MULTIMODAL FREIGHT TRANSPORTATION PROBLEM: MODEL,

ALGORITHM AND ENVIRONMENTAL IMPACTS

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A Dissertation submitted to the

Graduate School - Newark

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Management

Supply Chain Management Major

written under the direction of

Dr. Weiwei Chen and Dr. Lei Lei

and approved by

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Newark, New Jersey

May, 2017

ABSTRACT OF THE DISSERTATION

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Dissertation Directors: Dr. Weiwei Chen and Dr. Lei Lei

Multimodal transportation has become increasingly important and dominating in the freight transportation industry. Sustainability concerns and availability of eco-friendly transportation modes, such as high-speed rail, have called for an investigation on environmental impacts of multimodal operations. Motivated by a real-life business case, this research studies multimodal transportation problems with operational constraints and environmental considerations. Specifically, a mathematical model is developed, and a heuristic algorithm is proposed to solve the problem effectively and efficiently. Environmental and financial impacts are further studied for several model configurations.

First, we study an operations scheduling problem in a multimodal transportation network, subject to shipping capacity limits, resource availability, transshipment delays, customer service requirements, and environmental concerns. The objective is to minimize the total shipping costs and penalty costs due to delivery delays. To this end, we model the problem as a mixed integer linear program (MILP), which determines the routing of

customer orders, the transportation mode to use on each route segment, and the corresponding departure time of the selected mode.

Second, in view of the problem's large scale and computational complexity, we propose a Lagrangian relaxation model, and decompose the original MILP model into smaller-size subproblems. These subproblems are independent to each other, and hence can be solved in parallel to significantly speed up the computation. A sub-gradient heuristic is developed to solve the Lagrangian model by effectively searching for bounds and feasible solutions. We tested the proposed heuristic on 28 different problem settings, each with 30 randomly generated test cases. The results show that the proposed heuristic is effective in finding near-optimal solutions for small to medium sized problems benchmarked by the Gurobi MILP solver, and for large-scale problems, the heuristic outperforms Gurobi in both solution time and quality.

Finally, based on the aforementioned model and its variants, we perform simulation analysis and quantify the financial and environmental impacts of four scenarios. (1) We quantify the environmental benefits of multimodal transportation, compared to truck-only transportation. (2) We quantify the impacts on carbon emissions by varying usage of high-speed rail. (3) We investigate the financial and environmental impacts on logistics companies by imposing carbon emissions quota as an operational constraint. (4) For shipping capacities, the logistics company may use a pay-per-use scheme or a fixed-volume subscription. We compare two models and their resulting impacts on firm's operational costs and carbon emissions. Based on the numerical results of these analysis, we provide insights and suggestions on economic and environmental considerations for the future of multimodal transportation.

PREFACE

The thesis entitled "Multimodal Freight Transportation Problem: Model, Algorithm and Environmental Impact" is prepared by Zhe Jian through his Ph.D. program from 2012 to 2017, at the department of Supply Chain Management at Rutgers University.

ACKNOWLEDGEMENTS

First, I would like to express my appreciation to my mentors and advisors Dr. Lei Lei and Dr. Weiwei Chen for their unselfish and unfailing support and inspiration during this research and throughout my education. Their mentoring is indispensable for me to successfully finish my Ph.D. study, and their influence will go a long way in the rest of my life. It is my honor to be one of their students and to learn so much no matter research skill or personalities.

Second, I would also like to thank my dissertation committee members Dr. Xiaodong Lin, Dr. Benjamin Melamed and Dr. Tan Miller for their time and effort, helpful suggestions and valuable criticism. Their help on improving this dissertation were invaluable.

Finally, I thank my wife Jingjing Yang, my parents, Junming Liu and Mingfei Teng. They have given me a lot of support and help during my time of study at Rutgers University. I couldn't make it without their help.

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Chapter 1

Introduction

With the development of electronic commerce, the logistics industry has entered an era of rapid development. At the same time, the multimodal has attracted much attention in the freight transportation industry. In 2014, approximately 49% of total freight in Europe was transported via roads, 31.8 % via sea, 11.7% via rail, 4.3% via oil pipeline, and 16.8% via inland waterways (Eurostat, 2016). These statistics indicate that the road still plays an important role in transportation industry.

Multimodal distribution typically refers to moving containers or trailers by more than one mode of transportation (e.g., truck, rail, water, air, and more recently high-speed rail). A similar word "intermodal," is also frequently used. Here we use the definitions from the United Nations Economic Commission for Europe and European Commission (2001):

Multimodal: carriage of goods by two or more modes of transport.

Intermodal: movement of goods in one and the same loading unit or road vehicle, which uses successively two or more modes of transport without handling the goods themselves in change modes.

Intermodal are typically handled by different logistic companies in different legs of transportation, while multimodal shipments are typically under a single contract (or bill of landing). In our study, we are focus on operational aspects of transportation, and hence will use these two terms interchangeably.

Since the 2008 economic crisis, many countries have expanded their business processes in order to cut their costs and increase performance. Consequently, governments have promoted shippers, carriers, and other logistic services more than traditional truck transportation (Eurostat., 2015). Companies are choosing the more cooperative and integrated solution in order to utilize resources more efficiently. Thus, multimodal has become a popular choice. Multimodal helps industries address many urgent operational issues, such as long-haul trucking capacity shortages, increasing fuel costs, and the constant pressure from the government and environmental agencies to reduce the gas discharge and truck hours of service on the road. Any company that ships full truckloads should consider a multimodal which can bring great benefit.

Why multimodal is so popular? Here we cite an incisive comment from Jelly Belly Candy Company.

It's inexpensive, safe, super-reliable, and available when you need it. That's what proponents say about multi-modal transportation, and it explains why multi-modal carriers have been moving so much freight in recent years.

Jelly Belly Candy Company: Bringing in the Beans.

(http://www.inboundlogistics.com/)

As we know, safety is the priority of the U.S. Department of Transportation. Highway fatalities accounted for 94% of all transportation fatalities (BTS, National Transportation Statistics, 2012). Although highway fatalities have shown a downward trend in recent years, rail and high-speed rail remain safer than other modes.

Furthermore, since the development of modern cities, traffic congestion has become a key problem in the freight transportation system. Although truck can offer

convenient door-to-door service, it can take time to complete the job which is one main reason why logistic companies are increasingly choosing multimodal transportation. Rail or high-speed rail systems are super-reliable. Multimodal also provides a good way to address trucks' capacity problem.

In addition to economic factors, factors such as environmental issues have also become a high priority on the agenda. Trucks discharges carbon dioxide (CO2) and other carbon emissions which are the key contributors to the greenhouse gas problem. Governments have increasingly created new policies that restrict trucks' hours of service on the road and limit waste gas discharges. Emissions problems are considered under several trade regulations between different countries in the world. New regulations and related taxes have been created to encourage companies to use more sustainable solutions, such as multimodal. Companies can benefit from multimodal transportation while adhering to restrictive policies.

In recent years, many national governments have spent much money to upgrade their rail networks and service, such as high-speed rail. High-speed rail refers to a type of rail transport that operates significantly faster than traditional rail traffic. Most countries define the high-speed rail speed as 300 km/h (186 mph), compared to traditional rail speed of 100 km/h (62.5 mph). High-speed rail has become a priority in many countries because of its high efficiency. High-speed rail is cheaper than air travel, faster than general rail, and can load more than trucks. These strengths show a great potential ability in logistics. Although thus far it has primarily been used to transport human beings, it will undoubtedly be used to transport freight in the future.

Despite its popularity, the high-speed rail model of intercity freight flows has attracted less attention than passenger travel demand modeling. To the best of our knowledge, very fewer papers have examined a high-speed rail multimodal system in intercity freight flows.

Today, China owns more than 50% of high-speed rail networks in the world. China started building high-speed rail systems in 2007.In the past decade, the country has experienced an high-speed rail building boom, with generous funding from the Chinese government's economic stimulus program. By 2017, China had the world's longest high-speed rail network, at approximately 18,000 km (11,250 miles), which is planning to expand to 20,000 km (12,500 miles) by 2020. China has an aggressive expansion plan. By 2030, China targets to have 45,000 km (28,125 miles) of high-speed rail in total. Most major cities in the country will have high-speed rail. It will become China's new "Great Wall". Figure 1.1 below shows the China's current high-speed rail network map.
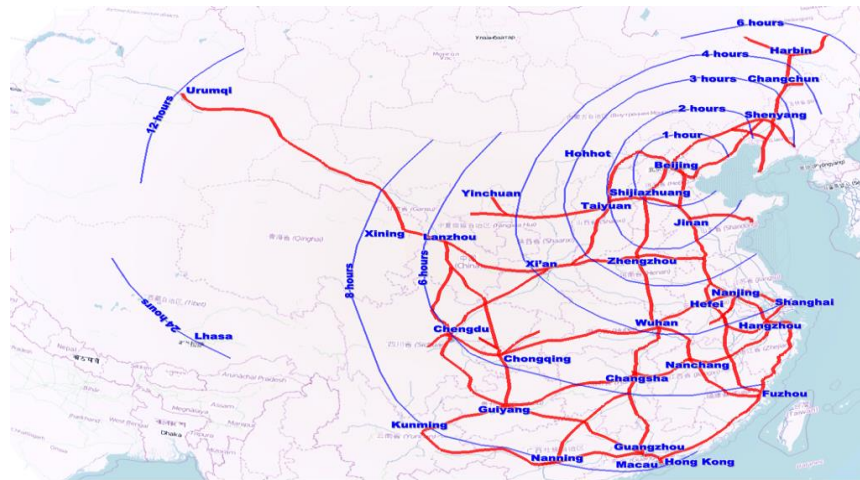
Figure 1.1 China High-Speed Rail Network Map 2030

(Source: https://www.www.rt.com/business/212719-china-opens-high-speed-train/)

U.S. has similar plan as China does. Figure 1.2 below shows U.S. high-speed rail building plan from 2015 to 2030.
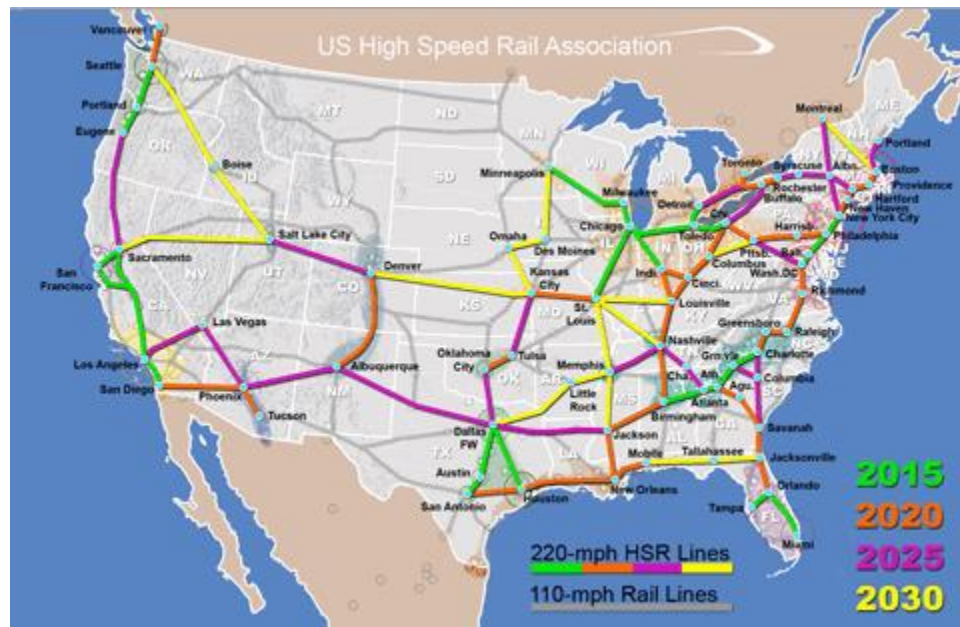
Figure 1.2 US High-Speed Rail Network Map 2030

(Source: https://www.ushsr.com/ushsrmap.html)

The case that motivated this study was from Resun Co. Ltd., a Chinese company specializing in producing surface active agents. Its headquarter is located in Beijing, China. Many of its products are in leading positions in the country. In the past, the company used trucks as their only transportation mode because trucks can offer door-to-door service. However, since China's transportation system has developed dramatically, the company can now also choose water, rail, high-speed rail or air transportation.

Specifically, the company is located at the intersection of east longitude 116°24' and north latitude 39°56'. Their customers include Unilever, PandG and other famous international companies. Companies like PandG, which can give Resun a huge order with a relatively short notice time, are considered VIP customers. Resun may lose these VIP

customers if it cannot deliver its goods on time. Resun also serves a lot of local customers located in cities throughout China. Because the production rate is really large and the company can produce in advance based on its accurate forecasting skills, it seldom encounters the shortage problems. However, it faces great challenges in terms of logistic problems.

Resun started working with China Railway Express Co., Ltd to make full use of the high-speed network system in 2014. China Railway Express Co., Ltd is subsidiary of China Railway, which is the national railway operator of the People's Republic of China, under the regulation of the Ministry of Transport and the State Railways Administration. China Railway Express Co., Ltd has a strong mission to help Resun to quickly solve its logistic problem during its busy periods.

This study focuses on multimodal freight flow transportation planning including high-speed rail to address routing problems as well as time constraints. Some potential business opportunities will be identified for other logistic companies. In sum, we seek to answer the following questions:

- What is the optimal multimodal routing?

- Which mode and time slot should be used in each arc in the optimal route?

- How should the goods be shipped through the network to satisfy customer service requirements?

- How should high-speed rail be made full use of?

- How should the environmental effect in multimodal transportation be measured?

- What is the effect of carbon emissions quota?

This remainder of this study is organized as follows. Chapter 2, reviews the relevant literature and introduces a formal definition of the multimodal problem, as well as a structure analysis of the problem. Chapter 3, proposes a mathematical programming framework based on sub-gradient heuristics, which is capable of finding near-optimal solutions within a reasonable time. Chapter 4, uses and extends the above model to analyze the environmental impacts of multimodal transportation. Chapter 5, offers future extensions and concludes this study.

Chapter 2

Literature Review and Mathematical Model

In this chapter, we present a literature review on multimodal freight transportation problem and propose a mathematical model to solve the problem under study.

2.1. Literature Review

In the current literature, academic researchers have spent an increasing amount of attentions on the development of freight transportation planning problem. Many papers have discussed routing problem or fright transportation problems. In this review, we focus only on the specific topics of interest in this proposal namely, multimodal freight transportation problems.

A comprehensive review of papers on multimodal freight transportation can be found in a recent survey by SteadieSeifi, Dellaert, and Nuijten (2014). The authors provided a structured overview of the multimodal transportation areas between 2005 and 2013. They followed the traditional structure of the freight transportation problem and divided the multimodal freight transportation problems into three categories: strategic, tactic and operational planning. Strategic planning problems focus on decisions related to the physical structure of existing infrastructures (e.g., how to locate the terminals and hubs). Tactical planning problems deal with decisions related to choosing the services or modes by the given infrastructures (e.g., how to choose modes). Operational planning problems are decentralized in operational units with a dynamic environment. (e.g., when time windows for pickup change, how to change the optimal route).

In short, the biggest difference between tactical and operational planning problems is that time factors play a very important role in the operational planning problems. In this chapter, we seek to find the best choice of services including different kind of modes, best itineraries, and the allocation of resources under the operational planning level. As we have real time constraints, we focus on dynamicity which are somewhat different from strategic and tactical problems. Hence, our target is to provide a fast algorithm that generates near optimal solution to the multimodal operations.

In the following discussion, we focus only on operational planning.

There are two main topics in the operational planning problems: resource management; and itinerary planning/replanning. Resource management problems focus on the distribution of all resources in the entire network while itinerary planning/replanning problems focus on the real-time optimization of routes, scheduling, and reactions of operational disturbance. Figure 2.1 provide a structured view of the multimodal freight transportation problems.
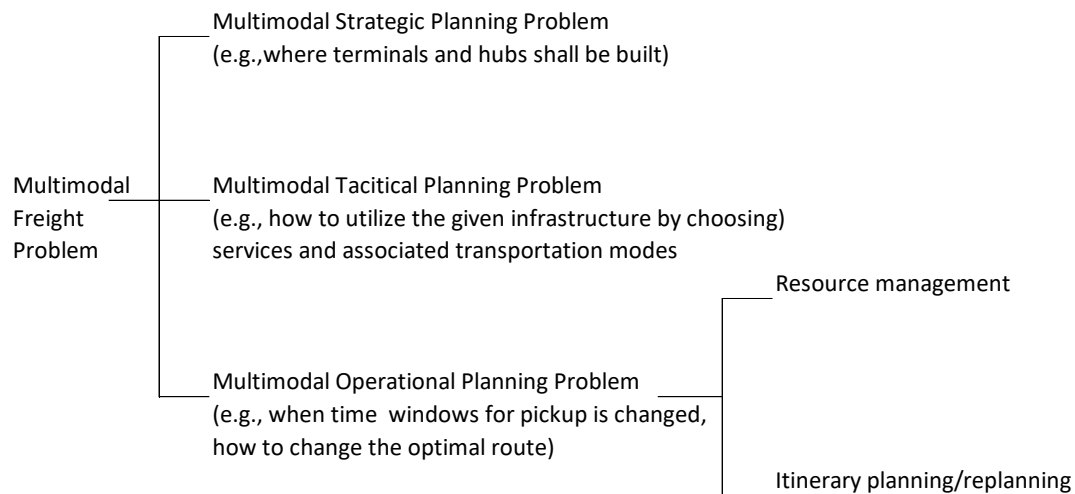
Figure 2.1 A Structure View of Multimodal Freight Transportation Problems

A lot of operational planning papers explore empty vehicle distribution and repositioning which are also called fleet management and, allocation of resources, respectively. Since the fleet management and allocation of resources literature have already been summarized in other research, we refer readers to the surveys by Crainic and Kim (2007) and Bektas and Crainic (2007). Our study focus on the optimal routing of goods in a logistics network, considering time constraints and time slots of different transportation modes. Thus, it is related to the operational planning/re-planning of multimodal freight distribution, which will be briefly review next.

Truck-rail multimodal transportation problem has been analyzed by many researchers. Bontekoning et al. (2004) reviewed the intermodal rail-truck freight transport literature. They found that the intermodal research is emerging and it can be a research field in its own right. Obviously, the first topic of the multimodal problem is how to choose the modes. An early representative work was reported by Harper and Evers (1993), who first mentioned the mode choice determinants and the sensitivity of mode to price and quality changes. Barnhart and Ratliff (1993) compared rail/road and road transport and proposed the shortest path algorithm to find the optimal routing in intermodal transportation problems.

In real life networks, direct shipment by trucks is normally used, but complete multimodal modes are not feasible. Haghani and Oh (1996) proposed a large-scale multi-commodity, multimodal network flow problem for disaster relief operation with time windows. Nozick and Morlok (1997) proposed a medium-term operation planning in a multimodal rail-truck system. They used the LP relaxation algorithm to find an optimal solution. Ziliaskopoulos and Wardell (2000) proposed a time-dependent intermodal least

time path algorithm (TDILTP) to solve a multimodal transportation problem for delays and arc switching points. Jansen et al. (2004) found a problem from the Deutsche Post World Net in Germany where goods could be transported using trains and trucks. Arnold et al. (2004) used a case study and LP model applied to the rail/road transportation system in the Iberian Peninsula. They had two main findings. First, goods are highly sensitive to the variation of the relative cost of rail. Second, a relocation of terminals has little impact on the market shares of the intermodal transportation. Moccia et al. (2011) combined many features, such as timetables, flexible-time transportation, and consolidation options into the target to suggest a column generation algorithm to solve the problems.

