)

k. Heuristic algorithm and column generation

Table 2.1: Literature Comparison

No.	Paper	a	b	c	d	e	f	g	h	i	j	k
1	Nagy and Salhi (2005)		✓	✓	✓							Heuristic algorithm
2	Nanry and Barnes (2000)			✓	✓	✓		✓				Tabu search
3	Derigs and Döhmer (2008)			✓				✓				Greedy decoding
4	Muter et al. (2014)		✓								✓	Column generation
5	Xu et al. (2003)			✓	✓	✓	✓		✓		✓	Column generation
6	Vidal et al. (2012)		✓									Meta-heuristic
7	Tarantilis and Kiranoudis (2002)		✓									Meta-heuristic
8	Ropke and Pisinger (2006)			✓								Heuristic algorithm
9	Parragh et al. (2012)			✓			✓	✓			✓	Column generation
10	Ileri et al. (2006)	✓		✓				✓		✓	✓	Column generation
11	Moon et al. (2012)			✓		✓	✓				✓	Genetic Algorithm
12	Bent and Van Hentenryck (2004)							✓				Simulated annealling
13	Nguyen et al. (2013)	✓			✓	✓					✓	Meta-heuristic
14	Chuah and Yingling (2005)			✓				✓			✓	Tabu search
15	Dondo and Cerdá (2007)		✓		✓						✓	Clustered heuristic
16	Kallehauge et al. (2005)	✓			✓			✓			✓	Column generation

Table 2.1. Continued: Literature Comparison

No.	Paper	a	b	c	d	e	f	g	h	i	j	k
17	Bolduc et al. (2008)								✓		✓	Meta-heuristic
18	Crainic et al. (2008)		✓									Meta-heuristic

2.2 Carrier selection

In the carrier-selection system, the objects are shippers and carriers. Some shippers are contract carriers eligible to hire common carriers in order to fulfill their transportation missions. Most importantly, shippers only care about service quality and service cost. Usually, shippers make an initial decision in terms of their past experience or statistical analysis, using shipper-carrier service criteria factors cited in Abshire and Premeaux (1991) and Kent and Stephen Parker (1999). Evers et al. (1996) described shippers' perceptions of various transportation service characteristics, but was only concerned with options for choosing carriers for long-term contracts.

Xu et al. (2003) and Bolduc et al. (2008) described a hybrid carrier-selection strategy in the routing problem. In these studies, different carriers' costs were not integrated with private fleet routing, but characteristics of equipment type and capacity consolidation were the focus. Moon et al. (2012) solved VRPTW with outsourced vehicles; meanwhile, drivers' overtime cost was considered in the MIP model by using outsourced vehicles, and a genetic algorithm was applied to solve this problem. Although Bolduc et al. (2008) considered the outsourced carriers in VRP, the time window was flexible and similar to multiple TSP without the pickup and delivery constraints. Although Bolduc et al. considered carrier selection during vehicle routing, this study presumes that, outsourcing the common carrier is less costly; therefore, in some situations, common carriers are still deployed even though DCC vehicles are not fully used, purely from a cost point of view. Sometimes, even though the common carrier has a lower cost than the DCC in one route, the DCC can still carry this order to minimize cost in multiple trips.

2.3 Cost structure

The trucking industry considers cost to be a key factor affecting carrier selection and routing strategy. When explaining cost methods useful in estimating the relationship between outputs and costs, statistical methods are frequently applied to analyze cost models Goldberg and Touw (2003). Smith et al. (2007) provided a big-picture analysis of how cost influences net tariff. In addition, detailed cost components and calculation methods were summarized by Trego and Murray (2010), Berwick et al. (2003), Berwick and Dooley (1997) and Goetschalckx and Jacobs-Blecha (1989). These studies indicated that eliminating empty miles and efficiently using backhaul opportunity (i.e., cargo or freight is carried on the return trip over all or part of the same route) contributes to saving a greater proportion of the total traveling cost.

Factors affecting costs in the trucking industry include the equipment size, recourse utilization, and the makeup of variable and fixed costs. In the trucking industry, cost is usually divided into four categories: fixed, variable, joint, and common Bowersox et al. (2002). Joint cost is similar to opportunity cost, which depends on the vehicle routing strategy in the TL transportation service, such as empty running cost on the back trip to the depot. Common cost arises when the facility generates other transportation services like terminal cost; common cost is considered as fixed cost in this study. Therefore only fixed cost and variable cost are considered in this thesis, as shown in Table 2.2.

Fixed costs are incurred whether a truck is logging miles or not Dooley et al. (1988).while variable costs easily change with output distance or time span Ferguson and Kreps (1965). Table 2.2 shows common fixed and variable costs. Variable costs are comprised of expenses a trucking company only pays if the truck is en route. These costs generally increase as the number of miles the truck travels throughout the usage time increases. Variable costs include fuel, driver pay, lodging, tires, and truck maintenance. Therefore, knowing the total variable expenses is essential before accepting a load. Drivers' wages and benefits and the trucks' fuel and oil costs account for the vast majority of variable costs Trego and Murray (2010). Tire cost is also considered an important component in variable cost Trego and Murray (2010),

Table 2.2: Categories of Cost

Categories of Cost	Items	
Fixed Cost	Equipment (Tractor and Trailer) Depreciation License, insurance and permit Office and overhead	
Variable Cost	Vehicle Based	Fuel and Oil Maitnenaince and Repair Tire Toll Stopoff
	Driver Based	Wage Benefit Other Bonus

Berwick and Dooley (1997), and Berwick et al. (2003). Since tires are petroleum-based products, tire costs increase in response to higher oil prices, as well as driving behavior and environmental conditions.

Furthermore, tolls as a type of variable cost may be a significant cost for motor carriers although they are highly dependent on the carrier's region of operation. Many carriers try to avoid tolls when possible since shippers rarely reimburse carriers for toll-related expenses Trego and Murray (2013). Stop-off charges are levied when shippers request that a shipment be partially loaded and/or unloaded at several locations in one route; but for this study's purposes, this charge is not addressed. Multiple trips may result in empty running costs, with no profit and inefficient use of trucks and drivers. Backhaul could compensate for this expense depending on whether some other customers have orders to transit on the back trip to the depot.

The distinguishing characteristic between fixed and variable costs is time. In the long run, all costs are variable, or can be changed. Although cost structure has been divided into very detailed substructures in many studies, carriers would like to compare total and variable costs for equipment in order to evaluate a routing system's performance, especially for DCCs.

Dooley et al. (1988) also used the information presented in Figure 2.1 to demonstrate the relationship to demonstrate the relationship among average fixed cost, equipment number, and empty running cost. Even as increments of output miles, maintenance cost (MC), average total cost (ATC), and average variable cost (AVC) Increase till some breaking points associated with output miles. Average fixed cost (AFC), however, decreases all the time. Reducing empty miles could postpone the appearance of break points and help DCCs enhance length of time to increase total profit. Trego and Murray (2010) noted that empty miles occupy an average of 12 to 20 percent of the total carrier miles.

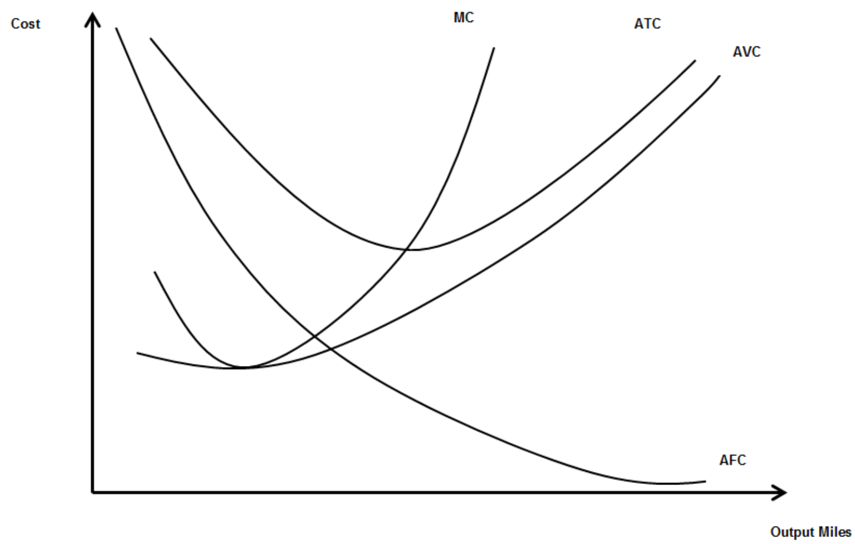


Figure 2.1: Cost-Distance Relation

The DCC prefers to use daily fixed cost per truck to calculate total cost, but neglects to address the issue of cost regarding idle trucks not participating in fleet routing. Unlike previous studies, this thesis considers cost allocation of equipment's fixed and variable costs when applying a new routing strategy in daily fleet operation.

Chapter 3

Model Development

3.1 Model development procedure

This study demonstrates four stages in the model procedure shown as Figure 3.1.

Stage one: source data

Source data is extracted from customers, shippers, the DCC, and common carriers. One shipper sends to the DCC transportation requests, which contain origin and destination pair (OD), volume, weight, earliest and latest service time, and several other pieces of information. When the DCC receives this information, the number of drivers and available vehicles must be updated daily. Quotes from common carriers for all requests are shared with the DCC through an instant information system.

Stage two: data transformation and clustering

The earliest and latest services times are defined in stage one. In stage two, the time-window definition calculates allowable arrival time for every location or request. The source data is transformed to the target inputs and format so as to match the requirement for optimization models. Meanwhile, the clustering technique is used to reduce the problem size for some models. The DCC summaries a distance dictionary as a reference because most data depends on distance. Used to employ this process, R studio is a free data and statistic software, which has professional performance and is more flexible.

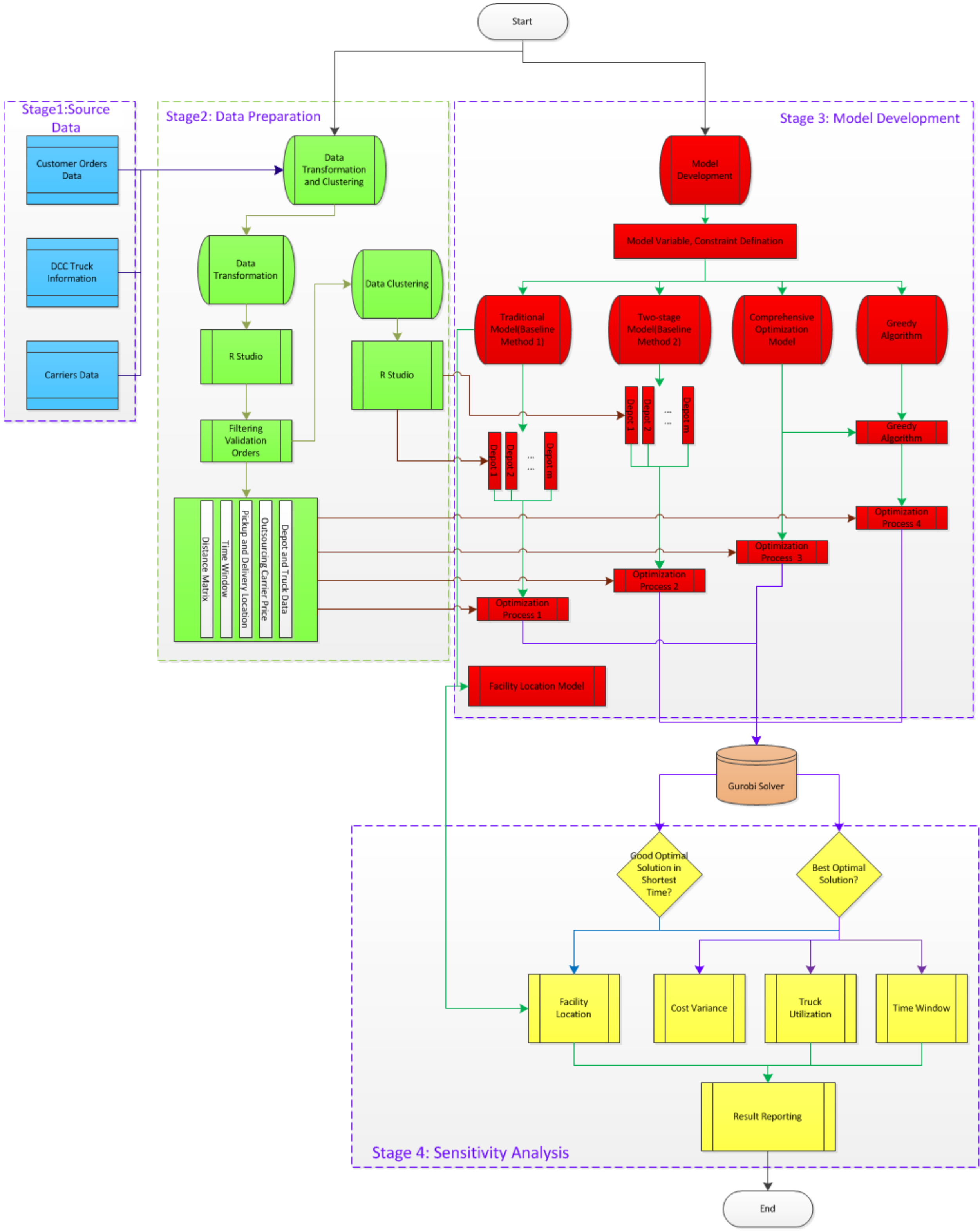


Figure 3.1: Model Development Map

Stage three: optimization model development

When necessary data is available, the baseline methods, comprehensive optimization model, and greedy algorithm are presented to solve the problem presented in this thesis. The traditional model and the two-stage optimization models used as baseline methods are commonly used to solve immediate problems. In addition, the comprehensive optimization model and the greedy algorithm are innovative methods presented in this thesis to provide better solutions compared to the baseline methods. The ultimate purpose is to determine which method provides the best solution. The baseline methods and the comprehensive optimization model use different strategies to solve the same problem, while the greedy algorithm as an alternative method has a lower solving time, as introduced in Chapter 1. A location model is developed and used in stage four to verify whether depot locations would provide the minimum routing cost beforehand. All models were solved in the GUROBI optimization solver.