In addition to truck-rail multimodal freight transportation problem, some papers focus on the combination of other modes. Min (1991) proposed a goal programming model based on costs, market coverage, average length of haul, equipment capacity, speed, availability, reliability and damage. Bookbinder and Fox (1998) obtained the optimal routings for intermodal containerized transport from Canada to Mexico. They proposed a shortest path algorithm to find the optimal route with the least time and minimum transportation cost for truck, rail and water combination. Corry and Kozan (2006) proposed a load planning assignment model to solve an intermodal problem at the operational level. Numerical analyses were used to evaluate the dynamic model under two different operation environments: a simplified case in which an optimal solution can be determined. And a second case is to figure out the tradeoff between excess handling time and mass distribution of rail. Bock (2010) solved a multimodal transportation problem with possible disturbance. He defined disturbances such as vehicle breakdowns or the deceleration of vehicles, traffic congestion, and street blockages. Truck, Rail and air modes have been considered in his

model. Goel (2010) used a simulation to show that on-time delivery performance can be significantly improved by increasing the level of visibility. Truck, rail and water have been used in the simulation. Kopytov and Abramov (2012) suggested using the analytic hierarchy process (AHP) as the most suitable approach for evaluation of different routes and modes of cargo transportation. Cost, time reliability and ecological are chosen criteria in the AHP. Ayar and Yaman (2012) mentioned a multicommodity routing problem for ground and maritime transportation network.

A few papers further investigate problems where operations of the multimodal transportation are considered simultaneously with two or more echelons of a supply chain. For example, Meisel et al. (2013) studied a joint problem including production and distribution. The decision of production and intermodal transportation planning in a supply network are both considered simultaneously. Resat and Turkay (2015) presented a multi-objective optimization mode for integrated network design and operation, and illustrate its use on a real world case in Turkey. Baykasoglu and Subulan (2016) proposed a multi-objective model for intermodal transportation network, considering both operational decisions and design decisions such as service type selection, outsourcing decision, and transportation mode selection.

As mentioned above, very few papers have considered high-speed rail in the multimodal freight transportation problems. Pazour et al. (2010) proposed a modeling approach that could be used in freight transportation planning to make use of the application of high-speed rail technology. They combined the normal truck and high-speed rail into a multimodal transportation model and suggest that a 20,000-mile high-speed rail network with 6-minute headways used by rail work would decrease the transit time by 38%

overall, with a 78% decrease in annual total truck highway miles traveled. This model can be used to measure the effect of a high-speed network on the current highway system by evaluating performance measures related to freight transit times and highway congestion problems.

The other area which high-speed rail can make full use of is express industry. Express shipment delivery problem is one kind of classical problem. Kim (1997) developed a model for multimodal express shipment service design and proposed a Brand-and-Price-and-Cut algorithm which is a generalization of the branch-and-bound algorithm with linear programming relaxations. Kim et al. (1999) implemented a generic model for large-scale transportation service. They exploited problem-specific characteristics and applied problem-reduction techniques. Table 2.1 shows an overview of literature discussed on multimodal operational planning problems.

However, a gap still remains between what is available in the literature and the needs to guide a better business practice for a multimodal network design and operational performance optimization. In addition, most existing literature on modeling and solution methodologies for multimodal networks are limited to two modes (e.g., trucking-water, trucking-rail), while in industries, the options for multimodal shipping have far exceeded those being studied. Multimodal shipping can now be any combination of rail, high-speed rail water, trucking, and air transportation through a global shipping network. A meaningful optimization model for such networks should also incorporate the selections of transshipment locations, transshipment delays, customer delivery requirements, and shipping capacity limits, among other factors. Our model includes four transportation modes: truck, rail, air, and high-speed rail. We aim to solve a multimodal freight

transportation problem subject to supplier and shipping capacity limits, resource availability, transshipment delays, customer service requirements and environmental issues.

This study contributes to the multimodal/intermodal transportation literature in the following aspects. First, it is motivated by a real-life case, where the capacity for each route of each mode, and the attendant departure time slots are taken into consideration. Second, because of the multiple departure times for each route of each mode, as well as the potentially large number of customers (commodities) in our problem, the optimization models can become very difficult to solve, and hence a sub-gradient heuristic based on Lagrangian relaxation and decomposition is developed, where substantial computational advantage can be achieved by solving decomposed subproblems in parallel.

Table 2.1 Practical Aspects of Operational Planning Problems

NO	Reference	JOURNAL	Year	Problem	Mode	Algorithm	Case study	Split / Combine delivery	Multi-commodity	Empty mode issue	Fixed-schedule	3PL issue	Time constraint	Multi objective
1	Harper and Evers	TJ	1993	RM	T;R	LP	Y						Y	
2	Barnhart and Ratliff	JBL	1993	RM	T;R	Shortest path algorithm							Y	
3	Haghani and OH	TR_PartA	1996	IP	T;R	Lagrangian relaxation			Y				Y	
4	Nozick and Morlok	TR_PartA	1997	IP	T;R	LP Relaxation	Y			Y			Y	maximize the quantity and min cost
5	Ziliaskopoulos and Wardell	EJOR	2000	IP	T;R	Least time path algorithm	Y			Y			Y	dynamic travel times and switching delays
6	Arnold et al.	TR_PartA	2004	RM	T;R	Intermodal Terminals Location Simulation	Y							
7	Jansen et al.	EJOR	2004	IP	T;R	Decomposition Algorithm					Y		Y	
8	Moccia et al.	WOL	2011	IP	T;R	Column generation algorithms	Y	Y						
9	Min	TR_PartA	1991	RM	T;R;W;A	Chance-constraint goal programming	Y	Y			Y		Y	Min cost and risk
10	Bookbinder and Fox	TR_PartE	1998	IP	T;R;W	Shortest path algorithm	Y				Y		Y	
11	Corry and Kozan	COR	2006	RM	T;R,W	Load planning assignment model					Y		Y	
12	Chang	COR	2008	RM	T;W;R;A	Lagrangian relaxation,Subgradient			Y		Y		Y	Bi-obj:cost and time
13	Bock	EJOR	2010	IP	T;R;A	Neighborhood search				Y		Y	Y	
14	Goel	IJLRA	2010	IP	T;R;W	Simulation						Y	Y	RFID and visibility
15	Kopytov and Abramov	TT	2012	IP	T;W	AHP evaluation approach					Y		Y	
16	Ayar and Yaman	COA	2012	RM	T;W	Lagrangian relaxation,LP			Y		Y	Y	Y	penalty for waiting at terminals
17	Pazour et al.	TR_PartA	2010	IP	T,H	shortest path algorithm	Y					Y		

TI:Transportation Journal,
TR_PartA:Transportation Research Part_A
JBL:Journal of Business Logistic
TR_PartE:Transportation Research Part E
EJOR:European Journal of Operataional Research
WOL:Wiley Online Library
COR:Computers & Operations Research
IJLRA:International Journal of Logistics Research and Application
TT:Transport and Telecommunication

RM:Recourse management
IP:itinerary planning/replanning

T:Truck
W:Water
R:Rail
A:Air
H:High speed

2.2.   Mathematical Model

2.2.1. Problem Description

The problem under study is based on a real-life business case from Resun Co. Ltd., which needs to ship products to their customers in a timely manner. In addition to four transportation modes (truck, rail, high-speed rail and air) that they can use, they may use third-party logistics (3PLs) to outsource their distribution during peak demand periods. Different customers have varied demand due dates and quantities, as well as priority levels. During the peak demand periods, the company may be willing to delay the delivery of certain non-urgent requests, while maintaining the service level for urgent requests and their VIP customers. In our model, we capture this in delay costs. Therefore, the company aims to minimize transportation costs, 3PL costs, and delay costs.

In this paper, we consider one single origin and one single destination. The model can be extended to support multiple origins and destinations. The transportation network then is a graph $G = (V; E)$ with V being the set of cities directly or indirectly connected to the origin and destination and E being the set of arcs (or routes) connecting each pair of aforesaid cities. On each route $(u, v) \in E$, there may exist a set of transportation modes M, such as truck, rail, high-speed rail and air. For each transportation mode $m \in M$ on route (u, v), there are a set of available departure times indexed by set $T_{(u,v,m)}$. Note that $T_{(u,v,m)}$ can be an empty set if the company does not operate mode m between city u and v. If the load is subcontracted to the 3PL, the total shipping time ST_{uv} is then specified. The company has $|K|$ customer orders, and needs to satisfy all demands.

Some additional model assumptions are listed below.

Assumption

- Split delivery is not allowed.

- All customers' demand must be satisfied.

- Compared to the limited transportation capacity, production capacity is high and hence does not create a bottleneck.

- No return transportation is considered.

- Each arc's capacity is dependent on the mode it uses.

- Upload time and download time at the switch points have been considered in the mode transportation time.

- The distance from city i to city j is the same as the distance from city j to city i.

- Congestion is not included.

- All travel time is known as a priori.

- Company has certain contracts for each transportation mode, and hence the shipping capacity on each city pair is determined in advance.

2.2.2. The Mathematical Model

Sets and Indices

$V = \{1, \dots, |V|\}$: set of cities, where each element represents the index of city (e.g., 1 represents the starting city(origin) and $|V|$ represents the ending city (destination)).

$E = \{(u, v): u, v \in V\}$: set of city pairs where there exist valid routes. $(u, v) \in E$ for $u, v \in V$ means that there is a route (directed arc) form city u to city v.

$P(v) = \{u \in V: (u, v) \in V\}, v \in V$: set of cities preceding city v with a valid route.

$S(v) = \{u \in V : (u, v) \in V\}, v \in V$: set of cities succeeding v with a valid route.

$M = \{1, \dots, |M|\}$: set of shipping modes, $m \in M$.

$K = \{1, \dots, |K|\}$: set of customer orders, $k \in K$.

$T_{(u,v,m)}, (u, v) \in E, m \in M$: set of indexes for an eligible departure times for mode m on route (u, v).

Parameters

$T_{k,}^0 \ k \in K$ earliest departure time of customer order k from the starting city.

$Q_k, k \in K$: desired shipping quantity from customer order k.

$p_k, k \in K$: unit penalty cost of late delivery for customer order k; the penalty for a high-priority customer is typically much higher than that for a regular customer.

C_{uvmt} , $(u, v) \in E, m \in M, t \in T(u, v, m)$: shipping capacity of mode m on route (u, v) for t-th departure time.

f_{uvmt} , $(u, v) \in E, m \in M, t \in T(u, v, m)$: unit shipping cost of mode m on route (u, v) for t-th departure time.

τ_{uvm} , $(u, v) \in E, m \in M$: transportation time of mode m on route (u, v), assuming that the difference of traveling time among different departure times are negligible, and the handling time at the end of route (u, v) is also included.

$ST_{uv}, (u, v) \in E$: shipping time of route (u, v) if 3PL is used.

DD_k , $k \in K$: due date of customer order k.

F_{uv}, $(u,v) \in E$: fixed cost of using 3PL for route (u,v).

DT_{uvmt}, $(u,v) \in E, m \in M, t \in T(u,v,m)$: t-th eligible departure time for mode m on route (u,v).

Variables

x_{kuvmt}, $(u,v) \in E, m \in M, t \in T(u,v,m)$: binary variable,$x_{knmt} = 1$ if customer order k is shipped by mode m on route (u,v) at t-th departure time, and 0 otherwise.

y_{kuv}, $(u,v) \in E, k \in K$: binary variable,$y_{kuv} = 1$ if customer order k is shipped by 3PL from the starting city of route (u,v) to the final destination, and 0 otherwise.

z_{kuv}, $(u,v) \in E, k \in K$: binary variable,$z_{kuv} = 1$ if customer order k is shipped on route (u,v), and 0 otherwise.

t_{kv}, $v \in V, k \in K$: arrival time of customer order k in city v, where $t_{k1} = T_k^0$ representing the earliest possible departure time of customer order k from the starting city.

TD_k , $k \in K$: tardiness of customer order k.

Model

The objective of the problem is to minimize the total costs, consisting of transportation costs 3PL costs and late penalty costs.

$$z = min \sum_{k \in K} Q_k \left(\sum_{(u,v)} \sum_{m \in M} \sum_{t \in T(u,v,m)} f_{uvmt} x_{kuvmt} + \sum_{(u,v) \in E} F_{uv} y_{kuv} + p_k TD_k \right). \tag{1}$$

The following constraints are considered.

Tardiness of each customer order is expressed as follows.

$$TD_k \geq t_{k|V|} - DD_k, \qquad \forall k \in K \tag{2}$$

For each route, a customer order can only choose one transportation mode or 3PL

$$\sum_{m \in M} \sum_{t \in T_{(u,v,m)}} x_{kuvmt} + y_{kuv} = z_{kuv}, \quad \forall k \in K, (u,v) \in E \tag{3}$$

The total shipping amount for each transportation mode on each route for each departure time cannot exceed its capacity.

$$\sum_{k \in K} x_{kuvmt} Q_k \leq C_{uvmt}, \qquad \forall (u,v) \in E, m \in M, t \in T (u,v,m) \tag{4}$$

Flow-balance constraints.

$$\sum_{v \in S_{(1)}} z_{k1v} = 1, \qquad \forall k \in K \tag{5}$$

$$\sum_{u \in P_{(v)}} z_{kuv} = \sum_{u \in S_{(v)}} z_{kvu}, \quad \forall k \in K, \ v \in V \tag{6}$$

Time constraints, where B is a big positive constant.

$$\sum_{m \in M} \sum_{t \in T_{(u,v,m)}} x_{kuvmt} (DT_{uvmt} + \tau_{uvm}) \leq t_{kv}, \quad \forall k \in K, (u,v) \in E \tag{7}$$

$$t_{ku} - B(1 + y_{kuv} - z_{kuv}) \leq \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} DT_{uvmt} X_{kuvmt}, \qquad \forall k \in K, (u,v) \in E \tag{8}$$

$$t_{ku} + ST_{uv} - B(1 - y_{kuv}) \leq t_{kv}, \quad \forall k \in K, (u,v) \in E \tag{9}$$

Variable domain constraints

$$x_{kuvmt} \in \{0,1\}, \qquad \forall k \in K, (u,v) \in E, m \in M, t \in T_{(u,v,m)} \tag{10}$$

$$y_{kuv} \in \{0,1\}, \qquad \forall k \in K, (u,v) \in E \tag{11}$$

$$z_{kuv} \in \{0,1\}, \quad \forall k \in K, (u,v) \in E \tag{12}$$

$$t_{kv} \geq 0, \qquad \forall k \in K, v \in V \tag{13}$$

$$TD_k \geq 0. \qquad \forall \, k \in K \tag{14}$$

All variables are non-negative. (15)

The target of function (1) is to minimize all the transportation costs, 3PL costs and tardiness penalty costs. Constraint (2) defines tardiness. Constraint (3) ensures that, for each route, each customer order can be served by only one mode or 3PL. Constraint (4) shows the route capacity limitation. Constraints (5) and (6) establish the flow-balance. Constraints (7), (8) and (9) address time constraints, ensuring that, for each route, the departure time plus transportation time are less than the arrival time. Constraints (10) through (15) are binary constraints and all variables are non-negative.

2.2.3. Computational Complexity

Computationally, searching for the optimal solutions to the multimodal network scheduling problem is challenging because of its combinatorial nature. Before we trying to solve the model, we first prove it is a NP hard problem.

Theorem 1. NP-hard in strong sense

Proof We prove by restriction. Consider the following restricted instance of problem IP_0:

- Set $M = \{1\}$, that is, only one single mode is available.

- Set $T(u, v, m) = \{1\}$ for all $(u, v) \in E, m \in M$, that is, only one single departure time slot is available.

- Set $p_k = 0$ for all $k \in K$, that is no late penalty is considered.

- Set $Q_k = 1$ for all $k \in K$, that is, each customer order has a unit quantity.

- Assume no 3PLs, such that y_{kuv} and related constraints can be dropped.

- Assume instantaneous transportation such that the time constraints (7) - (9) can be dropped.

With the restrictions above, problem IP_0 becomes the multi-commodity integral flow problem, whose decision problem is NP complete and its related optimization problem is NP hard. The multi-commodity integral flow problem is a restricted version of the optimization problem IP_0, thus concluding the NP hardness of problem IP_0.

Chapter 3

A Lagrangian Relaxation-Based Sub-gradient Heuristic

In this chapter, we first show a literature review on methodology in related multimodal freight transportation area. Then we propose a Lagrangian relaxation based sub-gradient heuristic.

3.1. Methodology

Figure 3.1 shows different methodologies in the multimodal freight transportation area. In the early time, researcher used linear programming or linear programming relaxation to find the close optimal solution. Harper and Evers (1993) used mail questionnaires to get the regression results. Nozick and Morlok (1997) used a heuristic method to relax some constraints so that the problem turns out to be linear program. Arnold et al. (2004) used a linear programming heuristic method in a case study in the Iberian Peninsula.
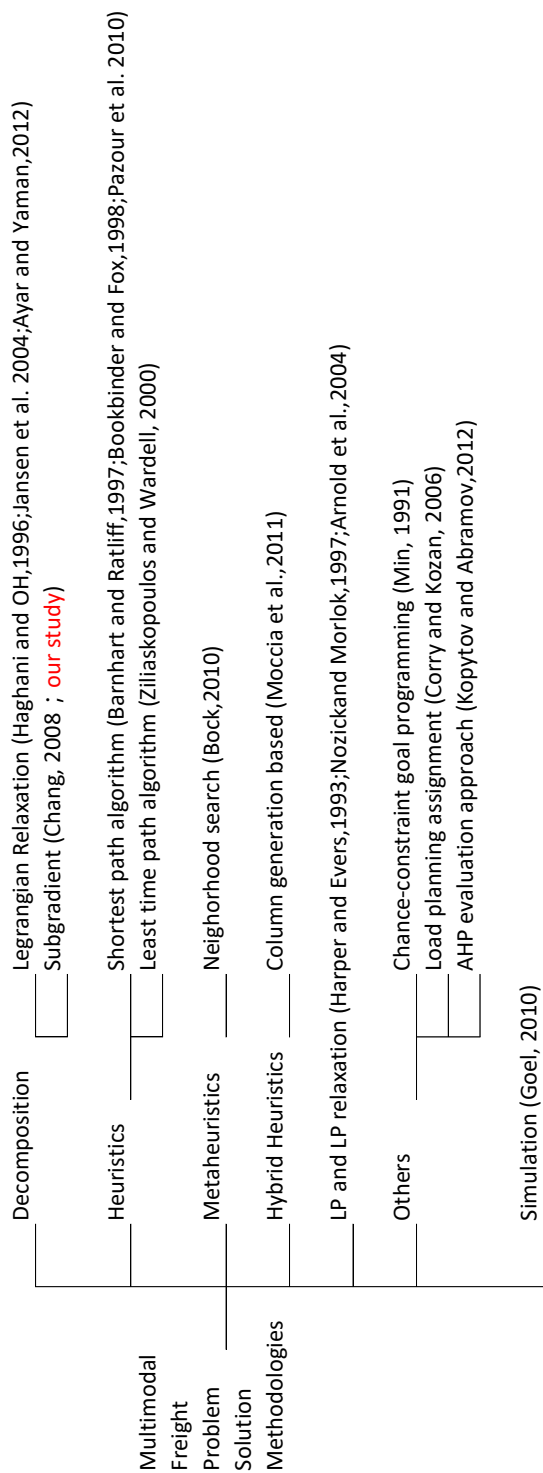
Figure 3.1 Solution Methodologies of Operational Planning Problems

Basically, shortest path algorithm has been used in the early time. The stochastic and time-dependent version is decomposed into subproblems. Pazour et al. (2010) proposed an uncapacitated network design model with a post-processing step for capacity based on shortest path algorithm.We can find related shortest path algorithm method in the following paper. (Barnhart and Ratliff,1997; Bookbinder and Fox,1998; Ziliaskopoulos et al. 2000)

Goel (2010) seek to quantify the value of visibility over assets moving through a multi-modal transportation network. He simulated the decision-making process with different levels of visibility. The computational experiments showed that on-time delivery performance can be significantly improved by increasing the level of visibility.

In the recent years, Lagrangian relaxation has been the most common solution method in the multimodal freight transportation area. Marshall Fisher (1973) first mentioned the sub-gradient method in the 1970s and subsequently provided many examples (Fisher, 1985, 2004). Michael et al. (1974) proved that sub-gradient optimization performed fairly well on large optimization problems. Haghani and Oh (1996) proposed two heuristic algorithms: the Lagrangian relaxation heuristic, which exploits an inherent network structure of the problem with a set of side constraints, and an interactive fix-and-run heuristic, which shows better results. Jansen et al. (2004) implemented a decomposition algorithm with subproblems, ultimately proposing a hybrid and iterative algorithmic approach. Ayar and Yaman (2012) used a heuristic algorithm based on Lagrangian relaxation to solve a routing problem for ground and maritime transportation network. Xiao et al. (2015) proposed a hybrid Lagrangian-simulated annealing-based heuristic to solve a lot-sizing and scheduling problems.

Bock (2010) solved a multimodal freight problem by a neighborhood search algorithm. Moccia et al. (2011) suggested a column generation algorithm. Other particular methods have been mentioned in the paper following paper: chance-constraint goal programming in Min (1991); load planning assignment in Corry and Kozan (2006); and AHP evaluation approach in Kopytov and Abramov (2012).

Park and Kim (2002) used a sub-gradient optimization technique to solve a container terminals scheduling problem. Chang (2008) proposed a multi-objective multimodal multicommodity flow problem (MMMFP) with three characteristics: 1) multiple objectives; 2) scheduled transportation modes and demanded delivery times; and 3) transportation economies of scale. He used Lagrangian relaxation and decomposition techniques to solve the problem.

In this sub-chapter, we propose a sub-gradient heuristic methodology to solve problem IP, we consider the original problem as IP_0 and then, construct a Lagrangian relaxation of IP_0 with a Lagrangian multiplier $\pi_{uvmt} \geq 0 \ (\forall(u, \ v) \in E, m \in M, t \in T_{(u,v,m)})$, by relaxing the capacity constraint (4). The resulting Lagrangian relaxation problem is denoted as $P(\pi)$, as follows.

$IP(\pi)$:

$$z(\pi) = min\left[\sum_{k\in K} Q_k(\sum_{(u,v)\in E}\sum_{m\in M}\sum_{t\in T_{(u,v,m)}} f_{uvmt}x_{kuvmt} + \sum_{(u,v)\in E} F_{uv}y_{kuv} +\right.$$

$$\left. p_k TD_k) + \sum_{(u,v)\in E}\sum_{m\in M}\sum_{t\in T_{(u,v,m)}} \pi_{uvmt}(\sum_{k\in K} Q_k x_{kuvmt} - C_{uvmt})\right] =$$

$$min \sum_{k\in K} Q_k\left[\sum_{(u,v)\in E}\sum_{m\in M}\sum_{t\in T_{(u,v,m)}}(f_{uvmt} + \pi_{uvmt})x_{kuvmt} +\right.$$

$$\left.\sum_{(u,v)\in E} F_{uv}y_{kuv} + p_k TD_k\right] - \sum_{(u,v)\in E}\sum_{m\in M}\sum_{t\in T_{(u,v,m)}} \pi_{uvmt} C_{uvmt}. \tag{20}$$

subject to:

Constraints (2) through (15), except (4).

This problem can be further decomposed into a sub problem for each customer k, denoted by $IP_k(\pi)$. Thus, for any given $\hat{k}$ and π_{kuvmt}, we have

$$z_{\hat{k}(\pi)} = min \left[\sum_{(u,v)\in E} \sum_{m\in M} \sum_{t\in T_{(u,v,m)}} (f_{uvmt} + \pi_{uvmt}) x_{\hat{k}uvmt} + \right.$$

$$\left. \sum_{(u,v)\in E} F_{uv} y_{\hat{k}uv} + p_{\hat{k}} TD_{\hat{k}} \right]. \tag{21}$$

Subject to

$$TD_{\hat{k}} \geq t_{\hat{k}|V|} - DD_{\hat{k}}, \tag{22}$$

$$\sum_{m\in M} \sum_{t\in T_{(u,v,m)}} x_{\hat{k}uvmt} + y_{\hat{k}uv} = z_{\hat{k}uv}, \quad \forall (u,v) \in E \tag{23}$$

$$\sum_{v\in S_{(1)}} z_{\hat{k}1v} = 1, \tag{24}$$

$$\sum_{u\in P_{(v)}} z_{\hat{k}uv} = \sum_{u\in S_{(v)}} z_{\hat{k}vu}, \quad \forall\, v \in V \tag{25}$$

$$\sum_{m\in M} \sum_{t\in T_{(u,v,m)}} x_{\hat{k}uvmt}(DT_{uvmt} + \tau_{uvm}) \leq t_{\hat{k}v}, \quad \forall (u,v) \in E \tag{26}$$

$$t_{\hat{k}u} - B(1 + y_{\hat{k}uv} - z_{\hat{k}uv}) \leq \sum_{m\in M} \sum_{t\in T_{(u,v,m)}} DT_{uvmt} X_{\hat{k}uvmt}, \quad \forall (u,v) \in E \tag{27}$$

$$t_{\hat{k}u} + ST_{uv} - B(1 - y_{\hat{k}uv}) \leq t_{\hat{k}v}, \quad \forall (u,v) \in E \tag{28}$$

$$x_{\hat{k}uvmt} \in \{0,1\}, \quad \forall (u,v) \in E, m \in M, t \in T_{(u,v,m)} \tag{29}$$

$$y_{\hat{k}uv} \in \{0,1\}, \quad \forall (u,v) \in E \tag{30}$$

$$z_{\hat{k}uv} \in \{0,1\}, \quad \forall (u,v) \in E \tag{31}$$

$$t_{\hat{k}v} \geq 0, \quad \forall v \in V \tag{32}$$

$$TD_{\hat{k}} \geq 0, \tag{33}$$

All variables are non-negative. (34)

Consequently, the Lagrangian dual problem is

$$\omega_{LD} = max\{z(\pi): \pi \geq 0\}, \tag{35}$$

Where

$$z_{(\pi)} = \sum_{k \in K} Q_k z_k(\pi) - \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} \pi_{uvmt} C_{uvmt}. \tag{36}$$

The benefit of such decomposition is that the problem size of each subproblem is much smaller than that of the original problem, and hence can be solved using a MILP solver (e.g., Gurobi) effectively. Another noticeable benefit is that $|K|$ subproblems are independent to each other, and thus can be solved parallel using parallel computing or distributed computing, which will significantly speed up the computation.

3.2. A Sub-gradient Heuristic Method

By relaxation and decomposition techniques, the original problem can be separate into smaller and easier subproblems. We propose to solve the Lagrangian dual problem (35) using sub-gradient method, as described in Algorithm 1.

Algorithm 1 has three key steps. 1) Update the lower bound of IP_0 by solving the Lagrangian relaxation problem, where computational benefits are achieved by decomposing the problem into $|K|$ subproblems, $IP_k(\pi^r)$. As mentioned above, parallel computing or distributed computing can be used here to solve the $|K|$

subproblems in parallel. 2) Obtain an upper bound (i.e., a feasible solution) of IP_0 by adjusting the optimal solution of the Lagrangian relaxation problem. Here, a heuristic algorithm (Algorithm 2) is developed to quickly find a feasible solution from the (possible infeasible) Lagrangian relaxation solution. 3) Update Lagrangian multiplier using Eq. (38) (Fisher, 1973, 1985; Held et al, 1974).

Algorithm 1. Sub-gradient Method for Solving IP_0.

Step 1. Initialization: Set the initial upper bound of the primal problem IP_0 as $z_{UB}^0 = B$ where B is a big positive number, and the initial lower bound of IP_0 as $z_{LB}^0 = 0$. Set the iteration counter $r = 1$, and the initial Lagrangian multiplier $\pi_{uvmt}^r = 0$.

Step 2. Update lower bound: In iteration r, solve $|K|$ problem $IP_k(\pi^r)$ to optimality using standard MILP solver (e.g., GUROBI or CPLEX). Denote the resulting optimal solution as $(\underline{x}_{kuvmt}^r, \underline{y}_{kuv}^r, \underline{z}_{kuv}^r, \underline{t}_{kv}^r, \underline{TD}_k^r)$, and its corresponding optimal objectives as $z_k(\pi^r)$ in Eq. (21). Then, compute the Lagrangian lower bound as follows.

$$z_{LB}^r = \sum_{k \in K} Q_k z_k(\pi^r) - \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} \pi_{uvmt}^r C_{uvmt}. \tag{37}$$

Consequently,

$$z_{LB}^r = max\{z_{LB}^{r-1}, z_{LB}^r\},$$

Step 3. Update upper bound: Obtain a heuristic solution of the primal problem IP_0 , $(\overline{x}_{kuvmt}^r, \overline{y}_{kuv}^r, \overline{z}_{kuv}^r, \overline{t}_{kv}^r, \overline{TD}_k^r)$, using Algorithm 2. Denote the corresponding optimal value of objective (1) as z_H^r. Update the upper bound by

$$z_{UB}^r = min\{z_{UB}^{r-1}, z_H^r\}.$$

Step 4. Update Lagrangian multiplier: Update the Lagrangian multiplier π by

$$\pi_{uvmt}^{r+1} = max\{0, \pi_{uvmt}^r + \delta^r(\sum_{k\in K} Q_k \, x_{kuvmt}^r - C_{uvmt})\} \quad \forall (u,v) \in E, m \in M, t \in$$

$$T_{(u,v,m)} \tag{38}$$

Where $\delta^r = \lambda^r \dfrac{z_{UB}^r - z_{LB}^r}{\sum_{(u,v)\in E}\sum_{m\in M}\sum_{t\in T_{(u,v,m)}}(\sum_{k\in K} Q_k \underline{x}_{kuvmt}^r - C_{uvmt})^2}$. $\tag{39}$

Here, λ^r is a scalar in the range of $[0,2]$ and $\lambda^1 = 2$. If the value of z_{UB}^r has not been improved for the previous $l = 3$ iterations, set $\lambda^{r+1} = 0.9\lambda^r$; otherwise, $\lambda^{r+1} = \lambda^r$.

Step 5. Stopping: if one of the following conditions is met, stop and output the current z_{UB}^r as the optimal value; otherwise, $r \leftarrow r + 1$ and go to Step 2.

- $\sum_{k\in K} Q_k x_{kuvmt}^r - C_{uvmt} \leq \varepsilon$ for all $(u,v) \in E, m \in M, t \in T_{(u,v,m)}$ satisfy $\pi_{uvmt}^r > 0$, where ε is a sufficiently small positive number.

- The total running time of this algorithm exceeds a limit.

- The total number of iteration r exceeds a limit.

The algorithm to obtain a heuristic solution of the primal problem IP_0 is described in Algorithm 2. The idea of this heuristic is based on tinkering the Lagrangian solution of $IP(\pi^r)$, that is $(\underline{x}_{kuvmt}^r, \underline{y}_{kuv}^r, \underline{z}_{kuv}^r, \underline{t}_{kv}^r, \underline{TD}_k^r)$. Notice that the capacity constraint (4) is relaxed and penalized in the objective function in problem $IP(\pi)$. Hence, the optimal solution of $IP(\pi)$ may not be a feasible solution of problem IP_0 (by violating the capacity constraint). However, if we add the capacity constraint to each problem $IP_k(\pi)$, and iteratively update the remaining capacity, we can guarantee that the capacity constraint is satisfied. The detail is described in the following algorithm.

Algorithm 2. Heuristic for Solving IP$_0$ Given $(\underline{x}^r_{kuvmt}, \underline{y}^r_{kuv}, \underline{z}^r_{kuv}, \underline{t}^r_{kv}, \underline{TD}^r_k)$.

Step 1. Set customer priorities: For each customer $k \in K$, compute a weight factor as

$\omega_k = \frac{Q_k p_k}{DD_k}$. Sort the customers based on the weight factors ω_k in the descending order, and

denote the obtained customer sequence as $\{k_1, k_2, \dots, k_{|K|}\}$.

Step 2. Determine fixed variables: For each route segment (u, v, m, t) where $(u, v) \in$

$E, m \in M, t \in T_{(u,v,m)}$, fix the variables as follows.

    (a) Set the initial remaining shipping capacity as $\hat{C}_{uvmt} = C_{uvmt}$. Set $i = l$.

    (b) If $\underline{x}^r_{kuvmt} = 1$ and $Q_{k_i} \leq \hat{C}_{uvmt}$, fix $x_{kuvmt} = \underline{x}^r_{kuvmt}$, and update $\hat{C}_{uvmt} =$

        $C_{uvmt} - Q_{k_i}$. If $i \leq |K| - 1$, set $i \leftarrow i + 1$ and go to step 2(b).

Step 3. Solve the remaining IP$_0$: Sequentially solve augmented IP$_k(\pi)$ as follows.

Set i=1.

    (a) Solving $IP_k(\pi)$: For $k = k_i$, solve $IP_k(\pi)$ using a MILP solver with the

        following additional constraint:

        $Q_k x_{kuvmt} \leq \hat{C}_{uvmt}$ $\forall (u, v) \in E, m \in M, t \in T(u, v, m)$ (40)

    (b) **Capacity update**: Update remaining shipping capacity as follows:

        $\hat{C}_{uvmt} \leftarrow \hat{C}_{uvmt} - Q_k x^*_{kuvmt}$ $\forall (u, v) \in E, m \in M, t \in T(u, v, m)$ (41)

        where x^*_{kuvmt} is the optimal solution obtained for problem IP$_k(\pi)$.

    (c) **Stopping**: If $i \leq |K| - 1, i \leftarrow i + 1$ and go to Step 3(a); otherwise, the

        objective value of current feasible solution is calculated.

Figure 4.2 provides the procedure of our sub-gradient heuristic method. The left side is

Algorithm 1 and the right side is Algorithm 2.
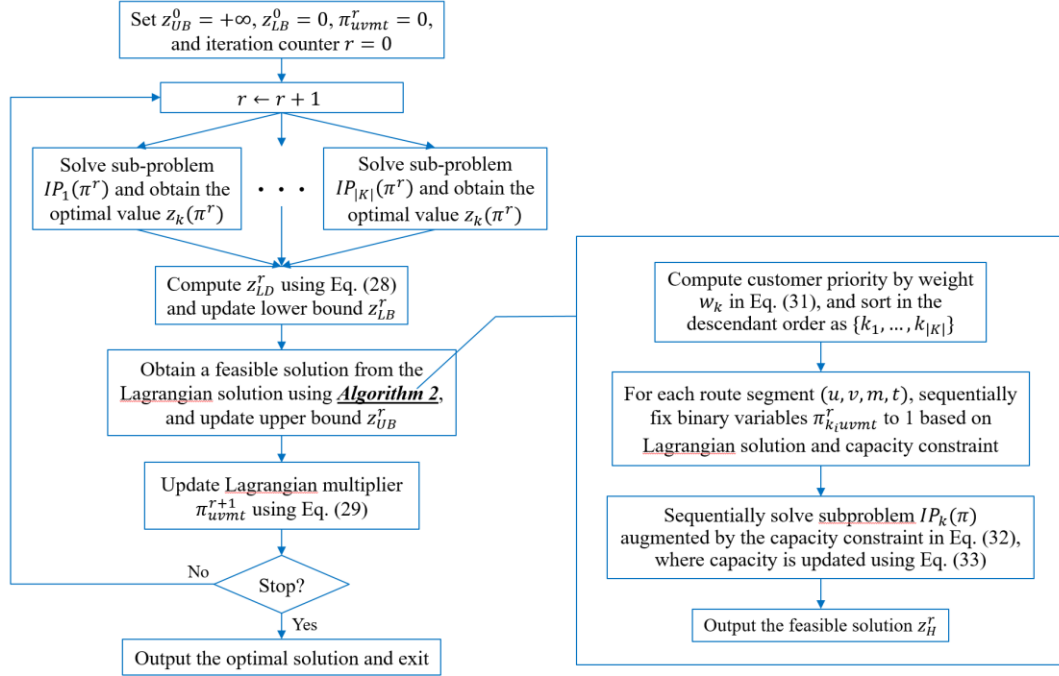
Figure 3.2 Flowchart of Algorithms 1 and 2

3.3. Numerical Examples

Next, we use proposed algorithm to demonstrate the computational efficiency with randomly generated numerical examples. The solution quality and computational time are compared to the best solutions obtained by the commercial Gurobi MILP solver. A computer with Intel Core i7-6600U 2.6 GHz CPU and 16 GB of RAM is used to test. As mention before the computational benefits can be achieved by solving $|K|$ subproblems in parallel in step 2 of Algorithm 1. In the tests, we solved 4 subproblems in parallel based on our computer level. Such a choice is to make sure that a fair comparison with Gurobi, as the latter used 4 parallel threads in its MILP solver in the tests. It is assumed that on a

computer with more CPU threads or GPUs, or in a distributed computer network, the computational time of Algorithm 1 will be further reduced.

The tests were based on the Resun Co. Ltd. case, where the network structure in consideration is shown in Figure 3.2. Note that in the network, there are one origin (factory) and one destination (customer) in the map, and others are middle points. We first use a smaller network to compare the performance of the proposed heuristic to that of the Gurobi MILP solver with the default setting. Then a larger network is included. Both networks consist of the origin, destination and critical connection nodes.

In the tests, we randomly generate the test cases using the parameters specified in Table 3.1.

Table 3.1 Parameters for Computational Time

Parameters	Data Range of Parameters
Size of customer order	$S = (10, 20, 30, 40, 50, 70, 100)$
Due Day (Hours)	$DD_k = uniform\ (11, 72)$
Penalty (RMB/Day-Ton)	$p_k = \ (50, 500)$
Demand of customers (Ton)	$Q_k \sim uniform\ (50, 250)$
Departure time	$DT_{uvmt} = \ (1, 2)$
Mode speed (Km/h)	$Speed = \ (60, 100, 250, 500)$
Unit cost of modes (RMB/Ton-1000km)	$f_m = \ (300, 500, 1500, 2000)$
Transportation time of 3PL (Hours)	$ST_{uv} = \ uniform\ (1, 14)$

Specifically, we varied the number of customer orders ($|K|$). The set of customer orders is {10, 30, 50, 70, 100}. For each value of $|K|$, 30 examples were tested by both the Gurobi solver and the proposed heuristic. The tests would be terminated if the Gurobi solver could find the optimality within 3600 seconds and return the current best solution as optimal.

We gave the definition of an empirical error gap (EEG) as follow.

$$Empirical\ Error\ Gap\ (EEG) = \frac{(G_H - G^*)}{G^*} * 100\%$$

G_H and G^* stand for the best solution obtained by the heuristic and Gurobi based on objective function values (using Intel Core i7 6600, 2.6GHz). A negative EEG indicates that the heuristic solution is better than the Gurobi solution.

Figure 3.3 shows a map of our small network. The factory is located at Beijing; we suppose all customers are in Guangzhou. The orders would ship to the customers through the middle points or directly.

Figure 3.4 shows a map of our large network. The factory is located at Beijing; we suppose all customers are in Guangzhou. The orders would ship to the customers through the middle points or directly.

Figure 3.3 Map of Problem (Small Problem)

We demonstrate the computational efficiency of the proposed algorithm using randomly generated numerical examples. The solution quality and computational time of the proposed algorithm are compared to the best solutions obtained using the commercial Gurobi MILP solver. Recall that computational benefits can be achieved by solving $|K|$ subproblems in parallel in step 2 of Algorithm 1. In our tests, we solved 4 subproblems in parallel. Such a choice is to ensure a fair comparison with Gurobi, as the latter used 4 parallel threads in its MILP solver in our tests. It is expected that on a computer with more CPU threads or GPUs, or in a distributed computer network, the computational time of Algorithm 1 will be further reduced.

Table 3.2 and 3.3 show the performance comparison between Gurobi and our heuristic. Note that for each parameter setting, the results shown are the average of 30 random test cases.