Stage four: sensitivity analysis

Sensitivity analysis (SA) compares all of stage three's results to determine which model provides the most optimal result, or a better result in a shorter term. SA also investigates the impact-to-cost variance, truck utilization, time window, and facility location.

3.2 Stage one: source data

There are four data sources: customers, shippers, the DCC, and common carriers. Figure 3.2 is an entity-relationship diagram (ERD) showing the relationship among data warehouse tables containing information from different sources. Customer-order data includes information on customers, products, pickups, and deliveries.

The order data table combines all of this information. When shippers collect order requests in the shipper table, data must be reorganized and reformatted for subsequent processing. However, before sending the data to the DCC, shippers have to add notes or additional information to clarify other requirements and ensure the data's accuracy. The DCC table provides a unique ID in the database for a specific shippers containing requirements for equipment numbers, equipment type and drivers' information. The DCC also uses this database to manage customers' and shippers' data for evaluating future transportation capacity.

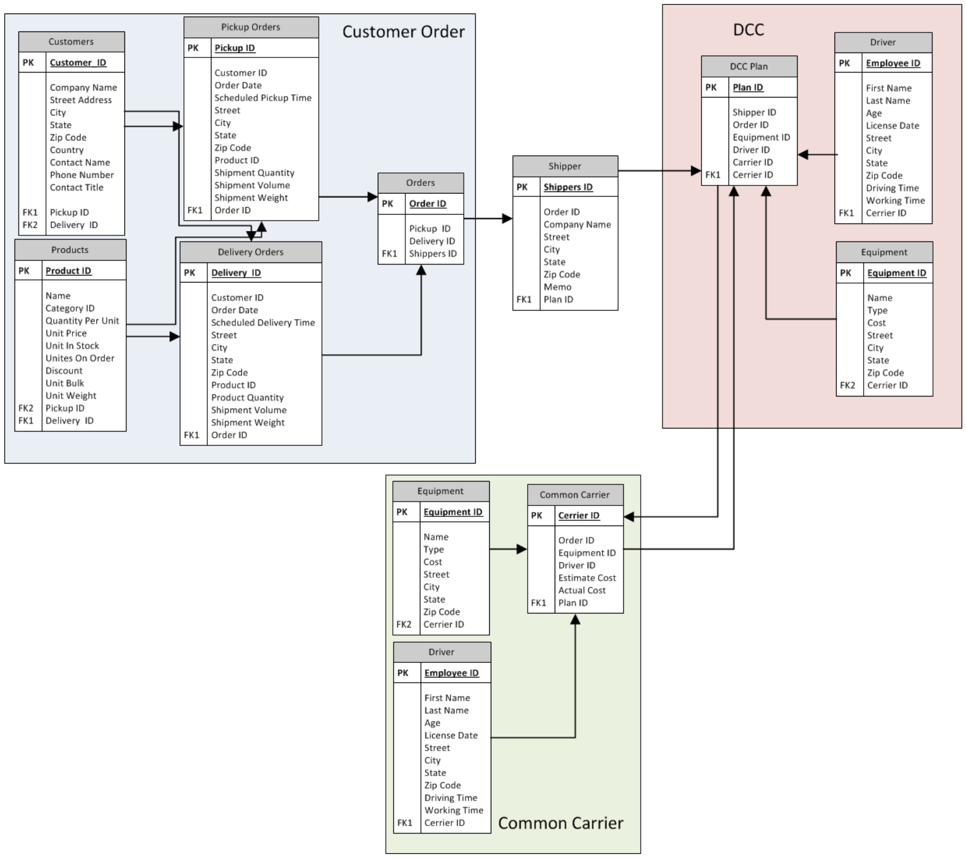


Figure 3.2: Source Data ERD

The DCC and common carriers share one instant information system to update quotes for every order. The DCC sends order information to common carriers. By evaluating equipment and drivers, common carriers estimate a common carrier rate for every request and sends it back to the DCC. Additionally, the DCC must estimate drivers' availability for a given day because government regulations require information regarding drivers' driving time, working time, recover time, etc.

3.3 Stage two: data transformation and clustering

3.3.1 Data transformation

Before importing data to models, source data from the customers, shippers, common carriers, and the DCC must be transformed into a proper data format to be used effectively in the models. For customers' requests whose volume or weight exceeds a vehicle's capacity, dividing a single shipment into several smaller shipments is necessary. As a result, truck's capacity may not be fully optimized. The transformed shipping request is shown in Table 3.1. The distance between any two locations is determined by zip code. Target data (cost and time, derived from distance) have different requirements depending on the baseline methods and the comprehensive optimization model.

Table 3.1: Before Data Transformation

Unique ID	Order Date	Customer ID	Pick Up Address	Scheduled Pickup Time	Delivery Address	Scheduled Delivery Time	Volume	Weight	Estimated Common Carrier Rate

The time-window definition in this section was used to calculate arrival time for every location or request. In addition, regulated driving and working time, as hard constraints, have to be considered and filtered before being imported to the model, as shown in Figure 3.3. One purpose is calculating the proportion of long-distance orders, which is helpful in developing the drivers' relay strategy. The other important purpose is reducing the number of variables.

3.3.2 Data clustering

After data transformation, the target data table is transformed to the desired format, which is conveniently used by either baseline methods or the comprehensive optimization model in GORUBI software. The format is shown as Table 3.2.

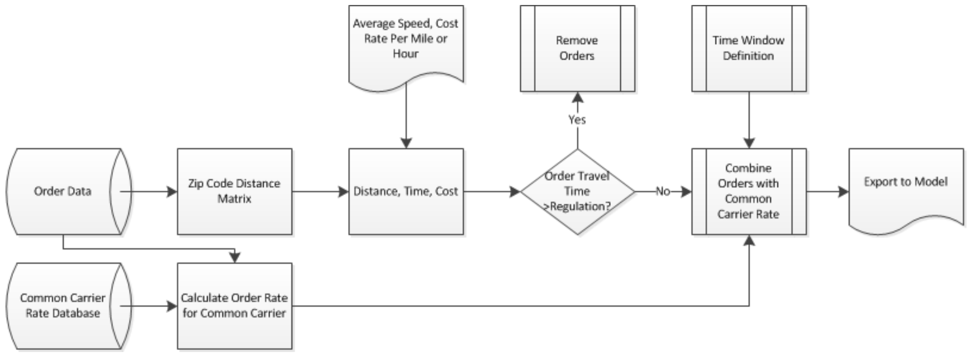


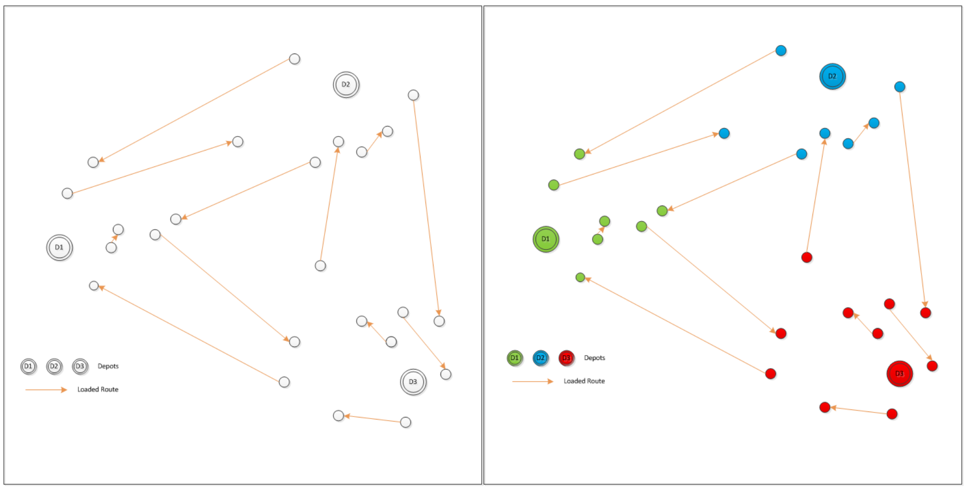
Figure 3.3: Data Transformation

Table 3.2: After Data Transformation

Unique ID	Earliest Arrival Time At Node Or Request	Latest Arrival Time At Node Or Request	DCC Traveling Cost Coefficient	DCC Traveling Time Coefficient	Common Carrier Accurate Cost

In this section, a traditional model and a two-stage model are used to solve multi-depot VRP according to customer-to-depot assignment based on zip code distance Simchi-Levi et al. (2014) and Crainic et al. (2008). To deconstruct the original problem into smaller ones, requests were divided into several clusters, with the number of clusters equal to the number of depots. Denote m was the number of depots. Every depot's number of vehicles was defined beforehand. All nodes were clustered into m clusters by searching the shortest distance from every node to every depot.

Pickup locations were the references to be allocated in three clusters in terms of the number of depots (as shown in Figure 3.4(a)) because in the real-world, DCC depots were located near customers' service nodes so as to serve requests promptly. However, from the view of global optimization, closer pickup locations did not mean lower costs for the requests. In addition, before clustering requests, some orders had to be eliminated from input data because of driving-regulation violations and, therefore, had to be taken by a common carrier according to triangle inequality: if one request's total driving time is greater than half the regulation time, total driving time is more than regulation driving time. As a result, one shipper's requests were divided into common carrier requests and other requests, which could be carried by either the DCC or common carriers, as shown in Figure 3.5. For easily illustrating every node's distance matrix to the depot after pickup nodes cluttering, the graph is colored according to distance from one node to the closest depot as shown in Figure 3.4(b). In this figure, most delivery nodes cross the two clusters, as is the nature of committed truckload transportation. Therefore, clustering pickup nodes could provide better service quality than whole orders.



(a) Nodes Map **(b)** Cluster Coloring

Figure 3.4: Nodes Clustering

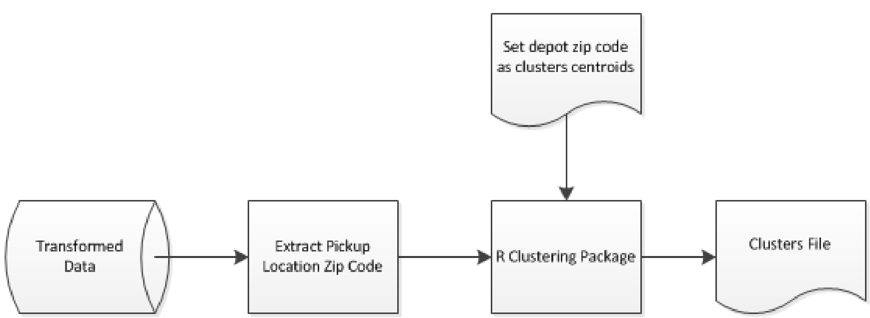


Figure 3.5: Clustering Orders Flow

3.4 Stage three: optimization model development

3.4.1 Variables

Considering a routing network as the example shown in Figure 3.6, represented by the directed graph $G(V, A)$, customers' service nodes (2, 3, 4, 5), and depots (1, 6). In VRP, variables are indicated as route sequences among nodes in graph in Figure 3.6 from 1 to 6, with every variable having three indexes relating to orientation and destination among service nodes in all routes for all vehicles. For example, x_{12}^{k} represents whether edge b is selected as a route traveled by vehicle k; the edge b between two nodes (1, 2) is associated with cost coefficient. This method of defining variables is more sophisticated and common in vehicle routing problems.

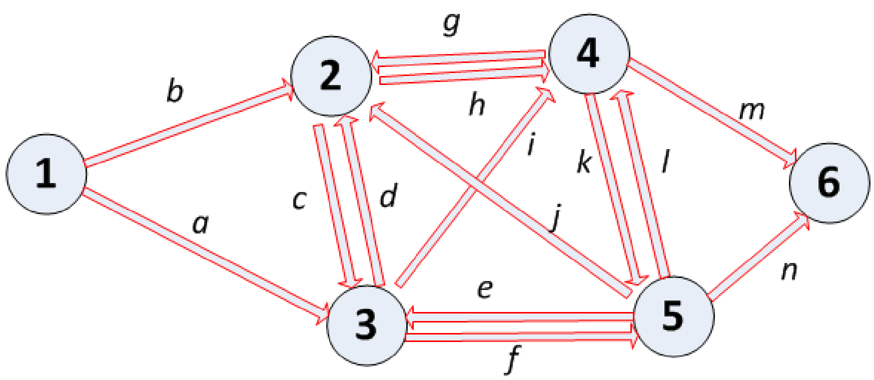


Figure 3.6: Network Graph

3.4.1.1 Node variables

For the traditional model and the two-stage optimization model, the multi-depot problem was divided by m single depot VRP using the clustering technique, where m is the number of depots. This method is commonly used to solve VRP. Order requests contained an identified route (pickup location and delivery location), time window (boundaries for arrival-time variables), cost coefficient, time coefficient, and common carrier cost. One request's two vertexes were defined by two nodes i and $n + i$, corresponding to pick-up spots and delivery spots, respectively. The letter n represented the number of orders, and digits 1 and $2n + 2$

represented the index of depot nodes for the number of orders. The set of pick-up nodes was denoted as P={2,3,4,...,n+1}, and the set of delivery nodes was D={n+2, n+3,..., 2n+1}. Every DCC vehicle had to depart from node 1, passing by a set of P and D. D had to follow P separately (for example, after visiting node 2, the DCC vehicle had to go to n+2 and finally return to 2n+2. In this scenario, node 1 and 2n+2 represented the same depot. Let V be the set of DCC TL vehicles containing k vehicles; the $(k+1)$th vehicle represented the common carrier vehicle, where vehicle set K={1, 2, ..., k, $k+1$}. This variable-definition method is derived and modified from VRPTW's classical mathematic model the classical mathematic model of VRPTW described in Kallehauge et al. (2005). This definition method generates $4(k+1)(n+1)^2$ binary variables. Additionally, arrival time S_i^k was the second variable when vehicle k arrived at node i, which was a semi-continuous variable used to relate to the time window. It indicated a vehicle's arrival time in a certain node and was linked to the total working time.

3.4.1.2 Arc variables

In the comprehensive optimization model and the greedy algorithm model, a new method of variable definition was applied. Due to truckload transportation's specialty, capacity consolidation was not allowed. Therefore, edge linking between origination and destination was ensured, and its relative two nodes were considered in this edge. In this thesis, one edge and its adjoining pickup and delivery nodes were defined as a request arc, which has its own cost coefficient. Unlike in the first scenario, variables in this scenario linked different request arcs. For example, in Figure 3.6, known edges h, f were customer requests related to pick-up nodes 2 and 3, delivery nodes 4 and 5, and depots nodes 1 and 6. Request arcs were $2-h-4$ and $3-f-5$, loaded mile cost was effected on request arcs. Binary variable x_{fh}^k indicated whether the DCC vehicle k linked two request arcs. Note that the empty mile cost was counted in this route as edge j shown in Figure 3.7. Suppose n was the number of orders, meaning there were n request arcs. Furthermore, the number of m indicated the number of depots; the cost on depot nodes was 0. Set O and I were used to distinguish request arcs and depots; Ω was their union. Indexes i, j represented any two elements in Ω,

x_{ij}^k, indicating whether the DCC vehicle k would drive from i to j. If a vehicle passed i, the binary variable was y_i^k meaning that the DCC vehicle k had arrived at i, and cost was C_i^d indexed by d and i. Otherwise, the common carrier is set as binary variable z_i whose cost is C_i^c indexed by c and i. y_i^k and z_i can be presented by x_{ij}^k. This method has $k(n+m)^2$ binary variables, far fewer than the previous scenario. Arrival time variable S_i^k was also denoted as a semi-continuous variable to record the time when the vehicle arrives at request arcs or depots. If the DCC vehicle did not visit any element in set of Ω, S_i^k was set to 0.

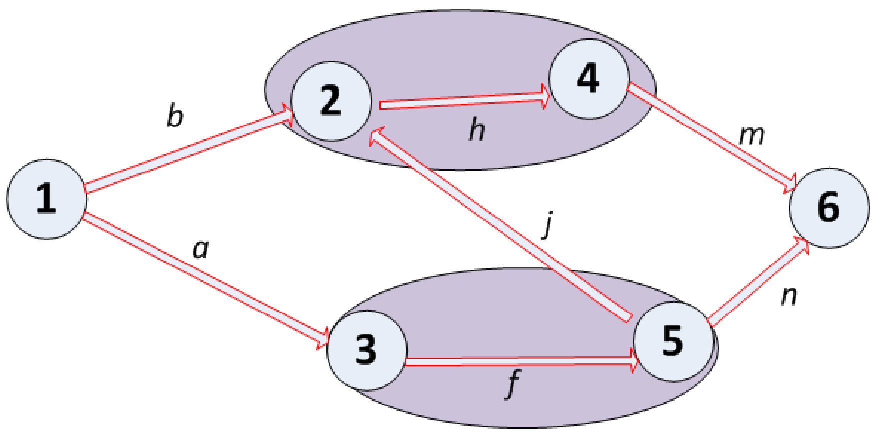


Figure 3.7: Request Arc

3.4.2 Constraints

3.4.2.1 Boundary of time window

The shipper precisely designates every pickup time and delivery time with every request. Loaded traveling time between any two nodes in the directed graph and service time were extracted from the motor carrier's supply chain management (SCM) system. All time parameters are static in this study. The total time consumption was the order duration, the sum of loading time at the pickup node, and the traveling time between two nodes. After arriving at the delivery node, the DCC vehicle must unload cargo; and the unloading time is equal to the loading time at the pickup node, the sum of both being considered service time. Shippers traced the carrier's actual arrival time to evaluate service quality. Additionally, in this thesis, waiting time was allowed when a truck arrived at a pickup node before the scheduled pickup time. In the models, the bound for variable arrival time S_i^k was specified beforehand in this section.

Node time window

Suppose for a certain request i, scheduled time, in pickup node i^+ and delivery node i^- were A_{i^+} and A_{i^-}, respectively. The duration was $T_i = A_{i^-} - A_{i^+}$. The driving time from i^+ to i^- was D_i. Loading time (unloading time) was defined as St. The order duration $T_i^o = D_i + St$. All of the data was transferred as a floating point. In the first circumstance, the lower bound for pickup node was A_{i^+}, and the upper bound was $A_{i^-} - T_i^o$. However, the lower bound for delivery node was $A_{i^+} + T_i^o$, and the upper bound was A_{i^-}. For convenience, $[A_i, A_i']$ represented the bound at any node i. Figure 3.8 provides an example: the time window of one order was [08:00, 16:00], the driving time was 1.5 hours, the service time was 0.5 hour, and the order duration was 2 hours. Therefore, the arrival time bound for the pickup node and the delivery node were [08:00, 14:00] and [10:00, 16:00], respectively.

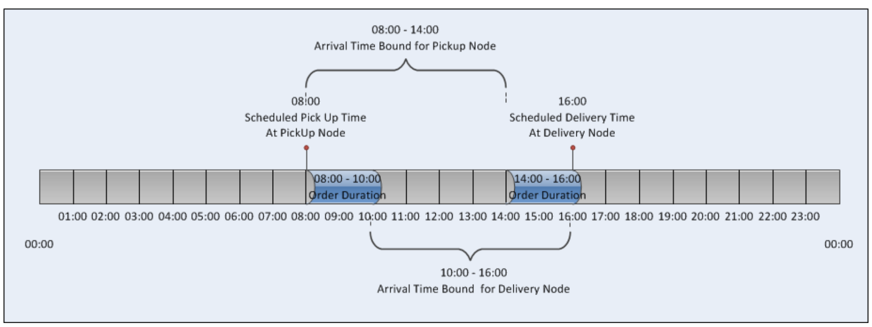


Figure 3.8: Arrival Time Bound

Arc time window

In the second circumstance, the arrival time bound for request arc i was $[A_{i^+}, A_{i^-} - T_i^o]$. Figure 3.9 provides an example containing two orders. Time windows were [08:00,13:52] and [11:44,18:00] for Order 1 and Order 2, respectively; and order durations were 3 hours and 2.5 hours, respectively. The bounds for the two orders were [08:00, 10:32] and [11:44, 15:30]. Note that between any two nodes or request arcs, both driving time and unloading time exist, and unloading time from depots to any pickup node or request arc is equal to 0.

.

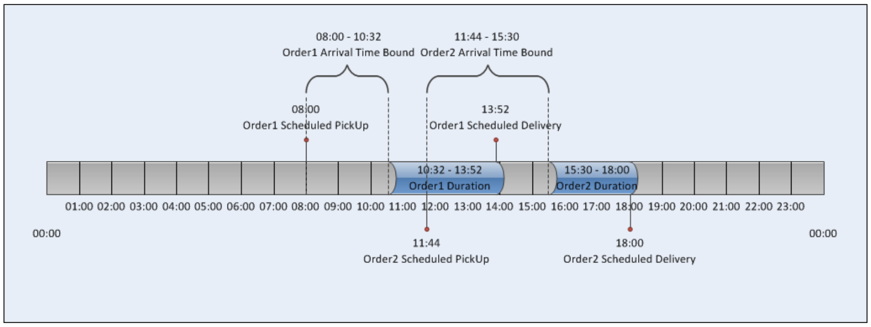


Figure 3.9: Time Window for Multiple Depots

3.4.2.2 Routing and truck capacity constraints

Every model works under a set of constraints. The model in this thesis proposes four categories of constraints: carrier selection, pickup and delivery, routing, and time relevancy. The carrier needed to satisfy the shipper's orders first and foremost; either the DCC fleet or the common carrier could serve one request arc only once. Every request consisted of two nodes (pickup location and delivery location) and scheduled arrival time, respectively. Vehicles were needed for loading cargo at the pickup node and unloading at the delivery location. The vehicle had to a corresponding delivery node after going to a pickup node. Every DCC vehicle had to depart from and return to its depot after it completed all tasks. Additionally, because the number of trucks in one depot was limited, DCC vehicles on pickup and delivery assignments could not be greater than that number. While completing one task, the DCC vehicle could choose to complete the next assignment or return to its depot.

3.4.2.3 Time windows and regulations

A time window was imposed upon every commissioned DCC vehicle. Each vehicle had to visit two nodes in one request between two scheduled time points of pickup and delivery location; otherwise, this request had to be assigned to a common carrier. The actual arrival time was the standard to judge whether DCC vehicles arrived at the pickup or delivery node on time. DCC vehicles were allowed to wait until the scheduled service time began without a penalty cost; however, this delay wasted utilization of vehicles and drivers.

Each of the drivers must obey driving and working time regulations. The working time was the difference between departure time and return time at the depot. Because every request was a full truck-load, irrespective of actual weight or volume, every truck was prepared to fit the volume or weight requirement before the routing operation. Assuming the supply chain system allocated a different product for each vehicle, the weight and volume constraints were not listed in the model of this thesis.

3.4.3 Assumptions

Before formulating mathematical models, several assumptions must be made:

- Travel speed and service time were constant in all the models.
- The truck number in any depot was stable and remained unchanged in spite of regulations concerning drivers' driving and working time. Working time was the sum of driving time, loading time at pickup node, and unloading time at delivery node.
- The distance between any two locations was the shortest path.
- The delayed time, resulting from such issues as road construction traffic congestion, was not considered in travel time between any two locations.
- In the facility location model, the fixed cost of a facility in all locations was assumed to be the same.

3.4.4 Baseline methods

3.4.4.1 Baseline method 1: traditional model

As shown in Figure 3.10, the traditional model does not involve multiple trips in one truck route. Instead, in this model, every truck in one depot has to return to its depot after completing one mission. If the common carriers have lower costs or trucks have conflicting schedules, common carriers would service the remaining orders. Since the cost of every order is known beforehand, this problem is created as a route-scheduling problem. This model schedules drivers to use the minimum equipment and driver overheads.

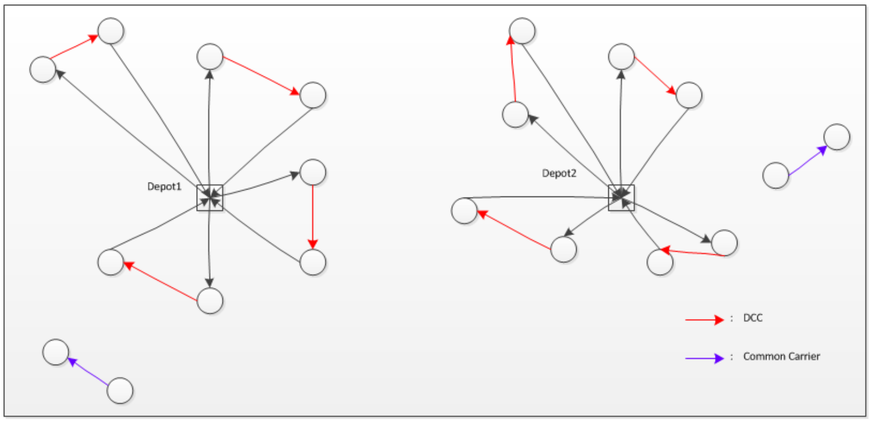


Figure 3.10: Traditional Model Route

Notations:

Sets and indexes:

V	DCC Vehicles Set
O	Orders set of one specific depot
i, j	Index of orders, $i \neq j$
k	Index of DCC vehicles

Parameters:

n	Number of Requests
m	Number of Depots
S	Average speed for DCC vehicle
C_u	Unit cost per mile of DCC vehicle
DT	Regulation driving time
WT	Regulation working time
St	Service time at any node
M	Big number
D_i	Distance for order i, $\forall i \in O$
C_i^d	Traveling cost for order i, $C_i = C_u * D_i$, $\forall i \in O$
C_i^c	Common carrier cost for order i, $\forall i \in O$
T_{i^+}	DCC travel time from depot to order i, $\forall i \in O$
T_{i^-}	DCC travel time from order i to depot, $\forall i \in O$
T_i^o	DCC travel time from pickup node to delivery node in order i, $\forall i \in O$
T_i	DCC service time for order i, T_i= T_{i^+}+T_{i^-}+T_i^o+$2St$, $\forall i \in O$
a_i	Earliest scheduled arrival time at order i,$\forall i \in O$
b_i	Latest scheduled arrival time at order i,$\forall i \in O$

Decision variables:

$$x_i^k = \begin{cases} 1 & \text{if DCC vehicle } k \text{ goes to take order } i, \forall i \in O, k \in V \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij}^k = \begin{cases} 1 & \text{if DCC vehicle } k \text{ goes to take order } j \text{ after order} i, \forall i \in O, k \in V \\ 0 & \text{otherwise} \end{cases}$$

$$S_i^k = \begin{cases} [a_i^1 - T_{i^+}, b_i^1 - T_i^o - T_{i^+} - St] & \text{if DCC vehicle } k \text{ arrive } i, \forall i \in O, k \in V \\ 0 & \text{otherwise} \end{cases}$$

Formulation:

$$Min \quad \sum_{k \in V} \sum_{i \in O} (C_i^d - C_i^c) x_i^k + \sum_{i \in O} C_i^c \tag{3.1}$$

S.t.

$$\frac{x_i^k + x_j^k}{2} - y_{ij}^k = 0 \qquad \forall i, j \in O, k \in V \tag{3.2}$$

$$S_i + T_i - S_j - (1 - y_{ij}^k) M \leq 0 \qquad \forall i, j \in O, k \in V \tag{3.3}$$

$$\sum_{i \in O} (T_{i^+} + T_{i^-} + T_i^o) x_i^k \leq DT \qquad \forall k \in V \tag{3.4}$$

$$\sum_{i \in O} T_i x_i^k \leq WT \qquad \forall k \in V \tag{3.5}$$

Objective function 3.1 minimized the variable routing cost. Constraints 3.2 and 3.3 forced a visiting sequence for every DCC truck k according to time restrictions at every location. Constraints 3.4 and 3.5 regulated the driving and working time for every DCC driver.