Table 3.2 Time Comparison Between MIP Solver and the Proposed Heuristic

(Small Network)

| Parameter | Computational Time (in seconds) | | | | | | | |
| | Gurobi | | | | Heuristic | | | |
|K|	Avg	Min	Max	Std	Avg	Min	Max	Std
10	26	12	46	7	45	38	89	7
20	288	148	592	83	67	62	71	2
30	3391	1452	7201	1015	95	90	101	2
40	7200	7200	7203	0.19	125	120	131	1.84
50	7200	7200	7201	0.06	164	146	182	6.8
70	7200	7200	7206	0.67	308	248	427	38
100	7201	7200	7202	0.13	323	312	341	5.36

Table 3.3 Error Gap Comparison between MIP Solver and Proposed Heuristic (Small

Network)

| Parameter | EEG (%) | | | | |
|K|	Avg	Min	Max	Std	Gurobi Gap
10	1.04	0	3.28	0.86	0
20	1.94	0.85	3.92	0.6	0
30	1.86	-0.97	3.39	0.59	2.8
40	0.67	-1.63	2.44	0.8	8.88
50	-0.27	-2.29	1.4	0.73	12.21
70	-1.72	-5.36	1.99	1.11	18.12
100	-18.69	-27.31	-5.93	4.58	31.16

Then we increase the size of the network by including more intermediate cities. Figure 3.4 below shows a larger network in our remaining tests. The factory (Beijing city) and destination (Guangzhou city) don't change comparing to the small network. But the number of intermediate cities has been increased from 7 to 17. Three fifth of all the big cities in China have been included. More potential routes could be chosen from factory to destination which makes the whole problem complex and close to the reality.

Figure 3.4 Map of Problem (Large Problem)

Table 3.4 Time Comparison Between MIP Solver and the Proposed Heuristic

(Large Network)

Parameter |K|	Computational Time (in seconds)							
	Gurobi				Heuristic			
	Avg	Min	Max	Std	Avg	Min	Max	Std
10	3436	78	7200	2840	110	13	144	11
20	7201	7201	7203	0.57	214	176	242	10
30	7201	7201	7206	0.87	378	312	467	34
40	7203	7202	7210	1.57	509	463	696	43
50	7202	7202	7206	0.6	611	578	637	14
70	7204	7202	7209	1.31	1008	858	1334	87
100	7205	7202	7210	0.83	1275	1182	1476	41

Table 3.5 Error Gap Comparison Between MIP Solver and Proposed Heuristic (Large

Network)

Parameter |K|	EEG (%)				
	Avg	Min	Max	Std	Gurobi Gap
10	0.07	-3.2	1.4	0.32	12.61
20	-1.43	-9.84	2.35	2.05	22.54
30	-6.45	-17.42	-0.41	3.27	30.78
40	-17.32	-26.72	-9.82	3.54	40
50	-24.49	-40.29	-15.67	4.7	49.29
70	-35.68	-54.52	-17.28	7.58	60.79
100	-37.99	-56.71	-23.39	11.9	62.6

In terms of the EEG performance measure defined in the equation above, the heuristic demonstrated a very competitive and robust performance. For small sizes (10-30 customers), Gurobi solved to optimality within one hour; our heuristic solves it within a

few hundred seconds, with an optimality gap ranging between 0.86% and 3.47%, which is fairly close.

Table 3.2 and Table 3.3 show the performance comparison between the proposed heuristic and the Gurobi solver for test cases on the small-size network described above. More specifically, the column "EEG (%)" shows the following statistics of the empirical error gaps between the heuristic and Gurobi across 30 random examples: mean (Avg), minimum (Min), maximum (Max), and standard deviation (Std). In addition, the column "Gurobi Gap" lists the average relative optimality gap when Gurobi was terminated (the relative gap between the upper and lower bounds found by the Gurobi solver when terminated). The column "Computational Time (in seconds)" shows similar statistics for the computational times by Gurobi and the heuristic, respectively.

From Table 3.2 and Table 3.3, it is seen that Gurobi could solve small problems ($|K| < 20$) to optimality within 2 hours, and hence the Gurobi solutions are better (on average) than the heuristic solution counterparts for these cases. As the problem size increases, Gurobi was not able to find the optimal solutions for most cases, and hence its computational time is about 2 hours (equivalently, 7200 seconds). On the other hand, the heuristic was much more efficient, solving the problems in 164 seconds on average for $|K| = 50$, and 323 seconds for $|K| = 100$. In terms of the solution quality, it is seen that the heuristic solutions are within 2% of the Gurobi solutions on average for $|K| = 40$. When the problem size further increases, e.g., for $|K| = 50$, the heuristic solutions beat Gurobi solutions on average. The performance improvement becomes more substantial as the problem size increases. To wit, the average improvement is 0.27% for $|K| = 50$, and 18.69% for $|K| = 100$.

To further demonstrate the computational advantages of the heuristic, we experimented on a larger network, consisting of all nodes shown in Figure 2. We varied the number of customer orders, |K |, in the set of {10, 20, 30, 40, 50, 70, 100}, where each value of $|K|$ was tested by 30 randomly generated cases. Sets and parameters in each test case were generated randomly according to Table 3.1. Similar statistics were collected as for the test cases in Table 3.2 and Table 3.3.

From Table 3.4 and Table 3.5, it is observed that the heuristic outperforms Gurobi solver for all cases with $|K| = 30$ (see the Avg, Min and Max columns of EEG). Similarly, to the observations in Table 3.2 and Table 3.3, the absolute value of average EEG becomes larger as $|K|$ increases, indicating the superior solution quality obtained by the heuristic. For $|K| = 100$, average EEG is -37.99%, which is a substantial improvement over the Gurobi solutions. Note that the heuristic achieved such solution quality improvements with much less computational time. For most cases in Table 3.4 and Table 3.5, Gurobi terminated in 2 hours without achieving the optimality. The relative optimality gap when Gurobi terminated remains large, e.g., more than 60% for $|K| = 70$ and $|K| = 100$. On the other hand, the heuristic was much more efficient, terminating in 1275 seconds on average for $|K| = 100$.

Figure 3.5 summarizes the computational time saving and solution quality improvement by the heuristic, compared to the Gurobi solver. Specifically, the horizontal axis lists the 14 tests settings in Table 3.2 to Table 3.5, where problem set 1 refers to the small-size network and problem set 2 refers to the larger-size network. The left vertical axis shows the computational time saved by the heuristic as a percentage of time spent on the Gurobi solver, where a negative value indicates that the heuristic takes a longer time

than Gurobi. The right vertical axis shows the EEG, where a negative value indicates that the heuristic solution is better. It is seen that the heuristic was able to achieve better solutions (e.g., 37.99% improvement for the largest case, (2,100)) using much shorter computational time (e.g., only 17.7% of the Gurobi time for the largest case, (2,100)). Note that although for case (1,10), the heuristic time is almost 80% longer, the absolute time difference is only 19 seconds.
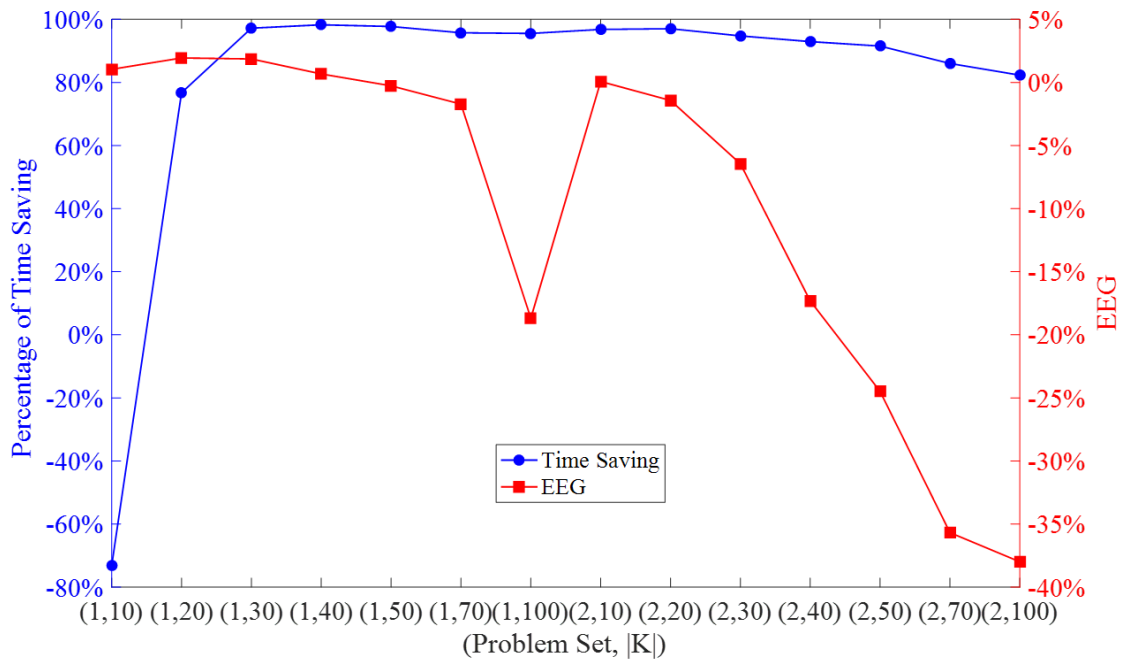
Figure 3.5 Computational Time Saving and Solution Quality Improvement by the Heuristic

For medium sizes (40-50), all Gurobi cases stopped at two hours, with 3.18% and 1.57% of optimality gaps on average at the time of stopping for 40 and 50 customers, respectively. Our heuristic finished within 400 seconds, and the gap between our results and the Gurobi results are within approximately 2%.

For a large size (100), Gurobi stopped at two hours, while ours stopped at around 1300 seconds. Our results started to become much better than Gurobi results (the negative error gap means our results are better than those of Gurobi).

3.4. Concluding Remarks

The multimodal freight transportation problem is a very complex optimization problem. In our study, we built a realistic model involving many customers and a set of business rules. Furthermore, this problem is a multimodal freight transportation problem at the operational level with time constraint, capacity limitation, customer service requirement. We demonstrated that the resulting MILP model is NP-hard. The problem can be decomposed to a multi-commodity integral flow problem which is a restricted version of the optimization problem and thus is NP hard problem. We proposed a Lagrangian relaxation based sub-gradient solution approach with a heuristic method to solve this problem. The sub-gradient method (Fisher, 1985) which is a popular approach used in solving Lagrangian problems fits our model well. There are two computational advantages using Lagrangian relaxation: (1) The original problem can be further decomposed into $|K|$ independent subproblems which can be solved in parallel, thus can achieve a computational benefit significantly. (2) a heuristic is developed to make to the infeasible Lagrangian solution into a feasible solution. We evaluated the performance of this approach by comparing it to a set of benchmark approaches commonly used in the past. Our computational experiments showed that our solution significantly outperforms the benchmark approaches, especially for large-size problems, in terms of both solution quality and computational time. In addition, the results can be used to assist logistic managers in

making better business decisions. The logistics company can also benefit from this model as a business strategy in multimodal transportation problems.

As we mentioned in Chapter 1, government and environmental agencies are measuring and converting the gas discharge from shipping and logistical impacts into carbon emissions. New traffic policies and regulations have been created by governments to encourage downlow the carbon emissions. In the next chapter, we will extend our model to include environmental considerations, where multimodal problem can be further divided into mode selection problem by the environmental requirements, such as regulated quota of carbon emissions. Furthermore, we will measure the potential benefit of using high-speed rail in the multimodal transportation problem with environmental issues. We believe that high-speed rail may play a vital role in freight transportation no matter cost factor or environmental factor.

Chapter 4

Environmental Analysis of Multimodal Transportation

In Chapter 3, we studied a multimodal freight transportation problem with shipping capacity limits, resources availability, transshipment delays, and customer service requirements. The objective was to minimize total shipping costs and any penalty costs due to delivery delays. In addition, we included a high-speed rail system in our model to explore the potential business benefits for logistics companies. We modeled the problem a Mixed Integer Problem (MIP). In view of its large scale and computational complexity, we proposed a Lagrangian relaxation model, and in so doing decomposed the original MIP into smaller subproblems. The sub-gradient method was used to solve the Lagrangian model, and a fast heuristic was developed to effectively search for feasible solutions.

In this chapter, we use and extend our model from Chapter 3 to analyze environmental issues. We measure the carbon emissions from a multimodal transportation system based on our model built in Chapter 3 to quantify the carbon emissions by the different modes in the multimodal system and the potential cost effects that can guide the logistic companies to reduce the pressure of social responsibility and government regulation on carbon emissions.

4.1. Background

In the past decades, the mainstream interest in environmental sustainability has blossomed, especially regarding carbon emissions in transportation. A key component of this understanding is the desire to create a model that can analyze and, measure the key factors,

quantify the metrics to solve the key issues and evaluate the potential benefits from a business point of view.

International and offshoring production fragmentation is a feature of globalization. Developments in both information and communication, tariffs reductions and the wider international markets that are becoming available are some of the reasons international trade is growing. However, what are the environmental effects of international transportation by globalization and/or offshoring? This is one of the questions we aim to answer in this chapter.

Transportation is the second largest source of all human-produced carbon dioxide emissions. Indeed, transporting goods and people around the world contributed 22% of world's fossil fuel related carbon emissions in 2010 (European Commission 2011). Freight and light-duty trucks have been the main contributors to emissions in the transportation industry since 1990. Furthermore, two-thirds of freight transport emissions are attributable to road transportation. The demands for freight transport in 2030 is anticipated to be 60% higher than its 1990 level, despite improvements in vehicle fuel efficiency (European Commission 2009). The increased demand for transportation is due to two trends: (1) highly developed global trade and (2) a global supply chain more spatially dispersed worldwide due to extensive offshoring business. The global emissions targets set by the United Nations Framework Convention of Climate Change may thus become unattainable if transport carbon emissions keep continue to increase at their current pace.

In response to these sharply increasing carbon emissions from transport, many governments have created new regulations and taxes to encourage companies to shift to other solutions that reduce gas discharge levels. Anderson and Walton (1998) offered a

method for evaluating multimodal transportation candidates for government funded access improvement. Ghiani et al. (2013) concluded that a multimodal approach is a good choice for efficient and effective transportation under such an environmental policy. The Chinese government also made a commitment that China would reduce its carbon intensity (CO_2 emissions divided by its gross domestic product) by 40%-45% by 2020 (Zhang et al., 2016).

In addition to reducing pollution, a multimodal policy also reduces congestion, thus improving safety while achieving economic objectives and infrastructure planning. Clarke et al. (1996) showed that multimodal transportation reduced fatal highway accidents by approximately 1% from 1992 to 1995.

The other contribution of this study is using high-speed rail in a multimodal model. High-speed rail refers to a type of rail that moves at a speed of 300 km/h (186mph) or faster compared to traditional rail, which moves at about 100 km/h (62.5mph). High-speed rail can load more freight than trucks, move faster than traditional rail and is cheaper than air modes. It also has an environmental advantage. Although high-speed rail is only used for passenger transportation in many countries, its potential for transporting freight will be explored in the future. We try to close this gap by examining the benefits of including high-speed rail in the multimodal modes for the logistics problems. Specifically, China now has the longest high-speed rail network in the world (nearly 22,000km as of 2017). The latest data shows that high-speed rail is currently in operation in more than 20 countries (including the UK, Germany, France, Belgium, Spain, China and so on). Thus, the potential benefit of using high-speed rail for freight transportation is huge.

In this study, we use simulation based on a real-life case to determine the carbon emissions of different transportation modes, based on the model developed in Chapter 3.

Then, we evaluate the effect of different scenarios (under similar regulations) for the carbon emissions of different transportation modes and their corresponding emissions. Based on the numerical results, we provide guidelines and suggestions for logistics companies to prepare for the future.

4.2. Literature Review

In this subsection, we review the literature related to the environmental issues in multimodal freight transportation problems.

Green supply chain management is the direct area of transport that addresses reducing emissions in the transportation industry. Srivastava (2007) provided an overview of the research on green supply chain management. Srivastava (2007, p.2) defined green supply chain management as "integrating environmental thinking into supply chain management including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers as well as end-of-life management of the product after its useful life". Similar topics have been discussed by Corbett and Kleindorfer (2001a, b); Kleindorfer, et al. (2005); Sasikumar and Kannan (2009); and Gupta and Lambert (2007).

The field of green supply chain is rapidly extending to include green inventory models that relate to inventory and ordering behavior and emissions. Benjaafar et al. (2013) proposed a lot-sizing problem that can combine the emissions into production, transport and inventory solutions. They evaluated several emissions regulation policies and how they affected both cost and emissions and suggested that shipping more products at once to decrease emissions. Tyworth (1991) focused on inventory-theoretic framework problem

including transportation mode selection, mentioning that because the transportation inventory models do not perform well under particular circumstances (e.g. quantifying the effects of transit time accurately is difficult under realistic conditions in which both item demand per period and lead time are random variables), researchers have restrictions on the shape of the distribution of demand, lead time, or demand during lead time and thus sacrifice flexibility and accuracy for tractability. Other similar papers on the topic include Bonney and Jaber (2011); Hua et al. (2011), Rosic and Jammernegg (2013); Penkuhn et al. (1997), and Yalabik and Faichild (2011).

Here we focus on reducing carbon emissions by transportation mode selection at the operational level based on existing infrastructure since this choice has a large impact on emissions. In this area, a logistics company has several available transportation modes from which to choose based on both real infrastructure and real time. A logistics company may also switch to multimodal modes to satisfy the current CO_2 emissions constraints.

Blauwens et al. (2006) analyzed the effectiveness of policy measures that aim at moving away from road transport to other transportation modes. They argued that a combination of certain policy measures can lead to significant mode shifts, from the use of roads to multimodal. Berry and Rondinelli (2000) suggested that all multimodal transportation networks must to be examined for potential environmental impacts from their activities to achieve significant improvement in environmental conditions. Bauer et al. (2009) proposed an integer linear programming formulation that can determines the best rail service network to use to minimize emissions. Leal and Almeida (2011) used a case study to show that multimodal transport alternatives that combine waterway and pipeline

are better than truck transportation to achieve lower costs and smaller adverse environmental impacts at the same time.

As multimodal shipping continues to integrate transportation and logistics, governmental agencies are measuring and converting the gas discharge from shipping and logistical impacts into specific carbon emissions. Arora (2010) and Ostrom (2009) provided a universal method for measuring the environmental impacts of multimodal shipping by measuring both effectiveness and economics impacts. To obtain an effective, efficient and environmentally responsible multimodal system, the transportation industry and its strategic partners should move from strategies based only on regulatory compliance to those emphasizing proactive environmental management. (Berry and Rondinelli, 2000). Multimodal shipping stakeholders who work together to achieve these transitions can then demonstrate their carbon emissions reductions as having a strategic performance advantage. One such demonstration of this performance advantage may be realized as part of the Port Newark expansion project (Kaysen, 2012). This research project offered an incredible opportunity to model, integrate and demonstrate how multimodal shipping leads to carbon emissions reductions. Environmental and emissions issues have plagued Port Newark and its transport, logistics and shipping infrastructure for many decades (NJDEP Report, Martin, 2011).

As one of the world's most critical shipping ports (Clark et al., 2002), Port Newark's economic and environmental carbon emissions multimodal decisions can be integrated by utilizing mathematical-programming based tools. These multimodal shipping models are critical because the goal of reducing carbon emissions for shipping containers arriving at Port Newark and from that point destined for distribution centers, warehouses,

and other destination points throughout New Jersey, the Northeast, and the United States is rapidly becoming an environmental requirement with serious economic implications (Garnaut, 2008; Ostrom, 2009). New regulations and taxes have been created to guide and encourage companies to switch to multimodal for the most sustainable logistics solutions (Duan and Heragu, 2015). Multimodal indeed has been called a cooperative and integrated solution among different transportation modes that claim to utilize different kinds of resources more efficiently. Hoen et al. (2013) considered a logistics company, that outsourced all transport activities to a third-party logistics (3PL) and decided to cap its carbon emissions from outbound logistics for a group of customers. They focused on switching transportation modes based on existing infrastructure to reduce emissions. They found that transport emissions can be reduced by 10% for at most a 0.7% increase in total logistics cost. Hoen et al. (2014) considered the results of carbon emissions under different emissions regulations. They found that switching to a different mode can lower carbon emissions dramatically, and the actual decision depends on regulation and non-monetary considerations, such as lead time variability.