3.4.4.2 Baseline method 2: two-stage optimization model

The two-stage optimization model allows multiple trips for trucks departing from any depot. The first phase, deconstructing the original problem into sub-problems, was finished in stage two using the clustering technique. The orders were assigned by several clusters equal to the number of depots. The common carrier was considered the $(k + 1)$th vehicle, which could appear in multiple routes simultaneously Kallehauge et al. (2005).

Notations:

Sets and indexes:

V	DCC vehicle set
K	The whole vehicle set
P	Pickup nodes
D	Delivery nodes
I	Depot nodes
Ω	All nodes set Ω
d	Index of departure depot node
r	Index of return depot node
i	Index of pickup nodes
i'	Index of delivery nodes corresponding to i
h	Index of any node in pickup nodes or delivery nodes
k	Index of vehicles

Parameters:

D_{ij}	Distance from i to j ,$\forall i, j \in \Omega$
C_{ij}^k	Cost for any vehicle from i to j for k,$\forall i, j \in \Omega$, $\forall k \in K$
T_{ij}	Traveling time from i to j for DCC,$\forall i, j \in \Omega$
A_i	Lower bound for arrival time at node i, $\forall i \in \Omega$
A_i'	Upper bound for arrival time at node i, $\forall i \in \Omega$

Decision variables:

$$x_{ij}^k = \begin{cases} 1 & \text{if vehicle } k' \text{ go through the path from } i \text{ to } j,\ \forall i, j \in \Omega, \forall k \in K \\ 0 & \text{otherwise} \end{cases}$$

$$S_i^k = \begin{cases} [A_i, A_i'] & \text{time window boundaries for any DCC vehicle at any node i, } \forall i \in \Omega, \forall k \in V \\ 0 & \text{otherwise} \end{cases}$$

Formulation:

$$Min \quad \sum_{k\in K}\sum_{i\in\Omega}\sum_{j\in\Omega} C_{ij}^{k}x_{ij}^{k} \tag{3.6}$$

S.t.

$$\sum_{j\in D\cup I_r} x_{ij}^{k} = 1 \qquad \forall k \in V, \quad i = I_d \tag{3.7}$$

$$\sum_{k\in K} x_{ii'}^{k} = 1 \qquad \forall i \in P \tag{3.8}$$

$$\sum_{i\in D\cup I_d} x_{ij}^{k} = 1 \qquad \forall k \in V, \quad j = I_r \tag{3.9}$$

$$\sum_{i\in\Omega} x_{ih}^{k} - \sum_{j\in\Omega} x_{hj}^{k} = 0 \qquad \forall k \in V, \quad \forall h \in P\cup D \tag{3.10}$$

$$S_i^k + T_{ij} + St - S_j^k - \left(1 - x_{ij}^k\right) M \leq 0 \qquad \forall i, j \in P\cup D, i \neq j, \quad \forall k \in V \tag{3.11}$$

$$\sum_{i\in\Omega}\sum_{j\in\Omega} T_{ij}x_{ij}^{k} \leq DT \qquad \forall k \in V \tag{3.12}$$

$$S_{I_r}^k - S_{I_d}^k \leq WT \qquad \forall k \in V \tag{3.13}$$

The linear objective function 3.6 minimized total travel cost. Constraint 3.8 stipulated that every request be satisfied by a set of vehicles, including DCC and common carrier vehicles. Constraints 3.7 and 3.9 indicated that every DCC vehicle had to depart from and return to its depot. A vehicle was considered idle if it did not transport an order. Constraint 3.10 required that DCC vehicles go to another new node after visiting one node, preventing them from going back to a previous node. Constraint 3.11 was the time window and sub-tour elimination constraint; when one DCC vehicle traveled between two nodes, the schedule was restricted in terms of the time- window requirement. Constraints 3.12 and 3.13 stipulated that for any DCC vehicle, driving and working time could not exceed government regulations.

3.4.5 Comprehensive optimization model

In the baseline methods, requests in terms of the number of depots were clustered according to Euclidean distance. Using this method, empty miles still occurred. Based on the data review, although some requests whose pickup and delivery locations were in two different clusters, many such requests in different clusters could be combined into a one-truck route. However, considering all depots in one optimization model, the number of variables increased exponentially, thus increasing the calculation time. Therefore, in this model, a new definition of variables and set notation appearing in Bolduc et al. (2008), Eglese (1994) and Letchford and Eglese (1998) was used to simplify the model. Similarly, invalid requests were eliminated before requests were fed into the model.

Notations:

Sets and indexes:

V	DCC Vehicles Set
O'	Request Arcs Set
I	Depots Set
Ω'	$I \cup O'$
k	Index of DCC vehicles
i, j	Indexes of request arcs or depots
d, r	Indexes of departure and return in one depot
u	Index of depots
p	Index of orders

Parameters:

K_u	Number of DCC trucks at Depot u, $u \in I$
D'_{ij}	Distance from i to j for every DCC vehicle, $\forall i, j \in \Omega'$
T_{ij}	Travel time from i to j ,$T_{ij} = D_{ij}/S$, $\forall i, j \in \Omega$
C'_{ij}	Travel cost from i to j for every DCC vehicle , $C'_{ij} = C_u * D'_{ij}$, $\forall i, j \in \Omega'$
$D_p^{o'}$	Distance for request arc p, $\forall p \in O'$
$T_p^{d'}$	Travel time for request arc p, $p \in O'$
$T_p^{o'}$	Duration for DCC vehicle at request arc i, $T_p^{o'} = T_p^{d'} + St$, $\forall p \in O'$
$C_p^{c'}$	Common carrier cost for request arc p, $\forall p \in O'$
$C_p^{d'}$	DCC cost for request arc i, $C_i^{d'} = D_p^{O'} * C_u$, $\forall i \in O'$
a_i	Earliest service time of request i, $i \in \Omega'$
b_i	Latest service time of request i, $i \in \Omega'$

Decision variables:

$$x_{ij}^k = \begin{cases} 1 & \text{if DCC vehicle } k \text{ go through the path from arc } i \text{ to arc } j, \quad i, j \in \Omega', \quad k \in V \\ 0 & \text{otherwise} \end{cases}$$

$$y_p^k = \begin{cases} 1 & \text{if DCC vehicle } k \text{ serve request arc } p, \ p \in O', k \in V \\ 0 & \text{otherwise} \end{cases}$$

$$z_p = \begin{cases} 1 & \text{if common carrier serve request arc } p, \ p \in O', \\ 0 & \text{otherwise} \end{cases}$$

$$S_i^k = \begin{cases} [a_i, b_i - T_p^{o'}] & \text{time window of node } i \text{ for dedicated vehicle } k, \ i \in \Omega', k \in V \\ 0 & \text{otherwise} \end{cases}$$

Formulation:

$$Min \quad \sum_{k\in V}\sum_{i\in\Omega'}\sum_{j\in\Omega'} C'_{ij}x^k_{ij} + \sum_{k\in V}\sum_{p\in O'} C^{d'}_p y^k_p + \sum_{p\in O'} C^{c'}_p z_p \tag{3.14}$$

S.t.

$$\sum_{k\in V} y^k_p + z_p = 1 \qquad \forall p \in O' \tag{3.15}$$

$$\sum_{u\in I} y^k_u \leq 1 \qquad \forall k \in V \tag{3.16}$$

$$y^k_r - y^k_d = 0 \qquad \forall d, r \in I, \quad \forall k \in V \tag{3.17}$$

$$\sum_{k\in V} y^k_u \leq K_u \qquad \forall u \in I \tag{3.18}$$

$$\sum_{\substack{i\in\Omega' \\ i\neq h}} x^k_{ih} - \sum_{\substack{j\in\Omega' \\ j\neq h}} x^k_{hj} = 0 \qquad \forall h \in \Omega', \quad \forall i \in \Omega', \forall p \in I, \forall k \in V \tag{3.19}$$

$$\sum_{p\in O'} x^k_{ip} - y^k_p = 0 \qquad \forall i \in \Omega', \forall k \in V \tag{3.20}$$

$$S^k_i + T_{ij} + T^{o'}_p y^k_p - S^k_j - (1 - x^k_{ij})M \leq 0 \qquad \forall i, j \in \Omega', \forall p \in O', \quad \forall k \in V \tag{3.21}$$

$$\sum_{i\in\Omega'}\sum_{j\in\Omega'} T_{ij}x^k_{ij} + \sum_{p\in O'} T^{d'}_p y^k_p \leq DT \qquad \forall k \in V \tag{3.22}$$

$$S^k_r - S^k_d \leq WT \qquad \forall d, r \in I, \forall k \in V \tag{3.23}$$

Formula 3.14 was the objective function to minimize the total cost in the routing network, and constraint 3.15 mandated that every request be satisfied by either the DCC fleet or common carrier vehicles. Formulas 3.14 and 3.15 could be combined as a new objective function as expressed in Formula 3.24:

$$Min \quad \sum_{k\in V}\sum_{i\in\Omega'}\sum_{j\in\Omega'} C'_{ij}x^k_{ij} + \sum_{k\in V}\sum_{p\in O'}(C^{d'}_p - C^{c'}_p)y^k_p + \sum_{p\in O'} C^{c'}_p \tag{3.24}$$

Constraints 3.16 and 3.17 stipulated that DCC trucks could not relocate among different depots and had to depart from and return to the same depot only once. I_d and I_r represented the same depot but different indexes. Constraint 3.18 stipulated that the number of trucks departing from one depot could not exceed the depot's truck number capacity. Constraints 3.19 and 3.20 were routing constraints; after visiting one order site, the DCC truck could not visit the same order site again. Constraint 3.21 ensured both the DCC trucks' schedule in the time window and the subtour elimination. Constraints 3.22 and 3.23 limited the drivers' driving time and working time.

3.4.6 Greedy algorithm

In this study, greedy algorithm operated in terms of the comprehensive optimization method. Every truck was put into the comprehensive optimization model, irrespective of the depot from which the truck was departing. Trigger Obj recorded the current optimal solution, and the initial solution was obtained from the traditional model. Once current truck k provided a new lower cost, the orders it visited were deleted from set O, k was also removed from its depot. If one depot was out of trucks, this depot would be deleted from set I. If Obj did not change, the algorithm had reached local optimality. The orders not assigned to the DCC were transported by a common carrier. The detailed procedure is presented in Algorithm 1:

Notation:

CT_u : Initial truck number for depot u, $u \in I$

Obj : Current Objective Value

K_u : Total number of DCC trucks at depot u

$TimeLimit$: Gurobi Termination Timelimit

L : Empty list

input : $K = \sum_{i=1}^{m} K_u$; $Timelimit$; CT_u; Obj; I; O'; Ω';

output: x_{ij}^k; y_p^k; z_p; S_i^k; L;

```
Initialization;
CT_u = 0;
Obj=Traditional Solution;
k = 1;
while k ≤ K do
    GRB.Optimal or GRB.Timelimit;
    if GRB.ObjVal ≤ Obj then
        for i in O' do
            for j in Ω' do
                if x_ij^k == 1 then
                L ← k , x_ij^k , S_i^k
                delet i from O';
            end
        end
        for p in I do
            if  y_p^k == 1 then
              CT_p+ = 1;
              L ← i;
              if CT_p == K_p then
               delet d,r from I;
               delet k from V ;
            else break;
        end
    end
    Obj = GRB.ObjVal;
    k+ = 1;
    else break;
end
for i in I do
    L ← z_p
end
```

Algorithm 1: Greedy Heuristic Algorithm

3.4.7 Facility location model

First, the facility location was investigated because it affects the fleet's routing cost. A mathematical model was developed to verify new depot locations. This model assumes that every truck departs from one depot, visits one order's pick-up node and delivery node, and finally returns to the same depot. This method is also described by Lysgaard (1997), who used the maximum saving method to solve VRP. All of the nodes listed in the database were candidates used to ascertain the optimal depot locations. The building facility's fixed cost was assumed to be equal in all locations. In the future, however, this factor may need to be considered variable from facility to facility. Binary variables in this model determined whether one location would be suitable for a depot operation. In this model, all locations (set I') could be considered depots, but a maximum of three locations could be established as depots. By calculating the total travelling cost associated with all requests, the optimal depot locations would lead to minimizing such cost.

Notation:

Sets and indexes:

O	Set of requests
I'	Set of depot candidates
i	Index of request
j	Index of depot

Parameters:

C''_{ij}	Cost from request i to depot j

Decision variables:

$$x_{ij} = \begin{cases} 1 & \text{If truck go to take request } i \text{ from depot } j,\ \forall i \in O, j \in I' \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{If location } j \text{ is the depot, } \forall j \in I' \\ 0 & \text{otherwise} \end{cases}$$

Formulation:

$$Min \quad \sum_{i \in O} \sum_{j \in I'} C''_{ij} x_{ij} \tag{3.25}$$

S.t.

$$\sum_{j \in I'} x_{ij} = 1 \qquad \forall i \in O \tag{3.26}$$

$$\sum_{j \in I'} y_j \leq 3 \tag{3.27}$$

$$x_{ij} - y_j \leq 0 \qquad \forall i \in O, \quad j \in I' \tag{3.28}$$

Formulation 3.25 minimized the total cost of allocating requests to a specific depot. Constraint 3.26 stipulated that every order was taken by a truck from one depot; and constraint 3.27 stipulated that three locations, at most, were to be chosen as depots. The relationship between x_{ij} and y_j was stated in constraint 3.28.