4.3. Problem Description

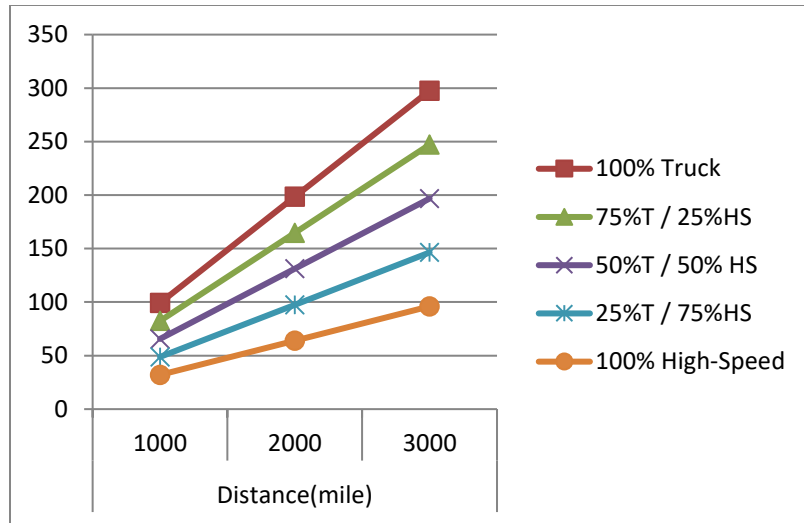In Figure 4.1, 4.2 and 4.3, we present several examples of the multimodal effect on CO_2 emissions. We use the truck's CO_2 emissions as a benchmark and compare it to rail, short-sea and high-speed rail separately.
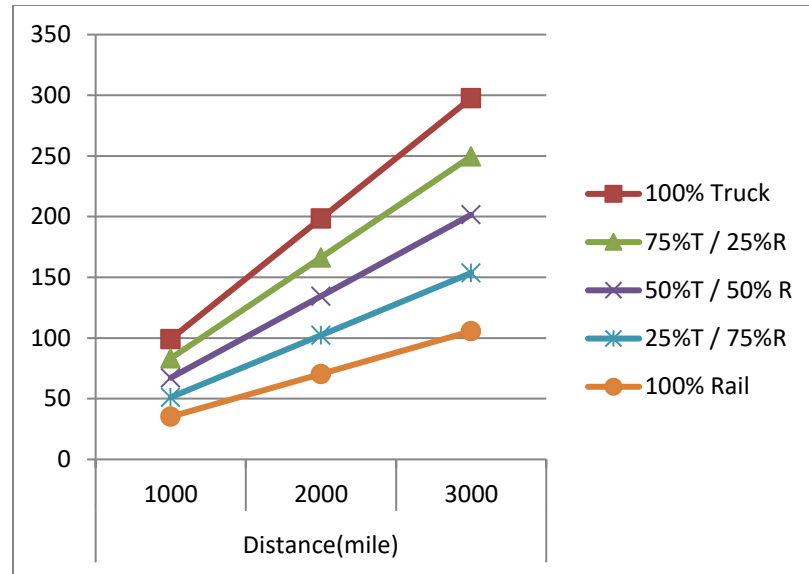
Figure 4.1 CO$_2$ Emissions of Truck and Multimodal (Truck & Rail)
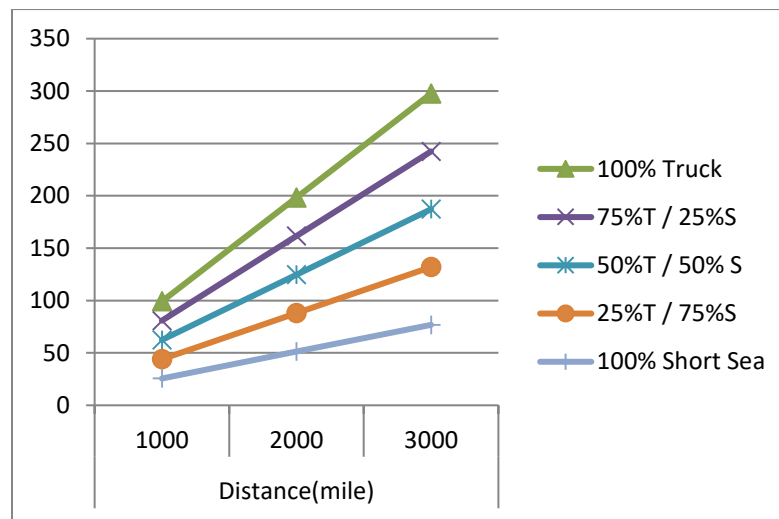
Figure 4.2 CO$_2$ Emissions of Truck and Multimodal (Truck & Short Sea)

Figure 4.3 CO_2 Emissions of Truck and Multimodal (Truck & High-Speed)

Figures 4.1, 4.2 and 4.3 demonstrate how pure truck transport produces much higher carbon emissions than any other types. High-speed rail, short sea, and rail, can all reduce emissions compared to truck-only transportation. Furthermore, we can combine them as multimodal in freight transportation based on the capacity limitation.

Since the road mode is the main transportation element in the freight industry, it will be difficult to switch fully to other modes. This is yet another reason why multimodal transportation has become popular recently.

Each mode has different characteristics in terms of costs, transit time, accessibility, and environmental performance. We thus present an illustrative comparison of the emissions for these modes. The measurement of carbon emissions is a requirement to ensure that different modes operate under the same comparative environment. Table 4.1 described carbon emissions index used:

Table 4.1 CO2 Emission Index of Different Modes (ECTA, 2011)

Modes	CO_2 (ton/ton-mile)
Truck	0.0992
Rail (Gasoil and electricity)	0.07
Short sea	0.0256
High-speed rail	0.032
Air	0.9632

Above, we use basic statistics to show three simple examples, in the remainder of this chapter, we study the financial and environmental impacts of multimodal transportation, based on the mathematical model introduced in Chapter 3 and its variants under four scenarios.

We also continued addressing the problem first mentioned in Chapter 2 which was based on a real-life business case. The problem is based on a real-life business case, Resun Co., Ltd. which needs to deliver products to its customers in a timely manner. Four transportation modes (truck, rail, high-speed rail, and air) can be used, and 3PLs are possibilities to help with delivery during peak demand periods. Resun may be willing to delay certain non-urgent products during the peak demand periods so their high-level customers' (VIP customers) requirements are fully met. We capture this kind of delay as delay costs in our model. Thus, the company's goal is to minimize its transportation costs, 3PL costs, and delay costs and still fulfill its environmental requirements.

More specifically, the four scenarios considered in this chapter are as follows.

First, we quantify the benefits of multimodal. We use truck-only with CO_2 emissions as our benchmark and compare that mode with the multimodal choice (the model introduced in Chapter 2). We aim to analyze carbon emissions reduction and the increase in transportation cost when using multimodal, compared to truck-only transportation (as traditionally used by Resun).

Second, we quantify the impact of using high-speed rail in multimodal recall that Resun was investigating its benefits. We change the weight of high-speed rail in the total percentage to determine what happens if we increase the use of high-speed rail.

Third, we quantify the impact of imposing a CO_2 quota on a logistics company. The Chinese government has announced that it will launch a national cap-and-trade program that involves six of its largest carbon-emitting industrial sectors (John Fialka and Climate Wire，2016). The transportation industry is one of them. To capture this constraint, we modify our model in Chapter 3 by adding a constraint on carbon emissions. We want to test how much transportation cost we must sacrifice to gain a certain percentage of carbon emissions reduction.

Finally, we compare the economic and environmental impacts of a pay-per-use scheme and fixed-volume subscription in a multimodal industry. In our model in Chapter 3, the shipping cost uses a pay-per-use scheme, that is, the logistics company pays whatever shipping amount used, subject to the available capacity. In practice, another scheme is that the logistics company subscribes (or reserves) a certain fixed shipping volume on chosen routes and time slots. These fixed-volumes are pre-determined (in the planning phase). Then, in operations, the company can use only these subscribed volumes. The fixed-volume is popular because it is easier for shippers to plan ahead, and the logistics company

also benefits by enjoying a lower unit shipping cost, than in the pay-per-use scheme. In this scenario, we examine the impacts of two schemes.

Similar to the numerical examples in Chapter 3, in the above numerical examples, we randomly generate the test cases using the parameters specified in Table 4.2. Note that uniform distribution was used to generate random cases, but other distributions can also be used.

Table 4.2 Parameters for Computational Time

Parameters	Data Range of Parameters
Size of customers	$S = (5, 10, 30, 50, 70, 100)$
B	$B = 1,000,000$
Due Day (Hours)	$DD_k = uniform\ (27, 250)$
Penalty (RMB/Day-Ton)	$p_k = (50, 500)$
Demand of customers (Ton)	$Q_k \sim uniform\ (50, 250)$
Fix cost of 3PL (RMB)	$F = 9000$
Departure time	$DT_{uvmt} = (1, 2)$
Mode speed (Km/h)	$Speed = (60, 100, 250, 500)$
Unit cost of modes (RMB/Ton-1000km)	$f_m = (300, 500, 1500, 2000)$
Transportation time of 3PL (Hours)	$ST_{uv} = uniform\ (1, 20)$

Here, we changed the examples from the ones in Chapter 3 as follows: we changed the customer orders ($|K|$) set to {5, 10, 30, 50, 70, 100}. For each value of $|K|$, 20 randomly generated examples were tested by the Gurobi solver. We terminated the Gurobi solver if

the optimality is not found to be within 3600 seconds, and thus obtain its current best solutions as the best optimization outputs.

4.4. Benefit of Multimodal Transportation

4.4.1. Problem Description

Different transportation modes can vary sharply in their carbon emissions profiles, and higher transportation emissions may offset emissions produced elsewhere in the same supply chain. For those supply chains that do span long distances, the truck will not be the best choice for delivering freight. Other potential options like rail, high-speed rail, air, or a combination of at least two options may also be solid considerations.

The economic crisis of 2008 was a lesson to numerous countries. Afterward, many countries reformed their business processes to cut costs and increase their efficiency. Consequently, the governments provided more encouragement for shippers, carriers, and other logistics services than traditional truck transportation (Eurostat., 2015). Logistics companies were encouraged to choose the more cooperative and integrated solutions to utilize all resources most efficiently. Thus, multimodal transportation became the priority option for some logistics companies. Multimodal transportation helps industries address urgent operational issues, such as long-haul trucking capacity shortages, ever increasing fuel costs, and the constant pressure from both government and environmental agencies to reduce gas discharges and truck hours on the road.

Furthermore, traffic congestion, an annoying problem for local governments, has become a major problem in the freight transportation system. On one hand, the demand for delivery remains high; on the other hand, the congestion problem cannot be easily solved

due to the road capacity. The truck is the first choice because it offers convenient door-to-door service. However, logistics companies may rethink that choice once they face a long-term job analysis of different congestion problems. Rail or high-speed rail systems are more reliable than road systems. Today, technology allows high-speed rail transportation to arrive on schedule with errors of only minutes.

In addition to the noted social and economic factors, environmental issues are also a primary agenda. New government policies now restrict trucks hours of service on the roads and limit gas waste discharges. Emissions problems are frequently mentioned in leaders' speeches in countries worldwide. New regulations and related taxes now encourage logistics companies to switch to other more sustainable solutions, such as multimodal. Both companies and society can benefit from multimodal choices while also adhering to ongoing new restrictive policies and regulations.

Since half of all freight transport emissions come from road transportation, what are the impacts of switching from single truck to multimodal transport? Here, to provide a fair comparison, we set a lower delay penalty and longer due date, since the truck is far slower that rail, high-speed rail and air.

4.4.2. Numerical Examples

The tests are similar to those in Chapter 3. However, the difference is that our target in the tests is to measure the impact of CO_2 emissions on different modes in the large network using randomly generated numerical examples. The solution quality and computational time of the benchmark is the multimodal model mentioned in Chapter 3 using the commercial Gurobi mixed-integer linear programming (MILP) solver. The benchmark is

the multimodal model introduced in Chapter 3 solved by the commercial Gurobi MILP solver. The capacity rate of multimodal in benchmark is as follows: truck: rail: high-speed rail: air = 70%:15%:5%:10%. The results were compared to those for truck-only transportation (i.e., only truck mode is available in 100%). All the tests were performed on a computer with an Intel Core i7-6600 2.60 GHz CPU and 16 GB of RAM. Table 4.3 is the results of the multimodal model and the truck-only model. The results are average results from 20 random test cases.

The test is based on the Resun Co. Ltd case mentioned in Chapter 2. The network structure in consideration is shown in Figure 3.4 in Chapter 3. Note that in the network, there are 17 connecting nodes between origin (factory) and destination (customer). We first compare the impact of carbon emissions of multimodal proposed in Chapter 3 based on the Gurobi MILP solver with default settings using the large network, consisting of the origin, destination and 17 connection nodes. In the tests, we randomly generate test cases using the parameters specified in Table 4.2.

Table 4.3 shows the performance comparison between the multimodal model and truck-only model. More specifically, the column "Transportation Cost" shows the statistics for mean (Avg), minimum (Min), maximum (Max), and standard deviation (Std). In addition, the column "CO_2 Emissions" shows similar statistics for carbon emissions for the multimodal model set up by Gurobi. Since the customer order size increased, the CO_2 emissions and transportation cost increased as well in both the multimodal and truck-only models. The multimodal model has lower CO_2 emissions and higher transportation cost than the truck-only model at the same customer order size.

Table 4.3 Benefit of Multimodal

	Multimodal (Capacity Rate, T: R: HS: A=70%:15%:5%:10%)							
	Transportation Cost (RMB)				CO2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	5803815	5605950	6183825	177288	123815	119594	131921	3782
30	12035775	10239225	14650425	1352100	256763	218437	312542	28845
50	14077175	13327350	15611700	540842	300313	284316	333049	11538
70	17519340	16228200	18309225	631632	373746	346201	390597	13475
100	20835406	19683225	23175000	743381	444489	419909	494400	15859
	Truck-only (Capacity Rate, T: R: HS: A=100%:0%:0%:0%)							
	Transportation Cost (RMB)				CO2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	854496	799020	911490	33175	282553	264209	301399	10970
30	2689620	2490900	2904900	142692	889367	823657	960553	47183
50	4326300	3935070	4687860	188140	1430563	1301196	1550119	62212
70	6714876	5799480	7958760	497554	2243868	2035108	2631696	155131
100	10717356	10209960	11139780	263563	3543872	3376093	3683554	87152
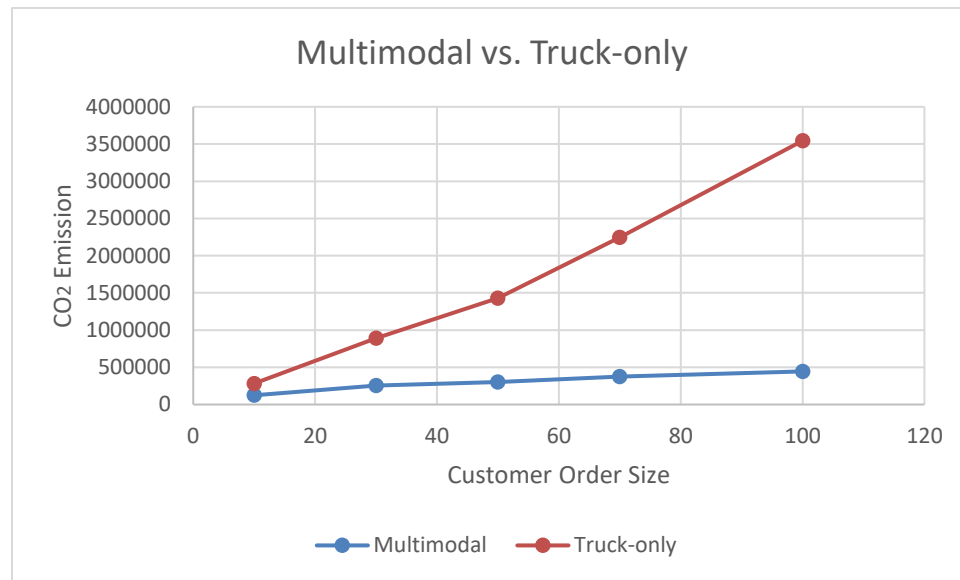
Figure 4.4 CO$_2$ Emissions Multimodal vs. Truck-only
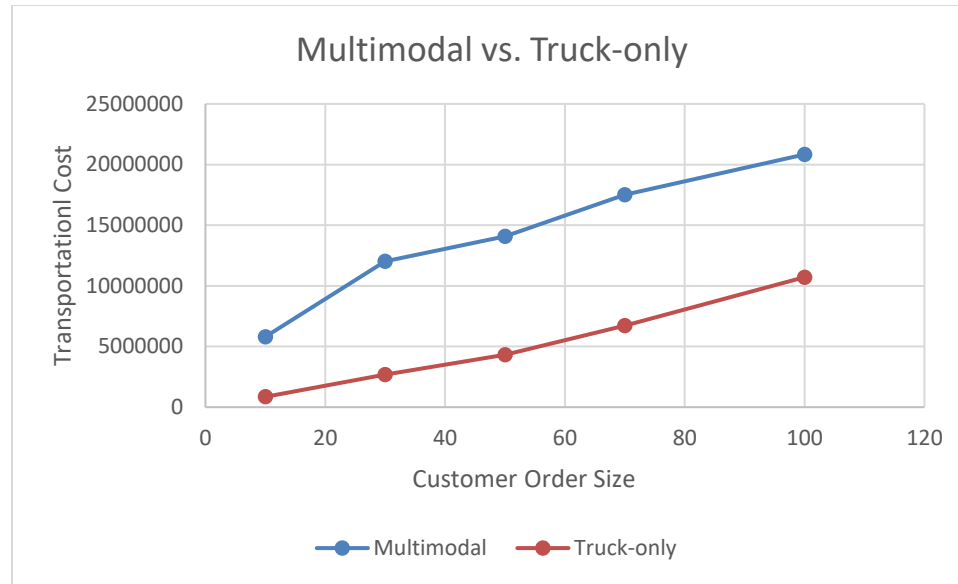
Figure 4.5 Transportation Cost Multimodal vs. Truck-only

Figure 4.4 and Figure 4.5 provided a summary of CO_2 emissions and total transportation cost from Table 4.3. Generally, the cheaper a mode is, the more carbon emissions the mode discharges. (air mode is an exception). From Figure 4.4 and Figure 4.5, we found that CO_2 emissions go up if we switch to truck-only but with less transportation cost. Since other transportation modes like rail, high-speed rail and air are more expensive than the truck mode, it makes sense that the total transportation cost of multimodal is greater than for the truck-only. In order to have a fair comparison, we lower the delay penalty and have loner due dates in the multimodal model, air mode seldom show up in the solution. That might be the reason why CO2 emissions of multimodal is smaller than those of truck-only. Based on the results, we argued that the multimodal mode has a great potential environmental benefit than the truck-only model. For example, when customer order equals100, the transportation cost of multimodal is about 1.94 times than that of truck-only, but the CO_2 emissions of multimodal is only about 12.54% of truck-only. We

mention that, in the benchmark solution, even though the weight of truck is 70% in the multimodal transportation, the results showed that few trucks were used in the optimal solution. This shows that multimodal transportation is a potential option if we want to reduce CO_2 emissions sharply with a relative transportation cost sacrifice in the future.