The best solution model would be used to compare results in scenarios of new and old depots. In addition, the trucks' utilization was another factor in examining the facility's availability. Long-term data was input into the greedy algorithm with a single depot, meaning that other depots were not involved in the model.

3.5 Stage four: sensitivity analysis

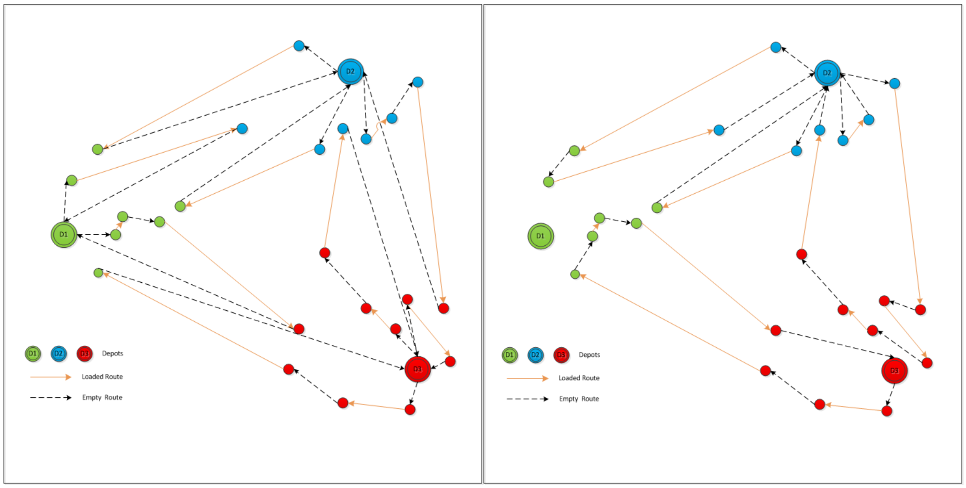
3.5.1 Utilization and cost

Utilization was used to evaluate capital's efficiency in order to make a profit; higher utilization results in higher revenue but also higher total cost. The concept of economies of utilization was employed in allocating fixed costs over the amount of equipment. Utilization in the trucking industry is usually affected by three factors: truck, load, and empty miles. However, in the TL service, load utilization seems to have little impact. DCCs care more about utilization of equipment and drivers, which are the most important factors affecting capital utilization, and a high usage rate tends to lower average fixed costs. Small changes in equipment usage would be expected to have a large impact on costs. Fixed costs are short-run costs that cannot be avoided or varied with output. DCCs equipment usage may be limited by the hours of service federal regulations allow. Equipment is the largest portion of total cost; and in order to control cost, DCCs need to run more efficiently than the common carrier. A truck's utilized lifetime was limited in terms of the truck's contribution to revenue, as calculated in the supply chain operation system. Deconstructing the overhead cost for every unit of equipment would transfer all cost to a daily fixed cost in terms of each truck. If the truck were used on a certain day, its utilization was considered as 100%. In addition, a driver's utilization was equal to a truck's utilization for DCCs.

$$Truck\,Utilization = \frac{Number\,of\,Used\,Trucks}{Total\,Number\,of\,Truck\,Allocated\,in\,Depot} \tag{3.29}$$

Equation 3.29 shows that truck utilization was decided by routing strategy, which affected the number of used trucks; inversely, a fixed number of trucks influenced the carrier selection in dedicated equipment fleet routing.

DCCs also focused on empty miles when only one truck was used in the route. Figure 3.11 shows the expected result from baseline method 2 (two-stage method) and the comprehensive optimization model. The two-stage method reduced as many empty miles as possible within the specified time-window constraints.



(a) Two-stage Model **(b)** Comprehensive Optimization Model

Figure 3.11: Expected routing map

Verification of the expected result is in Chapter 4. Reducing empty miles could keep cost levels low in terms of maintenance cost, average total cost, average variable cost, and average fixed cost. Equation 3.30

$$Loaded\,Miles\,Utilization = \frac{Loaded\,Mileage}{Total\,Running\,Mileage} \tag{3.30}$$

indicates that empty miles can reduce loaded mile utilization and that low truck utilization increases idle cost, which is equal to the fixed cost per truck as shown in Equation 3.31,

$$Average\ Fixed\ Cost = \frac{Capital\ +\ Total\ Overhead\ Cost}{Truck\ Number{*}Service\ Life\ Time} \tag{3.31}$$

Because average fixed cost is constant per day in a truck's service lifetime, if one truck is idle for a day, its fixed cost is wasted. An example can be seen in Figure 3.12; eight trucks are ready to provide transportation service, but only five trucks are needed in one day's routing, which is defined as the running fixed cost (RFC) with the red bar representing the amount of cost. The idle fixed cost (IFC) (yellow bar) is the same amount as the RFC, with both amounts equal to the average fixed cost (AFC). Every running truck has a running average Cost (RAC). Most DCCs only consider the sum of the RFC and the RAC as daily total cost for individual vehicles, but make the mistake of ignoring the IFC.

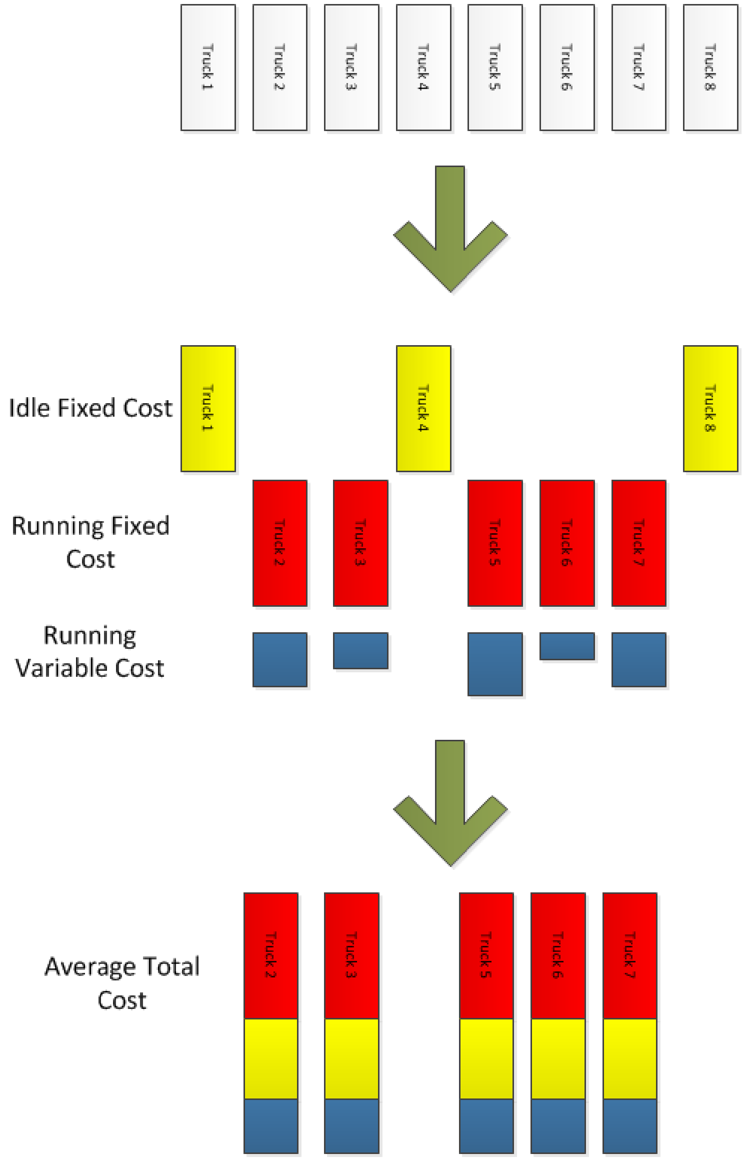


Figure 3.12: Cost Allocation

As a result, the AFC is indicated as Equation 3.32, and the average total cost (ATC) is shown in Equation 3.33

$$Actural\ Average\ Fixed\ Cost = \frac{Average\ Fixed\ Cost{*}Truck\ Number}{Running\ Truck\ Number} \tag{3.32}$$

$$Average\ total\ Cost = \frac{Average\ Fixed\ Cost\ *\ Truck\ Number + Toal\ Variable\ Cost}{Running\ Truck\ Number} \tag{3.33}$$

3.5.2 Time window

The time window is an indicator used to evaluate service quality. Because it affects the total variable cost when a time window is big enough, the VRPTW is changed to regular VRP. In this study, the range-of-time window was changed by 20 percent of the original time interval. In Figure 3.13, A and B represent the earliest and latest scheduled times for a specific time window; the bar length is the time interval; the centroid is indicated as the center time dividing the time interval into two equal parts. The bar length increases by intervals of 20% from 10% until the percentage is 250%.

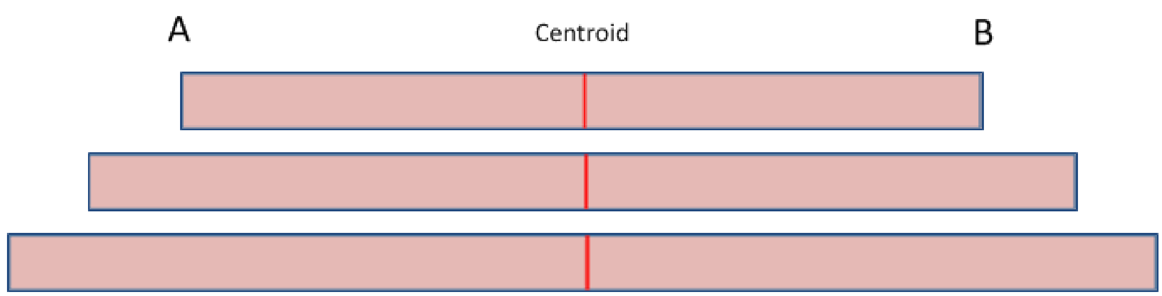


Figure 3.13: Average Fixed Cost

Chapter 4

Case Study and Result Analysis

4.1 Ryder System Inc.

An American-based provider of transportation and supply chain management products, Ryder System Inc. is especially known for its fleet of rental trucks. As a FORTUNE 500 company, Ryder specializes in fleet management, supply chain management, and dedicated contracted carriage. Ryder's dedicated contract carriage provides transportation solutions, including equipment, maintenance, and administrative services for a full-service lease with drivers additional services helping businesses to run lean. This combination provides customers with a dedicated transportation solution designed to increase their competitive position, improve risk management, and integrate their transportation needs with their overall supply chain. The U.S. dedicated contract-carriage market's revenue was estimated to be $13 billion in 2010. Ryder's dedicated contract carriage accounted for 57% of the company's supply chain solution (SCS) revenue by December 31, 2013 Ryder (2013).

The principle concern in designating a number of dedicated vehicles was not to satisfy the customer's requirement, but to pay attention to the internal use of equipment and drivers. The dedicated fleet's routing strategy sought to maximize capital utilization. As shown in Figure 4.1, Ryder used JDA software as the tool to manage dedicated fleet routing. Considering seasonality, Ryder negotiated with customers the number of dedicated equipment. Once the equipment number was fixed in the contract, DCC had to assume the risks of equipment shortage or high average fixed cost.

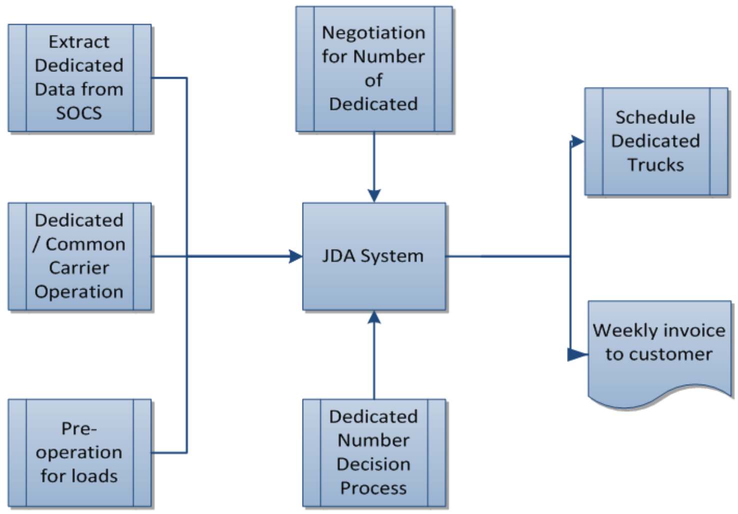


Figure 4.1: Current Procedure for Ryder

Dedicated services carried about 40% of the orders. According to the truck-routing strategy shown in Figure 4.2. when a DCC truck nished one task, it returned to the depot. Every truck was to be used according to the designated equipment capacity. Although utilization remained high with this routing method, the number of empty miles was also very high. Obviously, empty miles increased as more transportation requests are received. Ryder wanted to balance the cost and utilization, but cost minimization took priority over utilization.

4.2 Source data, data transportation and clustering

The case study in this thesis used data from one of Ryder's customers, Shell Incorporated. Eighty requests in one day were extracted from Ryder's database. All requests were reformatted, and some redundant data was cleaned beforehand. The data-transformation process generated a full-distance matrix, including three depots: Lafayette (LA, 70583), Houma (LA, 70363) and Houston (TX, 77530). Sixty-four trucks were assigned to three depots shown in Table 4.1. The truck number was assumed a constant; but in reality, this number relies on the driver's schedule and government regulations. Other parameters were indicated in Table 4.2.