4.5. Impact of Using High-Speed Rail

4.5.1. Problem Description

High-speed rail has many advantages. It reduces congestion on roads and at airports, is cost effective and convenient, improves mobility and has environmental benefits.

People once considered high-speed rail as an optional mode used to reduce congestion on highways by removing passenger car traffic. Seldom did people realize that it is also a good substitute of trucks to reduce highway congestion and also reduce freight traffic carbon emissions. Thus, several potential advantages exist for developing a national high-speed rail network system for freight distribution.

In the past decades, many governments have spent a lot of money to upgrade their rail networks systems and service levels (i.e., high-speed rail). High-speed rail has become a recommended transportation mode in many countries. It can reduce congestion when comparing to road use, is cost effective, is convenient, and improves mobility, while benefiting the environment. Furthermore, it is cheaper than air travel, faster than general rail, and can load more freight than trucks. These advantages give it great potential in the logistics industry. Although today high-speed rail is used primarily for delivering passengers, it will no doubt be used to deliver freight in the future. Most countries have defined high-speed rail speed as equal to or faster than 300 km/h (186 mph), compared to

traditional rail's speed of about 100 km/h (62.5 mph). Today's speed record for high-speed rail was achieved by the Yamanashi Maglev Test Line in Japan, with a speed of 578 km/h (361 mph) (CNN, 2003).

Japan and Germany are two of the earliest countries to build a high-speed rail network. However, China now owns the longest high-speed rail networks in the world. Although the main function of Chinese high-speed rail is delivering passengers, China has started shipping the freight by high-speed rail in the express industry now. Figure 4.6 below shows the newest China high-speed rail network map in 2017.

Figure 4.6 China High-Speed Rail Network Map 2017 (Source:

http://www.chinadiscovery.com/china-high-speed-train-tours/maps.html)

In the current study, we increased high-speed rail capacity allocated to a logistic company to estimate the potential impact in China. The carbon emissions are likely to be reduced if other transportation modes are switched to high-speed rail. Policy makers should consider the significant investment in freight distribution infrastructure and, the improvements that can be expected from increased high-speed rail capacity. We formulated the problem as a multimodal freight operational planning problem and measured the level of carbon emissions change before and after the change in high-speed rail capacity. We sought to find the relationship between these two key parameters.

To estimate high-speed rail's emissions impact, we used data similar to those used in Chapter 4.4 but varied the data based on different high-speed rail capacity.

4.5.2. Numerical Examples

The test is based on the Resun Co. Ltd case mentioned in Chapter 2. The network structure in consideration is shown in Figure 3.4 in Chapter 3. Note that the network has 17 connecting nodes between origin (factory) and destination (customers). We first compare the impact of carbon emissions of multimodal proposed in Chapter 3 based on Gurobi MILP solver with default settings using the large network, consisting of the origin, destination and 17 connection nodes. In the tests, we randomly generate test cases using the parameters specified in Table 4.2.

The tests are similar to those conducted in Chapter 3, but here our test target is to measure the impact of CO_2 emissions on high-speed rail. We first set the weight of high-speed rail out of all transportation modes to be 5%. Then we increase this weight and determine the impact on CO_2 emissions. Table 4.4 showed the results of different weights

on high-speed rail. The results are average results from 20 test cases. We first make the capacity rate of multimodal to: T: R: HS: A = 75%:15%:5%:5%; in other words, the weight of high-speed rail in multimodal is 5%. We measure the CO_2 emission and transportation cost based on that. Then we increase the weight of high-speed rail to 10% and decrease the weight of truck from 75% to 70%. The weight of rail and air keep unchanged. We follow the above process until the weight of high-speed rail goes to 25% and the weight of truck goes down to 55%. The results are shown in Table 4.4.

Table 4.4 Impact of High-Speed Rail

	Different Weight of HS (Capacity Rate, T: R: HS: A=75%:15%:5%:5%)							
	Transportation Cost (RMB)				CO_2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	2341954	1976390	2920660	323969	253610	215227	329334	35364
30	7322687	5097920	8919495	1137346	955951	737593	1130120	88986
50	10802346	5231250	12525315	2228438	1754617	1685785	1873205	47435
70	8221936	8097305	12558325	1387644	2507047	2245432	2622794	108577
100	12672460	11935640	13696775	633614	3515847	2995140	4022304	259650
	Different Weight of HS (Capacity Rate, T: R: HS: A=70%:15%:10%:5%)							
	Transportation Cost (RMB)				CO_2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	2817928	1976390	3821500	651070	232916	189000	306872	29582
30	7570323	5292980	10389705	1363143	853264	687624	983562	77677
50	15249274	13937840	16318545	824463	1613611	1543746	1804695	76434
70	8673643	8429745	14384370	2977313	2486792	2152113	2657276	237189
100	13742773	12599040	14477120	642160	3468574	3121232	3822598	174008
	Different Weight of HS (capacity rate, T: R: HS: A=65%:15%:15%:5%)							
	Transportation Cost (RMB)				CO_2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	2882450	1973900	3707420	511440	226198	189000	294298	27240
30	7636924	5232720	9734890	1098802	821347	676523	935651	68137
50	15392094	12973070	17427620	1829590	1517323	1392913	1734983	88904
70	8878385	9116110	19542595	3481742	2428368	2115205	2666184	187416
100	13795018	12721880	15491060	1015194	3439308	3125833	3694885	284526
	Different Weight of HS (Capacity Rate, T: R: HS: A=60%:15%:20%:5%)							
	Transportation Cost (RMB)				CO_2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	2816950	1686390	3707420	599362	214418	198956	294298	25578
30	7685045	5232720	9514090	1032640	799162	676523	894976	64320
50	14289823	12673250	15531695	1238834	1478648	1361311	1687033	85972
70	8988807	7699075	20597405	5408883	2429894	2345210	2839933	221575
100	13852480	12116220	16652415	2268098	3428249	3299796	3551852	126028
	Different Weight of HS (Capacity Rate, T: R: HS: A=55%:15%:25%:5%)							
	Transportation Cost (RMB)				CO_2 Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
10	2882450	1686390	3707420	557442	211929	189000	294298	27170
30	8182025	5232720	9354930	986955	789451	676523	865656	64245
50	13970059	12529535	15184330	1071579	1448664	1344021	1635723	79946
70	8998221	7688835	10111585	1211275	2418719	2374102	2672010	178954
100	12596557	11175590	13938315	8783563	3411485	3121123	3790835	189675

From Table 4.4, if the weight increases to 10%. Common sense suggests that since

more high-speed rail is being used, the transportation cost will increase and the CO_2

emissions will decrease. However, the results are surprising in some cases. Since we increased the customer order size, the transportation cost increased at the beginning, but then reached a peak when customer order equals 50. One possible reason is that the increased high-speed rail will not be fully employed when customer order equals 70 or air modes have been used in customer order equals 50 so that the transportation cost of customer order equals 50 is much higher than that of customer order equals 70. In other words, even though we increase the high-speed rail capacity, we could not control all the new extra high-speed rail capacity being fully used. That is the main reason why both transportation cost and CO_2 emissions increased after high-speed rail weight changes from 5% to 10%.

If the weight increases to 15%, the results are similar to those in weight equals 10%. CO_2 emissions keep increasing and transportation costs keep reaching their peak and then decreasing.

If the weight increases to 20%, the results are a little different than those in weight equals 15%. CO_2 emissions keeps increasing but transportation costs show a wave map, increasing from customer order size 10 to 50, reaching a peak, and then decreasing when customer order equals 70; they go up again when customer order equals 100. A possible reason is that when customer order size equals 70, air modes have switched to rail or high-speed rail and make the total transportation decrease. Then when customer order size equals 100, using of high-speed rail increases again and the total transportation costs go up.

If the weight increases to the maximum 25%, the results are similar to those in weight equals 20%.

Figure 4.7 and Figure 4.8 provide summary results of CO_2 emissions and total transportation costs gathered from Table 4.4. We can see that CO_2 emissions decrease as the weight of high-speed rail increases and the total transportation cost increases as the weight of high-speed rail increases. Basically, because high-speed rail is a comparably expensive mode, the total transportation costs are higher as more high-speed rail is used. Also, because the CO_2 emissions index of high-speed rail is really low (moving 1 ton of freight per kilometer causes how many tons of CO_2), CO_2 emissions decrease since more high-speed rail is being used. However, at a certain point, increasing the use of high-speed rail does not decrease emissions. The reason is that the air mode may have changed the result when testing small sizes since the air mode has a large CO_2 emissions index, which might change the result sharply. In other words, CO_2 emissions greatly depends on the air mode using small size, no matter if one is increasing the weight of high-speed rail.
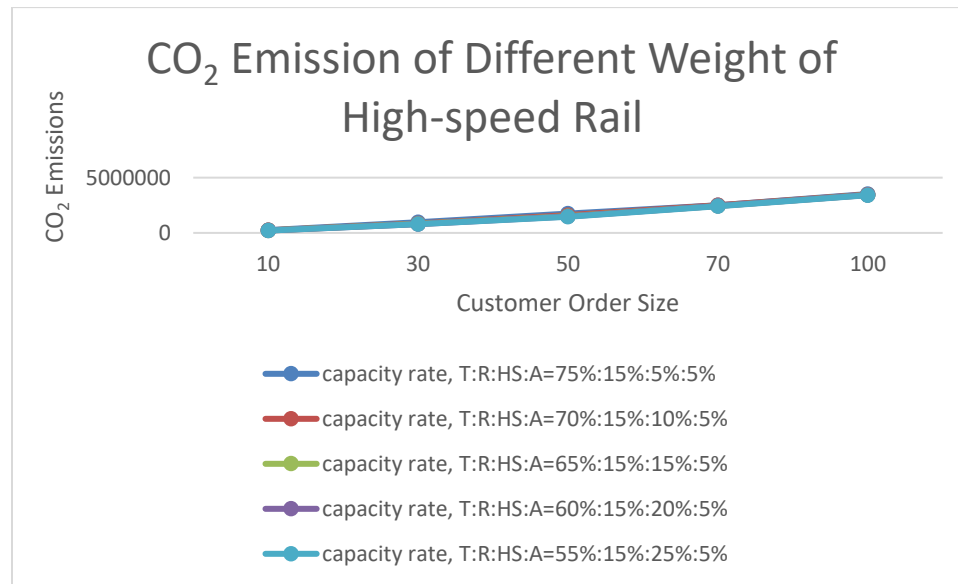
Figure 4.7 CO_2 Emissions Impact of Different Weights of High-Speed Rail
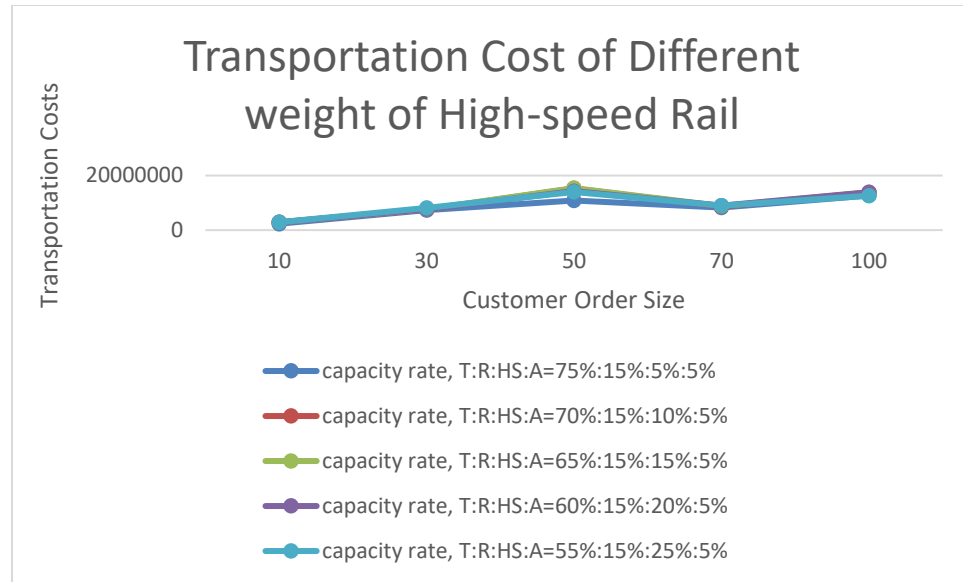
Figure 4.8 Transportation Cost Impact of Different Weights of High-Speed Rail

Figure 4.9 and Figure 4.10 show the CO_2 emissions and transportation costs based on different weights of high-speed rail for customer order equals 10. CO_2 emissions decreases and transportation costs increase as the weight of high-speed rail increases, because more high-speed rail has been used and both the economic and environmental impact have been amplified.
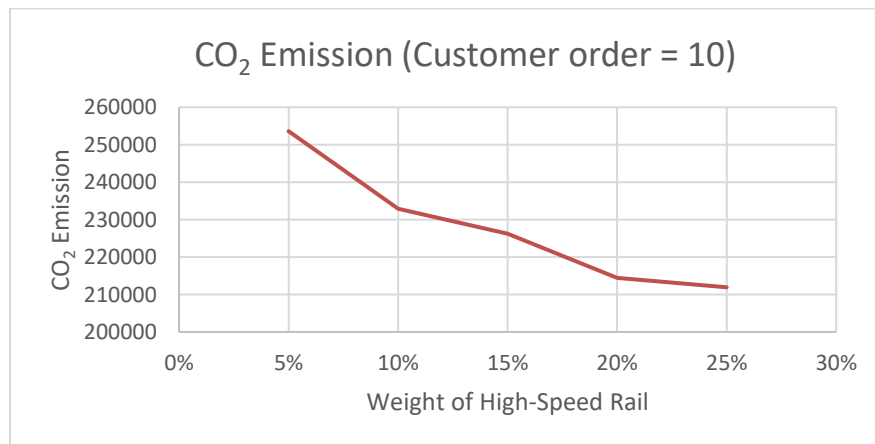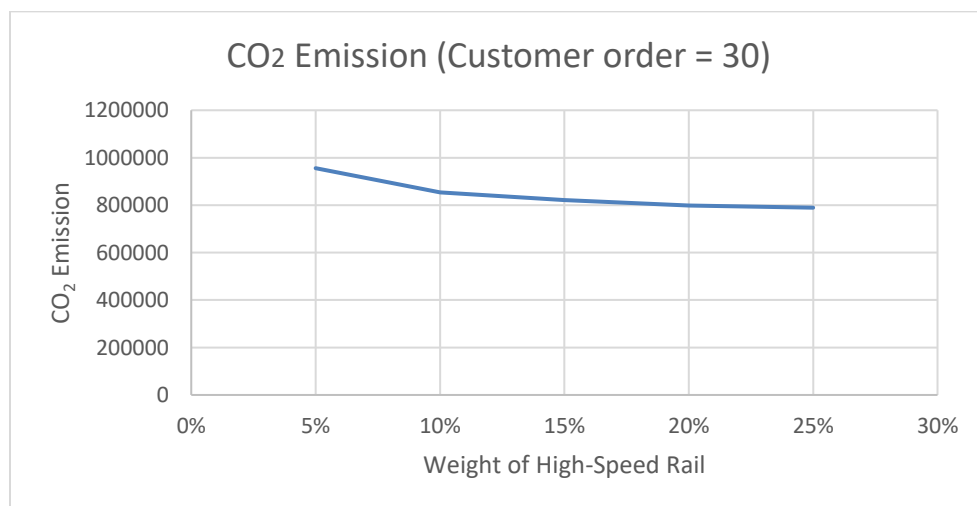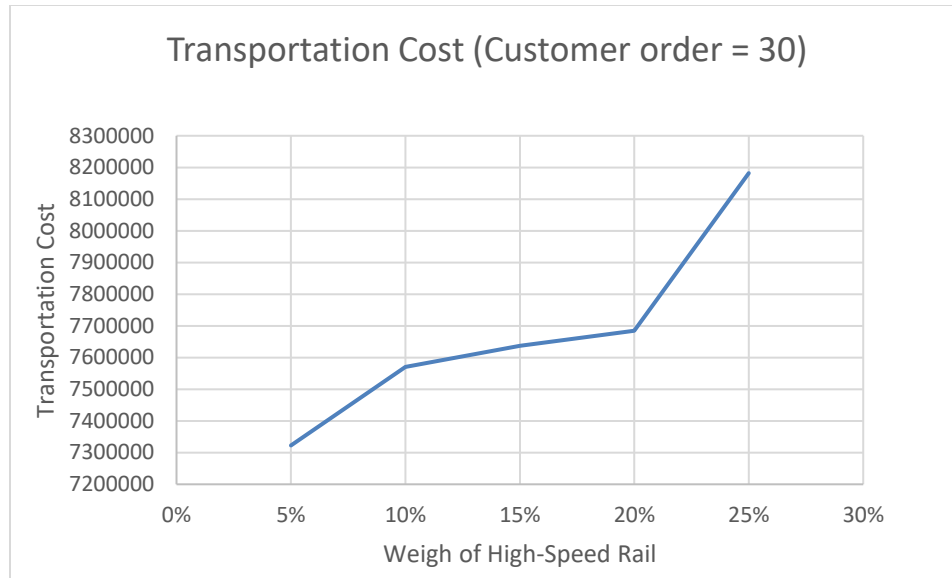

Figure 4.9 CO_2 Emissions of Different Weights of High-Speed Rail
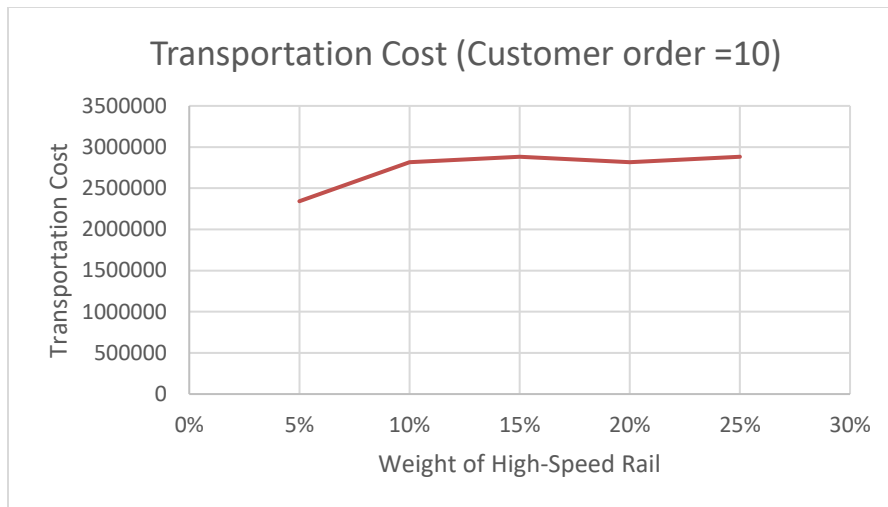
(Customer Order = 10)

Figure 4.10 Transportation Cost of Different Weights of High-Speed Rail

(Customer Order = 10)