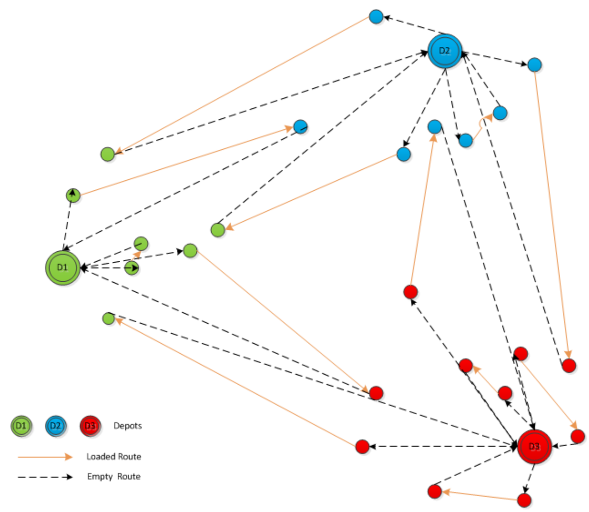


Figure 4.2: Current Routing for Ryder

Table 4.1: Depot Trucks and Drivers Information

Location	Total Trucks $ Drivers
Lafayette, LA(70583)	20
Houma, LA(70363)	24
Houston, TX(77530)	20
Total	64

Table 4.2: Parameter

Parameter	Value
Speed	50 mile per hour
Cost per mile	$ 1.66
Driving upper bound	11 hours
working upper bound	14 hours
Service time at any location	0.5 hour

The clustering technique introduced in Chapter 3 classified three clusters for this case study visualized in Figure 4.3, where all of the zip codes were assigned to corresponding depots, but a majority of the zip codes were located at depots 77530 and 70363 (details in Table 4.3).

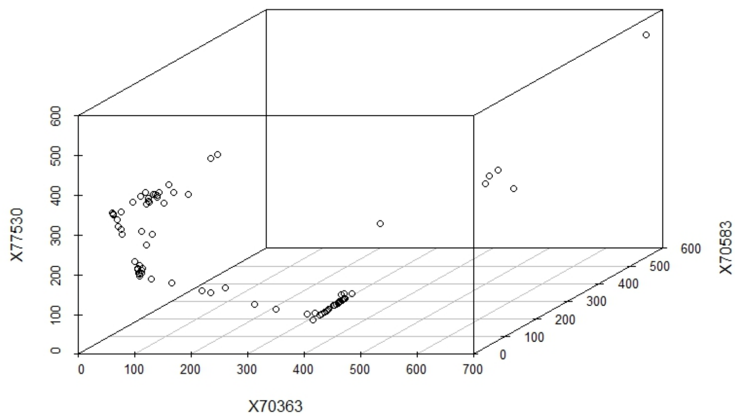


Figure 4.3: Clustering visualization

Table 4.3: Clustering Result

Depot 70583	Depot 70363		Depot 77530	
70510	70340	70380	77705	77041
70518	70037	70123	77532	77029
70631	70038	70130	75115	77092
70726	70438	70357	77554	77067
70533	70354	70394	77550	77066
70546	70734	70395	77049	77011
70508	70356	70458	77052	77530
70507	70056	70091	77014	78362
70501	70058	70094	77035	74038
70615	70363		77040	77494
70555	70360		77073	75662
70560	70364		77082	77571
70563	70062		77044	77584
70767	70067		77087	75023
70578	70373		77084	75074
70583	70471		77064	77386
70665	70072		77086	77665
70592	70001		77032	

No driver could exceed 11 hours of driving time and 14 hours of working time; these regulations were hard constraints for the DCC truck scheduling. In addition, some invalid requests were eliminated beforehand due to driving-time regulations. Eliminating those requests did not reduce the mathematical model's computational difficulty but was helpful in employing effective long-distance strategies, such as driver relays.

4.3 Model results comparison

Gurobi Optimizer was used to solve all four instances in two threads of four cores Intel(R) Core(TM) i5 2.50GHz, 4GB RAM. Results of comparisons from four categories of strategies are shown in Table 4.4. Baseline method 1 is the solution for Ryder System Inc.

Table 4.4: Result Comparison

Parameter	**Baseline Method 1**	**Baseline Method 2**	**Comprehensive Optimization Model**	**Greedy Algorithm**
Running Time	12.547	1690.136	10800.23	1210.755
Minimum Cost	14248.44	12142.89	9986.116	10604.64
Empty Mile Cost	8939.266	3213.428	1703.492	2285.82
Truck Utilization	25%	23.44%	20.31%	18.75%
Loaded Mile Utilization	37.26%	73.54%	82.94%	78.45%
Gap	0	0	5.20%	0
Common Loads	11	11	8	9
Trucks of Depot1	9	9	6	8
Trucks of Depot2	6	5	6	3
Trucks of Depot3	1	1	1	1
Actual Average Fixed Cost	2200.00	2346.7	2707.7	2933.3
Average Total Cost	3090.52	3156.19	3475.86	3523.43

The comprehensive optimization model had the lowest cost; but the computational time was approximately nine times greater than the greedy algorithm model's, which was 5.8% more expensive than the exact method. In contrast, Ryder's solution (baseline method 1) provided the highest truck utilization, total cost, and empty-mile cost. The definition of gap in the table appears in the branch-and-bound search technique applied in solving mixed integer problems, meaning that the model was not solved to optimality and terminated a percentage above a bound. The solution was obtained by the upper and lower bounds initially approximating each other as time elapses until reaching termination rules, such as time limit or number of nodes. The difference between the upper and lower bounds was known as the gap; when the gap was zero, optimality was achieved. This result demonstrates that truck utilization is inversely proportional to loaded mile utilization, actual average fixed cost, and average total cost. This result also proves that the truck number in a contract, which was 64 in this case study, affects utilization and is affected enormously by routing strategy as shown in Figure 4.4.

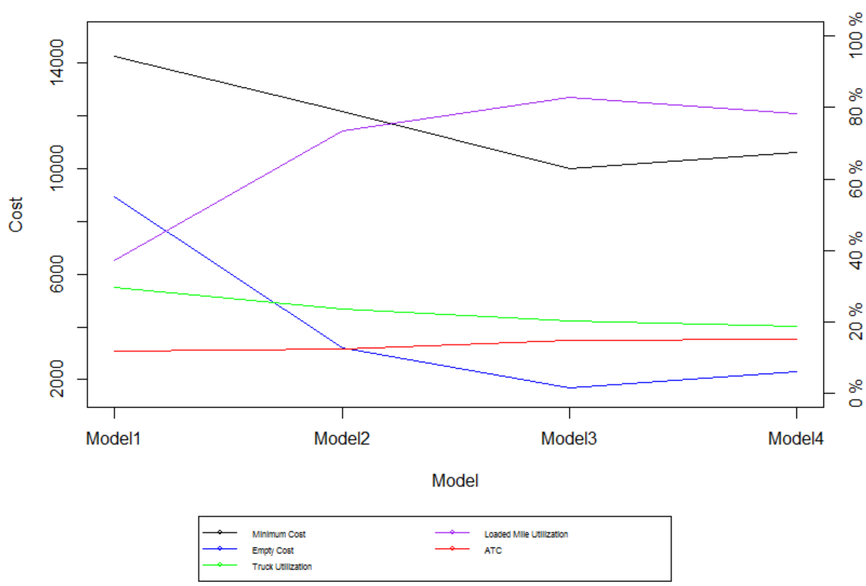


Figure 4.4: Result Plot

Some routes may have had confusion regarding departure time at the depot shown in Table 4.5; this route was taken by Truck 9 departing from Depot 1(70363) at 4:44am, 3/10/2014, but travel time was only 2 hours. In reality, the driver only needed to depart from a depot no later than 6am in order for that model to reach the maximum working time. More results are shown in Table A.1.

Table 4.5: Output Sample

Truck #	Node 1	Order#	Arrival Time at Node 1	Node 2	Arrival Time at Node 2	Empty Cost	Order Cost
Truck9	Depot1		3/10/14 4:44	Order9	3/10/14 8:00	162.514	
	Order9	1231137	3/10/14 8:00	Order25	3/10/14 14:19	220.448	220.946
	Order25	1231257	3/10/14 14:19	DepotR1	3/10/14 18:44	64.574	219.452

4.4 Sensitivity analysis

In the sensitivity analysis, the comprehensive optimization model was used as a routing strategy because it reported the most successful routing result. Twenty orders in one day were randomly selected for this section; and truck numbers in the 3 depots were still 24, 20 and 20, respectively. Time window, truck number, and facility location were considered in the sensitivity analysis.

4.4.1 Facility location

In the result table, depot 3 had only one truck involved in routing in the comprehensive optimization model and greedy algorithm, thus raising the question of facility location and its impact on operation cost. In this section, the facility location model was used to verify whether the existence of depot 77530 was necessary. The location-routing problem in Prodhon and Prins (2014) indicated a new routing strategy would affect facility location, but only analyzed the location problem under the baseline method 1, Ryder's strategy. All available data included 1,032 requests in the database. After data that violated government regulations was filtered out, 798 loads remained to be analyzed at depot locations. Because of these driving-time regulation violations, a common carrier handled the other loads.

As a result, the new depots' zip codes were 70360, 70518 and 77049, respectively. Then new depots were imported to the comprehensive optimization model in Chapter 3 and used as the same data for the case study. Based on the results summarized in Table 4.6, the new depots' solution had lower associated costs, while the number of trucks and requests common carriers accepted were almost the same. Although the difference was less than 2.5% compared to the old depots' calculation in this sample dataset, for long-term planning the solution could result in tens of thousands of dollars for Ryder. Therefore, new locations should be considered in the daily operation, and a historical analysis should be conducted to verify whether facility locations would affect long-term cost variance.

Table 4.6: Location Result Comparison

Model	Old Depots	New Depots
Cost	9986.116	9759.87
Run Time	10800.23	7998.3
Depot 1	70363	70360
Depot 2	70583	70518
Depot 3	77530	77049
Truck Number in Depot 1	6	6
Truck Number in Depot 2	6	5
Truck Number in Depot 3	1	1
Common Carrier	8(49)	9(49)

A geographical location map (Figure A.2) was plotted with green nodes indicating old depots and red nodes indicating the new depots. However, this map is not enough to illustrate that depot 77530 was necessary. Thus, the other two depots were eliminated, and the greedy algorithm was applied to evaluate truck utilization in nine days. The results shown in Table

4.7 indicate that the average utilization is 1.65% and the median is 1.5% based on 20 trucks; thus, depot 77530 is necessary. However, these results also suggest the number of trucks at depot 77530 should be reduced to a reasonable level.

Table 4.7: Depot77530 Greedy Result

Date	Total Loads	DCC Loads	CC Loads	Truck Utilization
10-Mar	156	5	151	0.05
11-Mar	123	26	97	0.3
12-Mar	204	7	197	0.05
13-Mar	215	21	195	0.15
14-Mar	161	42	119	0.5
15-Mar	79	21	58	0.2
16-Mar	21	2	19	0.05
17-Mar	41	30	11	0.35
18-Mar	3	0	3	0

4.4.2 Truck number and cost variance sensitivity

The pre-defined truck number was the standard when signing a service contract; and both parties had to review the shipping trend, historical data, and past experience. The wrong routing strategy could lead to miscalculating truck numbers. In this section of the sensitivity analysis, the total cost, variable cost, and truck utilization were compared by adjusting the truck number in different scenarios.

First, the optimal number of trucks in three depots was noted in Table 4.8's case 1 (4-3-0), which was defined as mode 1. This mode was treated as a cap to analyze sensitivity because no matter when trucks were added to any depot, the optimal solution remained constant. The truck number was decreased in order from mode 2 to mode 12 until all requests were carried by a common carrier, mode 13. The lowest point of total cost and variable cost are found in Figure, where the horizontal axis indicates mode. The dedicated rate was the ratio of requests DDC trucks carried to the total number of orders. As shown in Figure 4.5, mode

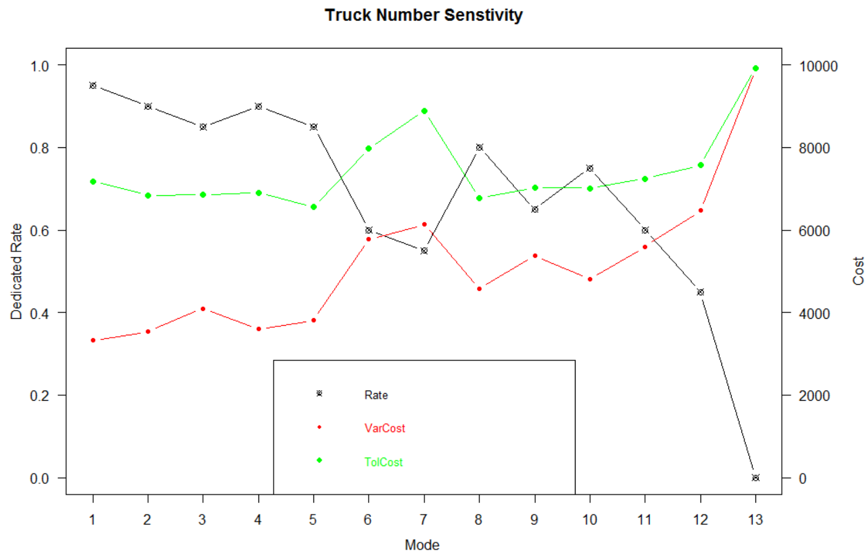
1 had the lowest variable cost and the highest dedicated rate, but mode 5 had the lowest total cost. To make the right decision, the DCC needed to observe different combinations of truck allocations to depots, comparing total and variable cost to determine which took priority. Under this premise, the dedicated utilized rate was more meaningful as a key performance indicator.