Figure 4.11 and Figure 4.12 show the CO_2 emissions and transportation cost based on weight of high-speed rail on customer order equals 10. Once we increase the high-speed rail capacity, the CO_2 emissions decreases and transportation increases. The slope of transportation cost becomes sharp from weight 20% to weight 25%.
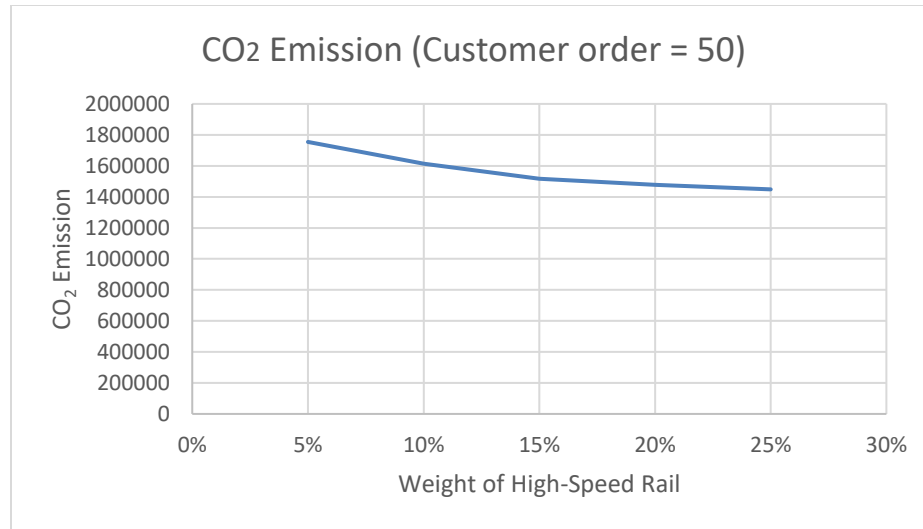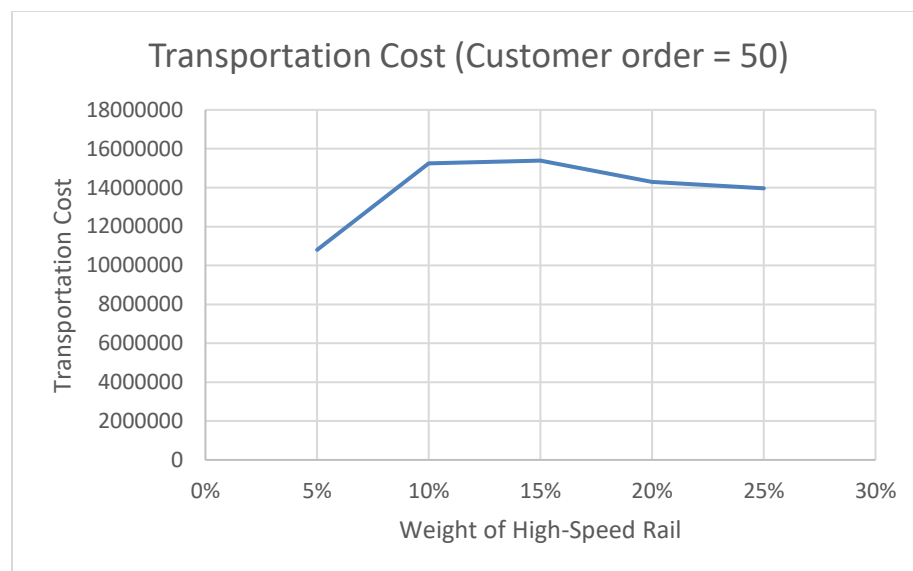

Figure 4.11 CO_2 Emissions of Different Weights of High-Speed Rail (Customer Order = 30)

Figure 4.12 Transportation Cost of Different Weights of High-Speed Rail

(Customer Order = 30)

Figure 4.13 and Figure 4.14 show the CO_2 emissions and transportation cost based on weight of high-speed rail on customer order equals 30. CO_2 emissions decrease as the weight of high-speed rail increases, but the transportation costs first increase then decrease. Once we increase the high-speed rail capacity, at the beginning, more trucks switch to high-speed rail and thus the transportation costs increase, but then, more air modes shift to high-speed rail, which makes the transportation cost decrease because air mode is much expensive than high-speed rail.
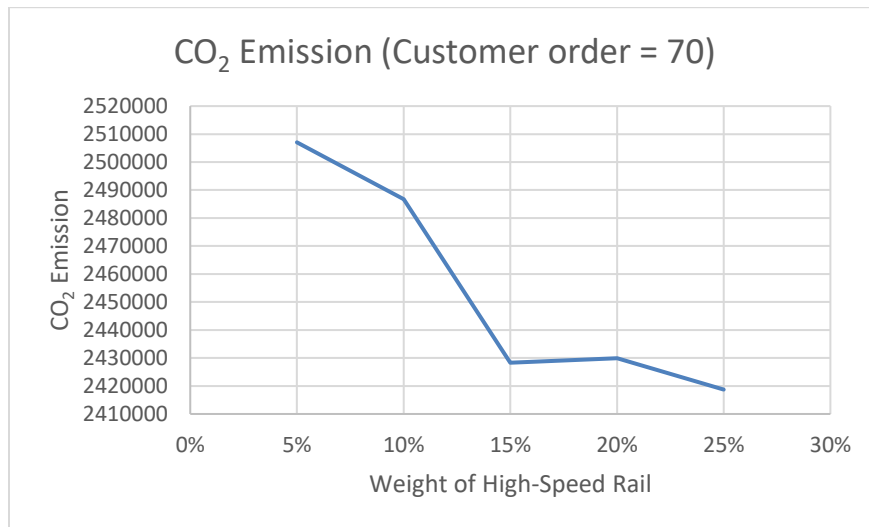
Figure 4.13 CO₂ Emissions of Different Weights of High-Speed Rail
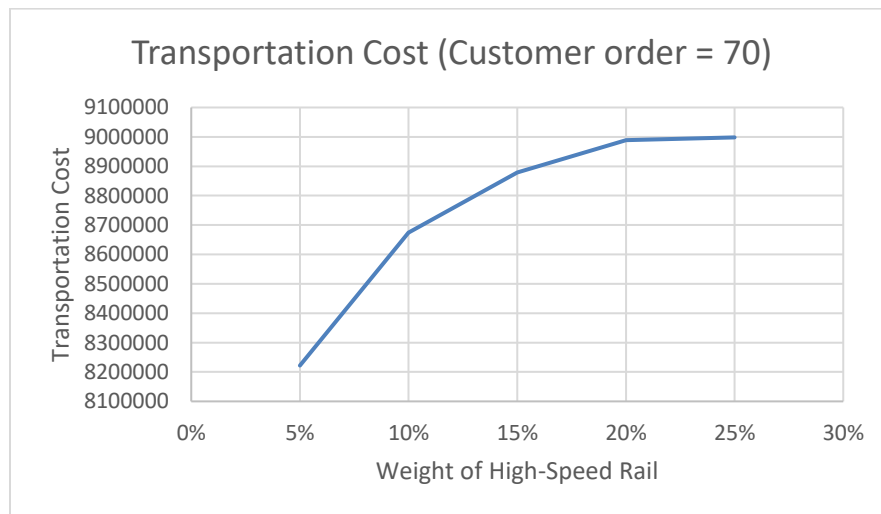
(Customer Order = 50)

Figure 4.14 Transportation Cost of Different Weights of High-Speed Rail

(Customer Order = 50)

Figure 4.15 and Figure 4.16 show the CO_2 emissions and transportation cost based on weight of high-speed rail on customer order equals 70. The results are similar to the

ones of customer order equals 10. CO_2 emissions decreases and transportation costs increase from weight 5% to 25%.
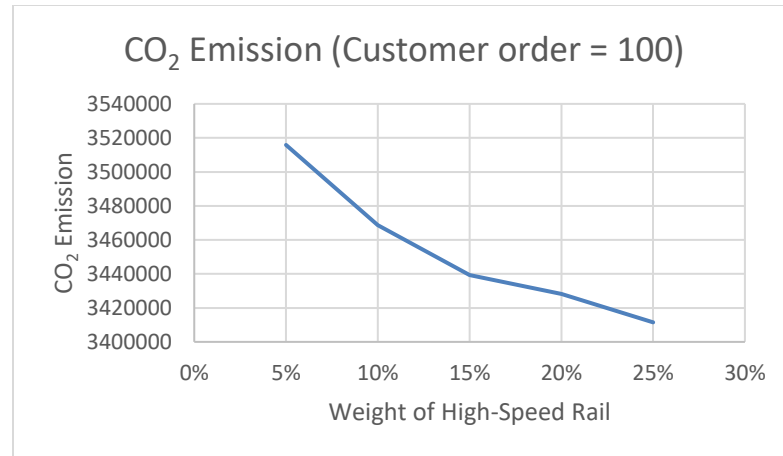
CO$_2$ Emission (Customer order = 70)

Figure 4.15 CO$_2$ Emissions of Different Weights of High-Speed Rail (Customer Order = 70)

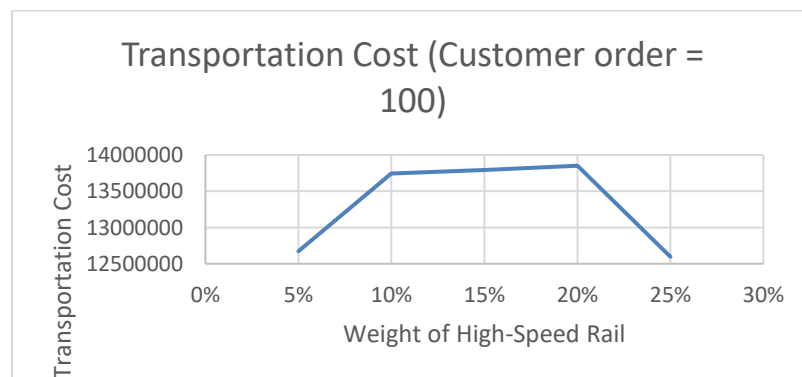**Transportation Cost (Customer order = 70)**

Figure 4.16 Transportation Cost of Different Weights of High-Speed Rail

(Customer Order = 70)

Figure 4.17 and Figure 4.18 show the CO_2 emissions and transportation cost based on weight of high-speed rail on customer order equals 100. We see that CO_2 emissions

decrease and the transportation costs increase from weight 5% to weight 20% then decrease again in weight 25%. This means that in the case of customer order equals 100, since we increase the capacity of high-speed rail, more high-speed rail is used at the beginning, but once the weight reaches 20%, it meets the ceiling of using of high-speed rail and, more airs are switching to rail or high-speed rail.

Figure 4.17 CO_2 Emissions of Different Weights of High-Speed Rail

(Customer Order = 100)

Figure 4.18 Transportation Cost of Different Weights of High-Speed Rail

(Customer Order = 100)

The general belief about transportation emissions is that the cheaper a mode is, the more carbon it emits (except the air mode). Although this intuition holds for single-mode transportation in general, it is not necessarily the case for multimodal transportation. Hence, minimizing total cost does not necessarily result in minimizing emissions. High-speed rail is a high efficiency transportation mode in all the modes in emissions reduction. The technology associated with high-speed rail network design likely will continue to evolve, as it will remain an active area of research. Thus, a more complex high-speed network will appear in the future, and efforts to improve the solvability of the incapacitated network design problem will become a future study. Furthermore, we assume the design of high-speed rail networks is a deterministic problem, whereas in reality, the existence of a high-speed rail network influences the demand surrounding this technology. For instance, logistics companies can locate near a high-speed rail network, a decision that is likely to change the whole structures of transportation companies. Therefore, dynamic and shifting demand structure related to having a high-speed rail network may be considered in our model in the future.

Finally, this kind of research must also consider issues related to developing a high-speed rail network for freight transportation from a strategic, public policy, and regulatory perspective, and future efforts can be undertaken using both strategic and tactical perspectives. The factors that cannot be ignored are transfer times and capacities, as well as determination of the new logistics and actual implementation of such a system. Additionally, operational trade-offs should be included: Will joining trucks together in a combination service or sending individual high-speed cars be more costly? Is there any cost benefit if we change the speed for high-speed rail since we are only focusing on freight

transportation? What is the best way to increase the capacity of high-speed rail in a network by adjusting carriages?

We can offer a few commonplace remarks by way of introducing our model approach. Our method is a modeling-based method that evaluates potential high-speed alternatives for freight transportation. More interesting questions can be answered in future research.

4.6. Impact of Imposing a Carbon Emission Quota

4.6.1. Problem Description

In Europe, an emission trading scheme (EU ETS) has been established (European Commission, 2010). In a trading scheme, an emission cap for companies is set to a specific ceiling limit. Each company has an amount of allowances (quota) for CO_2 emit during certain period of time without being penalized by the government. The companies that exceed that amount need to go the auctioned market (Teitenberg, 2001). Governments in Western Europe have already adjusted their fuel taxes to reduce the consumption of fossil fuels in the transportation arena. Similar regulations have also been posted as an extension of fuel taxes.

In 2017, China announced that it will launch a national cap-and-trade program involving six of its largest carbon-emitting industrial sectors (John Fialka and Climate Wire 2016). Since air pollution has become worse in China in recent years, the government hopes to learn from the U.S. acid rain program and European Union efforts. That is why China's strictest regulations are appearing now. Companies whose carbon emissions are below the government quota will be able to sell their excess allowances to companies that

do not meet the cap. In other words, the companies that exceed the cap will buy their allowances from others that have not. For those companies that do not buy allowances but still exceed the cap, the government will impose a penalty. This policy is a "strong reform signal" from the Chinese government to encourage further development of multimodal transportation for all freight transportation. Multimodal road-rail-water-air transportation can also help optimize China's overall transportation structure. This mode will alleviate traffic congestion, save land resources and reduce carbon emissions. In the past, a logistics company might have used roads as its only mode for transportation, but now, it can use rail, water, air, and even high-speed rail instead of roads. In 2017, the quantity of multimodal transportation is 12.9% of all freight transportation. However, in the U.S. and France, the percentage is 40% and 35%, respectively (http://www.chinawuliu.com.cn/zixun/201701/12 /318417.shtml).

Logistics companies have invested heavily in multimodal freight since it is an inexpensive, safe, reliable, and readily available alternative to conventional truck transportation. However, as we know, truck carbon emissions are the main contributors to the greenhouse gas problem worldwide. Thus, logistics companies are under constant pressure from environmental agencies to lower their carbon emissions.

However, many companies are voluntarily reducing their emissions. These kinds of changes can improve their market share, company image and company value. The Carbon Disclosure Project (2011) mentioned that 294 of the Global 500 companies now have imposed voluntary emissions reduction targets. However, new regulations coming from government will force all companies to move more quickly.

In this study, we considered a logistics company that is committed to reducing emissions under the pressure of government regulation. We know that the choice of transportation mode is one of the simplest ways to address abatement options. Moreover, this choice does not create a lot of costs, such as improving technical skills or relocating warehouses. It is generally recognized that switching to another mode is one of the key factors that determines the emissions coming from transportation. We still want to learn, however, what percentage gains in emissions reductions derives from such modal shifts.

Hoen et al. (2013) focused on reducing emissions by switching transportation modes within an existing network. They studied a logistics company that has outsourced transportation and decided to cap its carbon emissions. The problem was solved by decomposing the multiproduct problem into several single-product problems and the results indicated that emissions could be reduced by 10% at only a 0.7% increase in total logistics costs. While this paper focuses on 3PLs' transportation strategy, our study focuses on own transportation modes selection plus 3PL in emergency.

4.6.2. Modified Mathematical Model

We extend the model in Chapter 3 by adding the carbon emissions cap as an additional constraint. Here, we describe the extension of the model. Note that all the other parameters and variables are identical to those in Chapter 3.

New Parameters:

G: quantity of a company's CO_2 emissions limit imposed by the government.

CO_{kuvmt}: quantity of CO_2 emissions for customer order k at route (u, v) using mode m at time t.

The objective of the problem is to minimize the total costs, consisting of transportation costs 3PL costs and late penalty costs, the same as the objective (1) in Chapter 3 and restated below.

$$z = min \sum_{k \in K} Q_k \left(\sum_{(u,v)} \sum_{m \in M} \sum_{t \in T(u,v,m)} f_{uvmt} x_{kuvmt} + \sum_{(u,v) \in E} F_{uv} y_{kuv} + p_k TD_k \right). \tag{1}$$

subject to:

Constraints (2) to Constraint (15) in Chapter 2 and

$$\sum_{k \in K} \sum_{(u,v)} \sum_m \sum_t CO_{kuvmt} x_{kuvmt} \leq G. \tag{42}$$

The constraint (42) means that a company's total CO_2 emissions should not exceed the levels   defined by the government. We further denote the new problem as IP_0^E .

The sub-gradient heuristic proposed in Chapter 3 can be used to solve this new problem, with some modifications. First, in addition to the Lagrangian multiplier $\pi_{uvmt} \geq 0$ $\left(\forall (u, v) \in E, m \in M, t \in T_{(u,v,m)} \right)$ for relaxing the capacity constraint (4), we need to add another Lagrangain multiplier $\pi^E \geq 0$ for relaxing the carbon quota constraint (42). The resulting Lagrangian relaxation problem is denoted as $P^E(\pi)$, as follows.

$IP^E(\pi)$:

$$z^E(\pi) = min \left[\sum_{k \in K} Q_k \left(\sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} f_{uvmt} x_{kuvmt} + \sum_{(u,v) \in E} F_{uv} y_{kuv} + p_k TD_k \right) + \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} \pi_{uvmt} \left(\sum_{k \in K} Q_k x_{kuvmt} - C_{uvmt} \right) + \pi^E \left(\sum_{k \in K} \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} CO_{kuvmt} x_{kuvmt} - G \right) \right]. \tag{43}$$

Subject to:

$$Constraints (2), (3), (5) - (14)$$

Further examining the objective (43), it can be rewritten as:

$$z^E(\pi) = \min \sum_{k \in K} \left[\sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} (Q_k f_{uvmt} + Q_k \pi_{uvmt} + \right.$$

$$\left. \pi^E CO_{kuvmt}) x_{kuvmt} + \sum_{(u,v) \in E} Q_k F_{uv} y_{kuv} + p_k Q_k TD_k \right] -$$

$$\left(\sum_{k \in K} \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} \pi_{uvmt} C_{uvmt} + G \right). \tag{44}$$

Therefore, similar to problem $IP(\pi)$, problem $IP^E(\pi)$ can be decomposed into $|K|$ subproblems, each for one customer order k, denoted by $IP_k^E(\pi)$. Thus, for any given $\hat{k}$, π_{kuvmt} and π^E, we have

$$z_{\hat{k}}^E(\pi) = \min \left[\sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} (Q_{\hat{k}} f_{uvmt} + Q_{\hat{k}} \pi_{uvmt} + \pi^E CO_{\hat{k}uvmt}) x_{\hat{k}uvmt} + \right.$$

$$\left. \sum_{(u,v) \in E} Q_{\hat{k}} F_{uv} y_{\hat{k}uv} + p_{\hat{k}} Q_{\hat{k}} TD_{\hat{k}} \right].$$

Subject to:

Constraints (22) - (34)

The corresponding Lagrangian dual problem is

$$\omega_{LD}^E = \max\{z^E(\pi) : \pi \geq 0\}, \tag{45}$$

where

$$z^E(\pi) = \sum_{k \in K} z_k^E(\pi) - \left(\sum_{k \in K} \sum_{(u,v) \in E} \sum_{m \in M} \sum_{t \in T_{(u,v,m)}} \pi_{uvmt} C_{uvmt} + G \right). \tag{46}$$

Consequently, the sub-gradient method (Algorithm 1 in Chapter 3.2) developed for solving problem IP_0 will also work for problem IP_0^E, with minor modifications, including the objective function and the updating formula for the new Lagrangian multiplier π^E. Due to the similarities to Algorithm 1 and the different emphasis of this chapter, we do not present the details of the sub-gradient method for solving IP_0^E here.

4.6.3. Numerical Examples

We use numerical examples to answer the question regarding the impact of a CO_2 emissions quota. We measure the impact of a CO_2 emissions quota of multimodal based on these tests. Our benchmark is the multimodal model defined in Chapter 3. We use similar data to measure the total CO_2 emissions that we obtained in the benchmark as the benchmark of the CO_2 emissions quota. Next, we set 90% of the average CO_2 emissions of the benchmark as our quota at the different customer orders (e.g., the average CO_2 emissions of benchmark is 100 when customer order =10, we set 90 as the CO_2 emissions quota in the test model). The solutions have been changed based on the new constraint quota. Then we use 80% of the CO_2 emissions quota employing the similar idea. All the tests are performed on a computer with an Intel Core i7-6600 2.60 GHz CPU and 16 GB of RAM.