Table 4.8: Truck Number Sensitive Analysis

ID	Depot1	Depot2	Depot3	Dedicated Utilization	Cost
1	4	3	0	0.95	3328.428
2	4	2	0	0.9	3538.92
3	4	1	0	0.85	4098.854
4	3	3	0	0.9	3602.842
5	3	2	0	0.85	3813.334
6	3	1	0	0.6	5776.82
7	2	3	0	0.55	6135.97
8	2	2	0	0.8	4566.022
9	2	1	0	0.65	5377.928
10	1	3	0	0.75	4813.382
11	1	2	0	0.6	5594.86
12	1	1	0	0.45	6466.58
13	0	0	0	0	9923.457

4.4.3 Time window sensitivity

Although defined by shippers, the time window could still affect routing cost. However, when the time window was large enough, VRPTW would become regular VRP. Therefore, in terms of time-window sensitivity, the base was the sum of travel and service time, and the centroid of time window was equal to that of the original problem. As shown in Figure 4.6, the time window's increment was 20%. When the percentage was between 100% and 200%, the cost change was less pronounced, approximately 200 dollars. The time window also affected the carrier selection and truck utilization if the time window's range was tight and the pickup and delivery time were closed from one order to another.



1	2	3	4	5	6	7	8	9	10	11	12	13
4-3-0	4-2-0	4-1-0	3-3-0	3-2-0	3-1-0	2-3-0	2-2-0	2-1-0	1-3-0	1-2-0	1-1-0	0-0-0

Figure 4.5: Truck Number Sensitive Analysis

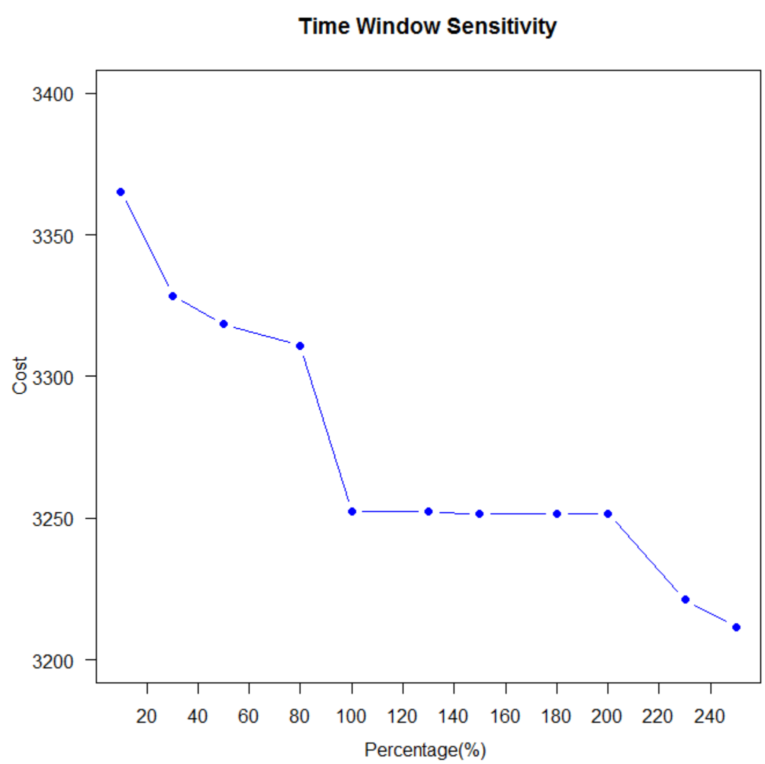


Figure 4.6: Time Sensitive Analysis

4.5 Analysis summary

Based on the analysis above, the comprehensive optimization model provided minimum empty running cost and maximum loaded utilization, while reducing the truck number significantly. Use of common carriers was decreased as well, enhancing the DCC's equipment utilization. The cost savings and utilization varied greatly by adjusting the equipment range of number in any depot. The facility location affected the long-term routing cost, and the time window seemingly had less impact on the cost savings for the sample data in this research. However, based on the long-term analysis, both models need to be monitored for sustainability.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis describes the vehicle routing problem's effect on the dedicated contract carriers' cost savings. This study aims to find an optimal routing strategy in order to help a DCC reduce empty running and to select a common carrier that doesn't exceed minimum operation costs, which are subject to pickup-delivery service within strict time windows among multiple depots. After an analysis of the comprehensive optimization model and two baseline models, the comprehensive optimization model is proposed as the best solution along with the greedy algorithm, which also achieved an acceptable result in a much shorter time than the comprehensive optimization model. The sensitivity analysis verified the initial fleet number could be reduced by implementing a new routing strategy. In addition, the truck allocation strategy achieved the lowest total and variable costs. This study also found time window's and truck- number cap's potential influence on variable cost. The depot locations were also included in the discussion as part of the location-routing problem, and changing depot locations was shown to affect costs.

5.1.1 Empty miles reduction

Having no effect on reducing empty running cost, baseline method 1 only considered carrier selection when scheduling DCC trucks; yet this method resulted in the highest equipment utilization. The two-stage optimization method was more successful in reducing empty miles than the first one, but cannot find potential empty running costs in terms of global optimization. As a result, the comprehensive optimization model and the greedy algorithm led to the best and second-best solutions, respectively, in a much shorter time. Based on the case study in Chapter 4, they reduced the empty running cost by 42.7% and 25.6%, respectively, and maintained a high ratio of loaded miles to total traveling distance.

5.1.2 Common carriers selection

Common carriers' participation in routing strategies decreased the daily operation's total variable cost. This thesis compared four models' performance regarding selection of carriers. On the one hand, the comprehensive optimization model used the fewest common carriers for all transportation missions; on the other hand, the comprehensive optimization model's loaded utilization more than doubled compared to the traditional model's.

5.1.3 Equipment utilization

Decision makers and customers affect equipment utilization in terms of numbers of trucks in the contract. When a DCC plans transportation for the customer, an improper routing strategy could lead to wrong decisions on a periodic contract, wasting greater fixed and variable costs, although having high equipment utilization. This thesis has discussed the relationship between cost and utilization and has emphasized that a new routing strategy (specifically, the comprehensive optimization model) is helpful for DCCs to reappraise dedicated contracts, thus decreasing capital input and maintaining stable equipment utilization. Finally, a new routing system could be created based on future studies.

5.1.4 Facility locations and time window

Changing facility locations influenced overall routing cost. Adjusting the time-window range had less impact on the results than the other three factors introduced in the above case study. However, the effects vary from case to case. Before applying a new routing strategy, facility locations should investigate factors minimizing the effect on routing cost; the time-window range could affect carrier selection and truck utilization.

Nonetheless, some limitations still existed, the MIP model was not expected to find an optimal solution within an acceptable time frame as the complexity increased, and data was too limited to track the trend of truck utilization.

5.2 Future work

In the future, a more efficient algorithm needs to be applied to decrease the model's solving time so as to provide faster and more accurate results. A time series analysis can forecast truck numbers and utilization in order to study truck usage according to multiple variables. In addition, less-than-truckloads should be considered for consolidating small volume or weight cargo to make full use of truck capacity.

5.2.1 More efficient algorithm

Tabu search is considered an effective algorithm to solve VRP. In this study, the greedy algorithm model has proposed a local optimal solution, and the tabu search could help improve this result for global optimization. By checking neighbors among different vehicles, the optimization process would exchange requests to find potential optimal solutions and allow poor results to appear in the process. Using short-term and long-term memory, each iteration's results would be stored in memory. This technique's purpose is to jump out of the loop of local optimal to find a better solution. Like other heuristic algorithms, this method cannot guarantee an absolute optimal solution, but approximates the optimal solution.

5.2.2 Truck number and utilization forecasting

Forecasting techniques such as time series and regression analysis could predict transportation demand's future. A new routing strategy would decrease the truck numbers, thus affecting equipment utilization's impact. On the one hand, applying new routing strategies over a long time period would accumulate necessary data according to time horizontal; on the other hand, this data could be used to formulate an expert system by using time series to evaluate truck demand in terms of future transportation demand.

5.2.3 LTL consolidation

This problem could be transformed to LTL consolidation in the future. Although TL is reliable and has high service quality, sometimes cargo is insufficient to fill to capacity, thereby increasing those truck numbers with similar commodities. CVPR's purpose is to consolidate loads to fit a vehicle's capacity. In the case of other unchanged constraints, problem complexity is raised. Thus, a more powerful algorithm is required to solve this sort of problem.

5.2.4 New system platform

Once the above factors are resolved, a new system platform for DCCs could be developed, combining modules like equipment forecasting, instant routing, statistical analysis, and reporting, as well as using mobile technology aided by GPS technology, whereby an operating center could communicate with drivers instantly and dynamically to plan a specific truck's new route.

Bibliography

Abshire, R. D. and Premeaux, S. R. (1991). Motor carriers'and shippers'perceptions of the carrier choice decision. *Logistics and Transportation Review*, 27(4). 17

Adelzadeh, M., Asl, V. M., and Koosha, M. (2014). A mathematical model and a solving procedure for multi-depot vehicle routing problem with fuzzy time window and heterogeneous vehicle. *The International Journal of Advanced Manufacturing Technology*, 75(5-8):793–802. 14

Bent, R. and Van Hentenryck, P. (2004). A two-stage hybrid local search for the vehicle routing problem with time windows. *Transportation Science*, 38(4):515–530. 16

Berwick, M. D. and Dooley, F. (1997). Truck costs for owner/operators. Technical report, Upper Great Plains Transportation Institute, North Dakota State University. 18, 19

Berwick, M. D., Farooq, M., et al. (2003). Truck costing model for transportation managers. Technical report, Mountain-Plains Consortium. 18, 19

Bolduc, M., Renaud, J., Boctor, F., and Laporte, G. (2008). A perturbation metaheuristic for the vehicle routing problem with private fleet and common carriers. *Journal of the Operational Research Society*, 59(6):776–787. 17, 39

Bowersox, D. J., Closs, D. J., and Cooper, M. B. (2002). *Supply chain logistics management*, volume 2. McGraw-Hill New York. 18

BTS (2014). Report of national transportation statistics. 1

Chow, G. (1978). *The Economics of the Motor Freight Industries*. Garland Chow. 2

Christofides, N. (1979). Combinatorial optimization. In *A Wiley-Interscience Publication, Based on a series of lectures, given at the Summer School in Combinatorial Optimization, held in Sogesta, Italy, May 30th-June 11th, 1977, Chichester: Wiley, 1979, edited by Christofides, Nicos*, volume 1. 13

Chuah, K. H. and Yingling, J. C. (2005). Routing for a just-in-time supply pickup and delivery system. *Transportation Science*, 39(3):328–339. 16

Cordeau, J.-F., Gendreau, M., Hertz, A., Laporte, G., and Sormany, J.-S. (2005). *New heuristics for the vehicle routing problem*. Springer. 14

Cordeau, J.-F., Gendreau, M., Laporte, G., Potvin, J.-Y., and Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research society*, pages 512–522. 14

Crainic, T. G., Mancini, S., Perboli, G., and Tadei, R. (2008). Clustering-based heuristics for the two-echelon vehicle routing problem. *Montreal, Canada, Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation*. 17, 26

Dantzig, G. B. and Ramser, J. H. (1959). The truck dispatching problem. *Management science*, 6(1):80–91. 8, 12

Dantzig, G. B. and Wolfe, P. (1960). Decomposition principle for linear programs. *Operations research*, 8(1):101–111. 13

Derigs, U. and Döhmer, T. (2008). Indirect search for the vehicle routing problem with pickup and delivery and time windows. *OR Spectrum*, 30(1):149–165. 15, 16

Desaulniers, G., Desrosiers, J., and Solomon, M. M. (2002). *Accelerating strategies in column generation methods for vehicle routing and crew scheduling problems*. Springer. 13

Desrosiers, J., Dumas, Y., and Soumis, F. (1986). A dynamic programming solution of the large-scale single-vehicle dial-a-ride problem with time windows. *American Journal of Mathematical and Management Sciences*, 6(3-4):301–325. 13, 15

Dondo, R. and Cerdá, J. (2007). A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows. *European Journal of Operational Research*, 176(3):1478–1507. 16

Dooley, F. J., Bertram, L. M., and Wilson, W. W. (1988). Operating costs and characteristics of north dakota grain trucking firms. *UGPTI PUBLICATION;*, (N67). 18, 20

Eglese, R. W. (1994). Routeing winter gritting vehicles. *Discrete applied mathematics*, 48(3):231–244. 39

Eksioglu, B., Vural, A. V., and Reisman, A. (2009). The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering*, 57(4):1472–1483. 13

Evers, P. T., Harper, D. V., and Needham, P. M. (1996). The determinants of shipper perceptions of modes. *Transportation journal*, pages 13–25. 17

Ferguson, G. and Kreps, J. (1965). *Principles of Economics*. Rinehart and Winston Inc., Toronto. 18

Ford Jr, L. R. and Fulkerson, D. R. (1958). A suggested computation for maximal multi-commodity network flows. *Management Science*, 5(1):97–101. 13

Goetschalckx, M. and Jacobs-Blecha, C. (1989). The vehicle routing problem with backhauls. *European Journal of Operational Research*, 42(1):39–51. 12, 18

Goldberg, M. S. and Touw, A. (2003). *Statistical methods for learning curves and cost analysis*. Institute for Operations Research and the Management Sciences (INFORMS). 18

Ileri, Y., Bazaraa, M., Gifford, T., Nemhauser, G., Sokol, J., and Wikum, E. (2006). An optimization approach for planning daily drayage operations. *Central European Journal of Operations Research*, 14(2):141–156. 14, 16

Kallehauge, B., Larsen, J., Madsen, O. B., and Solomon, M. M. (2005). *Vehicle routing problem with time windows*. Springer. 16, 29, 37

Kent, J. L. and Stephen Parker, R. (1999). International containership carrier selection criteria: shippers/carriers differences. *International Journal of Physical Distribution & Logistics Management*, 29(6):398–408. 17

Kontoravdis, G. and Bard, J. F. (1995). A grasp for the vehicle routing problem with time windows. *ORSA journal on Computing*, 7(1):10–23. 7

Lahyani, R., Khemakhem, M., and Semet, F. (2015). Rich vehicle routing problems: From a taxonomy to a definition. *European Journal of Operational Research*, 241(1):1–14. 13

Letchford, A. and Eglese, R. (1998). The rural postman problem with deadline classes. *European Journal of Operational Research*, 105(3):390–400. 39

Lysgaard, J. (1997). Clarke & wrights savings algorithm. *Department of Management Science and Logistics, The Aarhus School of Business*. 44

Minocha, B. and Tripathi, S. (2013). Two phase algorithm for solving vrptw problem. 14

Mitrovic-Minic, S. (1998). Pickup and delivery problem with time windows: A survey. *SFU CMPT TR*, 12:1–43. 13

Moon, I., Lee, J.-H., and Seong, J. (2012). Vehicle routing problem with time windows considering overtime and outsourcing vehicles. *Expert Systems with Applications*, 39(18):13202–13213. 16, 17

Muter, I., Cordeau, J.-F., and Laporte, G. (2014). A branch-and-price algorithm for the multidepot vehicle routing problem with interdepot routes. *Transportation Science*, 48(3):425–441. 16

Nagy, G. and Salhi, S. (2005). Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries. *European journal of operational research*, 162(1):126–141. 14, 16

Nanry, W. P. and Barnes, J. W. (2000). Solving the pickup and delivery problem with time windows using reactive tabu search. *Transportation Research Part B: Methodological*, 34(2):107–121. 14, 16

Nguyen, P. K., Crainic, T. G., and Toulouse, M. (2013). A tabu search for time-dependent multi-zone multi-trip vehicle routing problem with time windows. *European Journal of Operational Research*, 231(1):43–56. 16

Padberg, M. and Rinaldi, G. (1991). A branch-and-cut algorithm for the resolution of large-scale symmetric traveling salesman problems. *SIAM review*, 33(1):60–100. 10

Parragh, S. N., Cordeau, J.-F., Doerner, K. F., and Hartl, R. F. (2012). Models and algorithms for the heterogeneous dial-a-ride problem with driver-related constraints. *OR spectrum*, 34(3):593–633. 13, 16

Pisinger, D., Sigurd, M. M., and Sig, M. (2004). The pickup and delivery problem with time windows and precendences. *Transportation Science, Forlag: INFORMS*, (38):197–209. 14

Prodhon, C. and Prins, C. (2014). A survey of recent research on location-routing problems. *European Journal of Operational Research*, 238(1):1–17. 56

Ropke, S. and Pisinger, D. (2006). A unified heuristic for a large class of vehicle routing problems with backhauls. *European Journal of Operational Research*, 171(3):750–775. 16

Ryder (2013). 2013 ryder system inc. annal report form 10-k. Technical report, Ryder System Inc. 50

Savelsbergh, M. W. and Sol, M. (1995). The general pickup and delivery problem. *Transportation science*, 29(1):17–29. 13

Simchi-Levi, D., Chen, X., and Bramel, J. (2014). Network planning. In *The Logic of Logistics*, pages 379–402. Springer. 26

Smith, L. D., Campbell, J. F., and Mundy, R. (2007). Modeling net rates for expedited freight services. *Transportation Research Part E: Logistics and Transportation Review*, 43(2):192–207. 7, 18

Tarantilis, C. and Kiranoudis, C. (2002). Distribution of fresh meat. *Journal of Food Engineering*, 51(1):85–91. 15, 16

Trego, T. and Murray, D. (2010). An analysis of the operational costs of trucking. In *Transportation Research Board 2010 Annual Meetings CD-ROM. Washington, DC*. 18, 20

Trego, T. and Murray, D. (2013). An analysis of the operational costs of trucking. In *Transportation Research Board 2010 Annual Meetings CD-ROM. Washington, DC*. 19

Vidal, T., Crainic, T. G., Gendreau, M., Lahrichi, N., and Rei, W. (2012). A hybrid genetic algorithm for multidepot and periodic vehicle routing problems. *Operations Research*, 60(3):611–624. 16

Xu, H., Chen, Z.-L., Rajagopal, S., and Arunapuram, S. (2003). Solving a practical pickup and delivery problem. *Transportation science*, 37(3):347–364. 13, 16, 17

Yuan, Z. and Fügenschuh, A. (2007). Parameterized random greedy algorithms for the heterogeneous vrp with time windows. *SLS-DS 2007*, page 52. 7

Appendix

Appendix A

Summary of Figure and Table

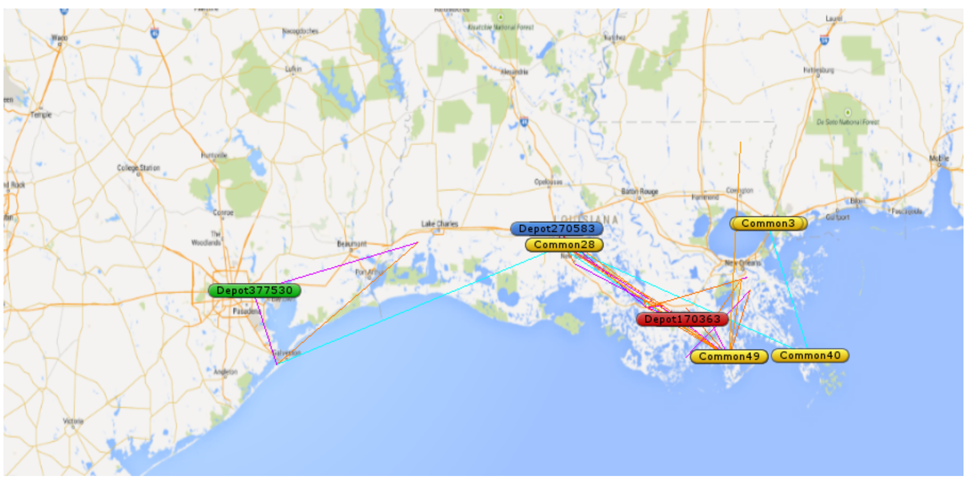


Figure A.1: Route Animation

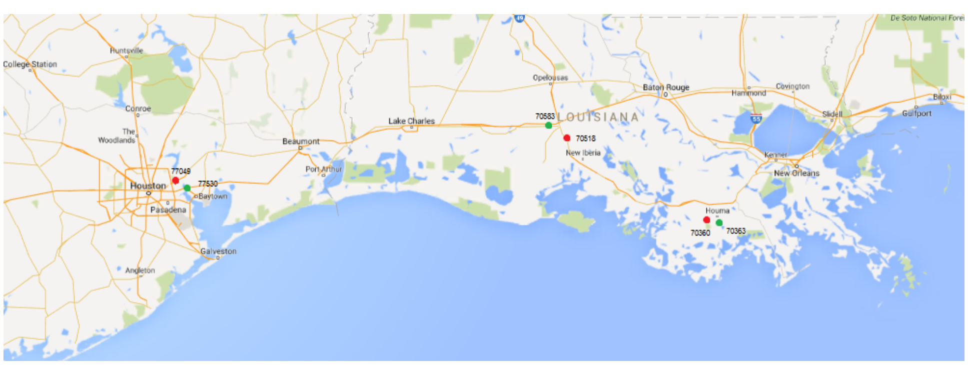


Figure A.2: Old Depots VS. New Depots

Table A.1: The comprehensive optimization model result

Truck #	Node1	Order#	Arrival Time at Node1	Node2	Arrival Time at Node2	Empty Cost	Order Cost
Truck2	Depot1		3/10/14 8:41	Order8	3/10/14 8:59	25.398	
	Order8	1231133	3/10/14 8:59	Order15	3/10/14 11:18	26.062	83.83
	Order15	1231258	3/10/14 11:18	Order26	3/10/14 14:00	0	93.956
	Order26	1231258	3/10/14 14:00	Order38	3/10/14 17:00	0	124.334
	Order38	1231258	3/10/14 17:00	DepotR1	3/10/14 22:41	64.574	109.726
Truck3	Depot2		3/10/14 10:06	Order6	3/10/14 10:20	19.754	
	Order6	1231119	3/10/14 10:20	Order44	3/10/14 20:11	0	220.946
	Order44	1231603	3/10/14 20:11	DepotR2	3/11/14 0:06	19.754	221.278
Truck5	Depot2		3/10/14 13:02	Order20	3/10/14 13:17	19.754	
	Order20	1231442	3/10/14 13:17	Order33	3/10/14 15:30	0	100.928
	Order33	1231442	3/10/14 15:30	Order36	3/10/14 17:42	0	100.928
	Order36	1231503	3/10/14 17:42	Order41	3/10/14 23:05	0	220.946
	Order41	1231452	3/10/14 23:05	DepotR2	3/11/14 3:02	135.29	110.556
Truck6	Depot2		3/10/14 0:30	Order1	3/10/14 1:00	0	
	Order1	1231242	3/10/14 1:00	Order5	3/10/14 7:00	0	240.368
	Order5	1231172	3/10/14 7:00	Order22	3/10/14 13:00	81.008	120.848
	Order22	1231431	3/10/14 13:00	DepotR2	3/10/14 14:30	19.754	22.41
Truck7	Depot1		3/10/14 8:42	Order12	3/10/14 8:42	0	
	Order2	1231641	3/10/14 10:28	Order16	3/10/14 12:15	0	64.242
	Order12	1231112	3/10/14 8:42	Order2	3/10/14 10:28	0	64.574
	Order16	1231221	3/10/14 12:15	Order31	3/10/14 16:13	0	64.574
	Order31	1231532	3/10/14 16:13	Order48	3/10/14 21:38	0	64.242
	Order48	1231588	3/10/14 21:38	DepotR1	3/10/14 22:42	0	5.478
Truck9	Depot1		3/10/14 4:44	Order9	3/10/14 8:00	162.514	
	Order9	1231137	3/10/14 8:00	Order25	3/10/14 14:19	220.448	220.946
	Order25	1231257	3/10/14 14:19	DepotR1	3/10/14 18:44	64.574	219.452
Truck22	Depot2		3/10/14 6:06	Order4	3/10/14 6:20	19.754	
	Order4	1231262	3/10/14 6:20	Order14	3/10/14 10:35	0	220.946
	Order14	1231412	3/10/14 10:35	Order19	3/10/14 13:02	0	120.018
	Order19	1231439	3/10/14 13:02	Order35	3/10/14 15:50	0	120.848
	Order35	1231526	3/10/14 15:50	DepotR2	3/10/14 20:06	19.754	221.278
Truck42	Depot1		3/10/14 9:34	Order27	3/10/14 14:00	0	
	Order27	1231387	3/10/14 14:00	Order32	3/10/14 16:33	64.242	64.574
	Order32	1231387	3/10/14 16:33	Order39	3/10/14 19:14	0	64.574
	Order39	1231588	3/10/14 19:14	Order42	3/10/14 21:01	0	64.242
	Order42	1231532	3/10/14 21:01	DepotR1	3/10/14 23:34	64.574	64.574
Truck47	Depot3		3/10/14 21:30	Order17	3/10/14 22:30	83.996	
	Order17	1231382	3/10/14 22:30	DepotR3	3/11/14 4:57	196.876	255.64
Truck48	Depot1		3/10/14 9:41	Order11	3/10/14 10:18	51.792	
	Order11	1231332	3/10/14 10:18	Order24	3/10/14 13:00	0	15.438
	Order24	1231457	3/10/14 13:00	Order30	3/10/14 14:31	0	43.824
	Order30	1231392	3/10/14 14:31	Order43	3/10/14 18:00	0	143.258
	Order43	1231562	3/10/14 18:00	DepotR1	3/10/14 23:41	64.574	220.946
Truck49	Depot2		3/10/14 15:54	Order46	3/10/14 19:30	0	
	Order45	1231603	3/11/14 1:56	DepotR2	3/11/14 5:54	19.754	221.278
	Order46	1231562	3/10/14 19:30	Order45	3/11/14 1:56	0	240.368
Truck51	Depot2		3/10/14 11:31	Order18	3/10/14 11:45	19.754	
	Order10	1231767	3/10/14 21:37	DepotR2	3/11/14 1:31	19.754	221.278
	Order18	1231392	3/10/14 11:45	Order23	3/10/14 15:07	32.536	144.254
	Order23	1231452	3/10/14 15:07	Order10	3/10/14 21:37	0	109.726
Truck53	Depot1		3/10/14 5:02	Order7	3/10/14 8:00	25.398	
	Order7	1231132	3/10/14 8:00	Order13	3/10/14 10:30	0	83.83
	Order13	1231412	3/10/14 10:30	Order37	3/10/14 16:30	97.276	127.82
	Order37	1231524	3/10/14 16:30	DepotR1	3/10/14 19:02	64.574	63.08

Vita

Zhixin Han was born in Changchun, Jilin in China to the parents of Xianfeng Han and Yanping Gu. He obtained a Bachelor of Engineering and a Bachelor of Administration, respectively, at College of Mechanical Engineering and College of Business Administration, affiliated to Changchun University of Technology where he graduated with distinction in 2007. Following the completion of his undergraduate degree, Zhixin started his career as a system engineer in Suzhou and Beijing, China from 2007 to 2012. He accepted a graduate research assistantship at University of Tennessee, Knoxville, in the Master's program in the Industrial and Systems Engineering. During his Masters he got straight A grades, and has worked with various projects on industries and academy. In 2015 he graduated with Master of Science in Industrial Engineering.