Table 4.5 shows a performance comparison for the multimodal model with/without a CO_2 quota. More specifically, the column "Transportation Cost" shows statistics for mean (Avg), minimum (Min), maximum (Max) and standard deviation (Std) of total transportation cost by Gurobi. In addition, column "CO_2 Emission" shows similar statistics for the carbon emissions of the multimodal model by Gurobi. We first show the CO_2 emission and transportation cost of benchmark based on the capacity weight of multimodal T: R: HS: A=70%:15%:5%:10%. Then we measure the CO_2 emission and transportation cost for the CO_2 quota.

Table 4.5 Impact of CO$_2$ Emission Quota

	CO$_2$ Quota (Capacity Rate, T: R: HS: A=70%:15%:5%:10%)							
	Transportation Cost (RMB)				CO$_2$ Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
5	1321060	1091400	1668700	255684	218667	74605	498121	152143
10	2223277	1376500	2516615	338711	423094	194525	841130	188889
30	5543042	3861720	6734125	833463	1673235	977696	2182698	326871
50	18800095	17261310	21917725	1250245	7900625	6901629	9669413	710395
70	31985547	28629480	34363915	2131102	14156744	12440680	15594482	1177089
100	55532456	51374795	63722180	3204770	21973359	20029439	23765802	966117
	90% CO$_2$ Quota (Capacity Rate, T: R: HS: A=70%:15%:5%:10%)							
	Transportation Cost (RMB)				CO$_2$ Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
5	1468625	1102020	2137165	336232	157143	74605	307951	82464
10	2299202	1376500	2880520	369081	366320	194525	612656	133909
30	5740422	3861720	7267030	959154	1460744	977696	1760637	217547
50	21011853	18735043	25638993	747952	7105747	6592019	7994723	360890
70	36286840	28984328	42159530	4387514	12735428	11868691	13459790	593801
100	60281142	53951730	67988128	3615160	19774978	18799899	20672177	484306
	80% CO$_2$ Quota (Capacity Rate, T: R: HS: A=70%:15%:5%:10%)							
	Transportation Cost (RMB)				CO$_2$ Emission (ton)			
Size	Avg	Min	Max	Std	Avg	Min	Max	Std
5	1616190	1112640	2605630	416780	95618	74605	117780	12785
10	2375127	1376500	3244424	399451	309545	194525	384181	78928
30	5937801	3861720	7799935	1084845	1248253	977696	1338575	108223
50	23223611	20208775	29360260	245660	6310869	6282408	6320032	11384
70	40588132	29339175	49955145	6643926	11314112	11296701	11325098	10513
100	65029827	56528665	72254075	4025550	17576597	17570359	17578551	2495

Figure 4.19 and Figure 4.20 provide the summary results of CO$_2$ emissions and total transportation cost from Table 4.5. The results suggest that emissions reductions are achieved with relative profit reductions. The first 10% emissions reduction requires an average 8.65% cost increase. When customer order size is small, like 10 or, 30, the emissions reduction doesn't cost much, with on average about a 3.49% cost increase if we achieve a 10% emissions reduction. However, with large customer order sizes of 50, 70, and 100, the numbers change to 11.76%, 13.45% and 8.55%, respectively. In other words,

the carbon quota scenario has a high efficiency in the large size. It does not appear to be sensitive to different price-elasticity scenarios. A 20% emissions reduction is achieved at an average 17.3% cost increase. It seems that a linear relationship exists between the emissions reduction and cost increase. For this data set, the emissions reductions are mainly achieved by switching from road and air to rail and high-speed rail transportation, because of the characteristics of the Chinese network and the problems of the environment. However, we only consider part of the Chinese high-speed rail network (maximum distance) that is currently used. If the method is applied to a large-scale case study with intercontinental transportation, we can expect more emissions reductions, because switching from air to high-speed rail results in an extremely substantial emissions reduction. For intercontinental transportation, the less carbon-emitting transportation options (ocean or rail) have a higher share of the total transportation because the first and last segments will only be a small part of the total distance.
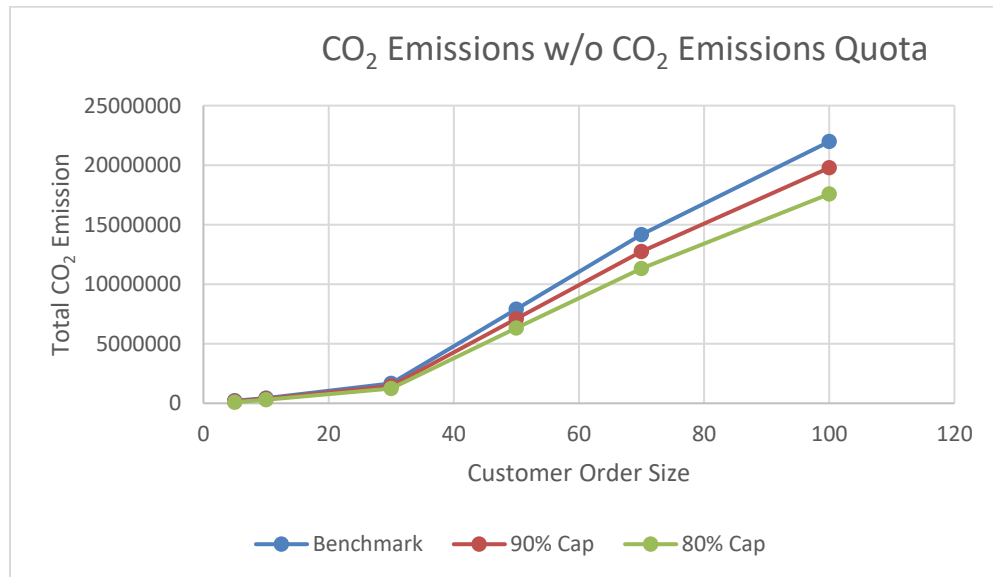
Figure 4.19 CO_2 Emission w/o CO_2 Emission Quota

Transportation Cost w/o CO_2 Emissions Quota
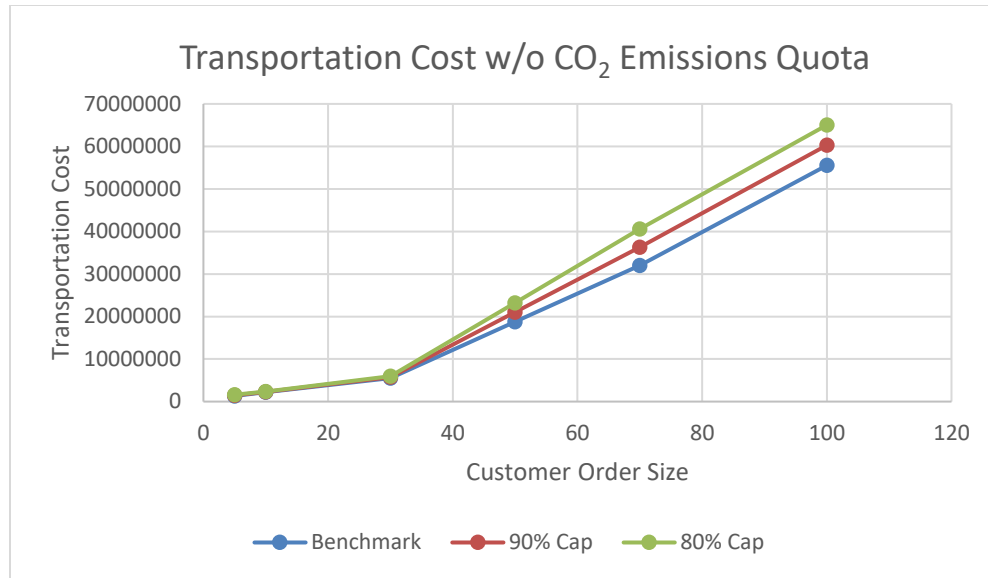
Figure 4.20 Transportation Cost w/o CO₂ Emission Quota

4.7. Impacts of Shipping Capacity Subscription Scheme

4.7.1. Problem Description

The mode in Chapter 2 uses the pay-per-use subscription. That is, the logistic company pays whatever amount of shipping capacity used, as specified by the optimal solution obtained. However, many logistics companies prefer the fixed-volume subscription due to the economic benefits. Fixed-volume subscription is similar to the "pay first, then eat" policy. Since technology is developing rapidly, the forecasting models can forecast the customer demand more accurately. Thus, it is beneficial for logistics companies to prepay for a fixed-volume to set the delivery schedule on the agenda to minimize the uncertainty of shortages in transportation in the demand peak period. For example, hotels and tour companies used to sign a long-term contract for how many rooms per year. The reason is that the rooms are in short in the peak period time. Tour companies hope to book the rooms

in advance so that they would not lose customers. To obtain a win-win result, tour companies need to prepay minimum rooms fee to hotels no matter rooms being used or not. The other example is the food industry, because the products are highly perishable and cannot be stored, the potential supply is determined by the available time and transportation capacity. Thus, some logistics companies are essentially bargaining over the terms of trade for a fixed-volume of the modes and sign contracts with a food farm to build a long-term relationship. The food farm would like to prepay the transportation capacity to minimize the risk of delivering shortage. Issaka and Mathematics (2010) conclude that given discounts on cost of transportation could lead to increased productivity of producers. This is a result of the fact that wholesalers and retailers, have to pay less on transport for buying in large quantities; subsequently, consumers will buy at lower cost comparatively.

4.7.2. Modified Mathematical Model

Next, we redefine the notation and the mathematical model from Chapter 2.

The objective of the problem is below:

$$z = \min\left[\sum_{(u,v)} \sum_{m\in M} \sum_{t\in T(u,v,m)} ff_{uvmt} C_{uvmt} + \sum_{k\in K} Q_k\left(\sum_{(u,v)\in E} F_{uv} y_{kuv} + p_k TD_k\right)\right]. \tag{47}$$

where $ff_{uvmt} = Discount * f_{uvmt}$. $\tag{48}$

subject to Constraints (2) through (14) in Chapter 2.

We further denote this problem as IP_0^F. The objective of the problem is to minimize the total costs, consisting of prepaid costs, 3PL costs and late penalty costs. The unit of prepaid cost has a linear relationship with the original cost. Comparing to objective (1) in Chapter

2, we see that the new objective (48) has changed. In the new model, we use capacity to replace the quantity based on the fixed-volume subscription. In the fixed-volume scenario, we assume that the forecasting of demand is accurate and as a result, we can prepay the capacity. The prepay strategy can greatly increase the negotiation ability with the contractor and thus reduce the transportation unit cost. This is the main reason why we want to choose the fixed-volume scenario.

Therefore, similar to problem $IP(\pi)$, problem $IP^F(\pi)$ can be decomposed into $|K|$ subproblems, each for one customer order k, denoted by $IP_k^F(\pi)$. Thus, for any given $\hat{k}$ and π_{kuvmt}, we have

$$z_{\hat{k}}^F(\pi) = \min\left[Q_{\hat{k}}\left(\sum_{(u,v)\in E} F_{uv}y_{\hat{k}uv} + p_{\hat{k}}TD_{\hat{k}}\right)\right]. \tag{49}$$

Subject to:

$$\text{Constraints (22) - (34)}$$

The corresponding Lagrangian dual problem is

$$\omega_{LD}^F = \max\{z^F(\pi): \pi \geq 0\}, \tag{50}$$

where

$$z^F(\pi) = \sum_{k\in K} z_k^F(\pi) - \sum_{(u,v)} \sum_{m\in M} \sum_{t\in T(u,v,m)} ff_{uvmt}C_{uvmt}. \tag{51}$$

Consequently, the sub-gradient method (Algorithm 1 in Chapter 3.2) developed for solving problem IP_0 will also work for problem IP_0^F, with minor modifications. Due to the similarities to Algorithm 1 and the different emphasis of this chapter, we do not present the details of the sub-gradient method for solving IP_0^F here. In a nutshell, the sub-gradient for solving IP_0^F has three similar steps: (1) update the lower bound by solving the Lagrangian relaxation problem, (2) obtain an upper bound (i.e., a feasible solution)

by adjusting the solution of the Lagrangian relaxation problem, and 3) update the Lagrangian multiplier by its definition based on the results of (1) and (2).

4.7.3. Numerical Examples

The purpose of these tests is to measure the financial and environmental impacts if the company switches from pay-per-use to fixed-volume. Our benchmark is the multimodal model defined in Chapter 3 using the commercial Gurobi MILP solver. We change to fixed-volume scenario and measure the CO_2 emissions and transportation costs using the same data in the benchmark. All the tests are performed on a computer with an Intel Core i7-6600 2.60 GHz CPU and 16 GB of RAM.

Table 4.6 and Table 4.7 are the results of benchmark and fixed-volume subscription. We use two types of data, one is data of accurate demand which means the total demand is close to the prepay capacity, and the other is the one of inaccurate demand which means total demand is not close to the prepay capacity. Both CO_2 emission and transportation between benchmark and fixed-volume with different unit cost are shown using these two types of data. We mention that since we terminated Gurobi within 1 hour of time limit, the results reported below may not be optimal, but should be near-optimal.

Table 4.6 Fixed-Volume of Accurate Demand

	Pay-Per-Use	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	108500	22626
30	304500	64938
50	507500	108230
70	710500	151522
100	1015000	216460
	Fixed Volume (ff=0.9f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	122160	27935
30	314400	79818
50	524000	133030
70	733600	186242
100	1048000	266060
	Fixed Volume (ff=0.8f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	108640	27935
30	279600	79818
50	466000	133030
70	652400	186242
100	932000	266060
	Fixed Volume (ff=0.7f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	81500	27935
30	244500	79818
50	407500	133030
70	570500	186242
100	815000	266060

Table 4.7 Fixed-Volume of Inaccurate Demand

	Pay-Per-Use	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	4722175	1355789
30	13092765	4358519
50	14589385	4817114
70	18715265	6701450
100	17549860	6248864
	Fixed Volume (ff=0.9f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	5221110	1660526
30	14901654	5429614
50	15754348	5585052
70	20216250	7610640
100	17424368	6764020
	Fixed Volume (ff=0.8f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	4641408	1660526
30	13247796	5429614
50	13766480	5585052
70	17152000	7610640
100	15489864	6764020
	Fixed Volume (ff=0.7f)	
Size	Total Transport Cost (RMB)	CO_2 Emission (ton)
10	3197092	1660526
30	11788905	5429614
50	11941116	5536643
70	15723250	7652230
100	14534348	6764020

Figure 4.21 through Figure 4.24 show the summary results of CO_2 emissions and transportation costs from Table 4.6 and Table 4.7.
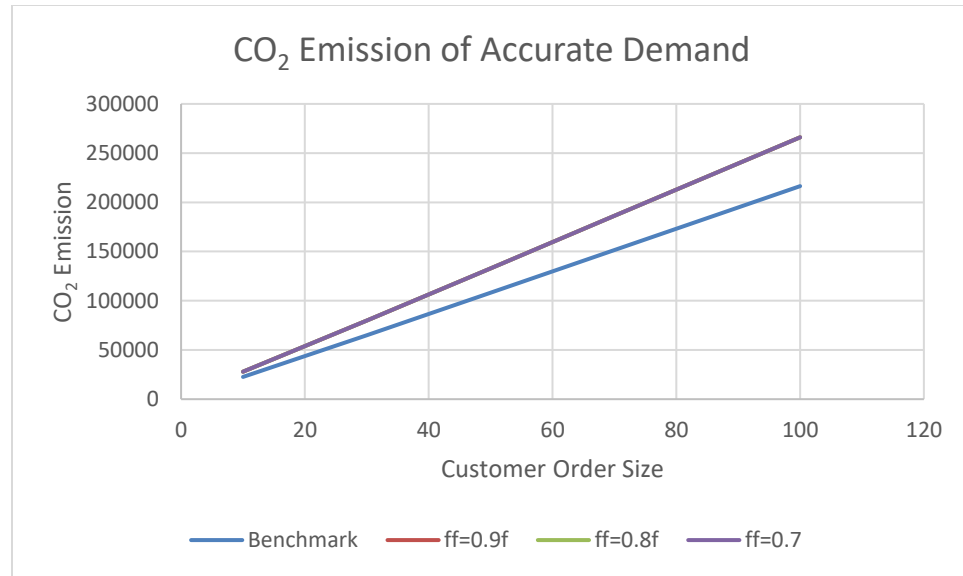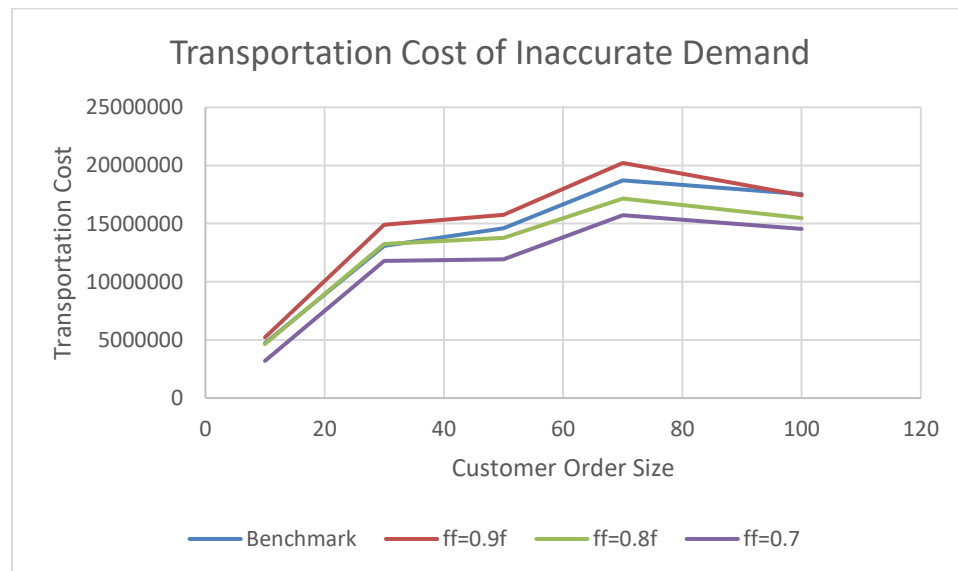
Figure 4.21 CO₂ Emissions of Accurate Demand
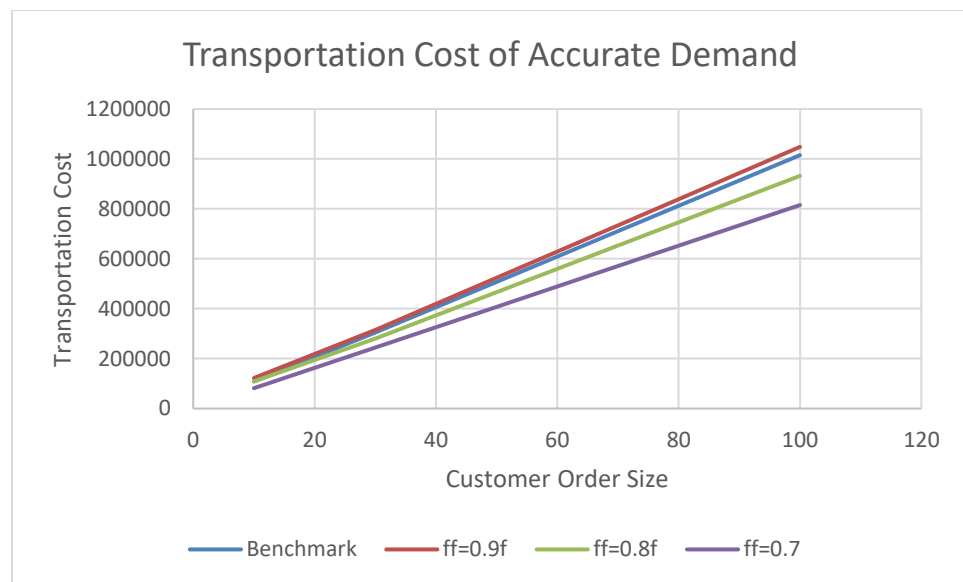
Figure 4.22 Transportation Cost of Accurate Demand
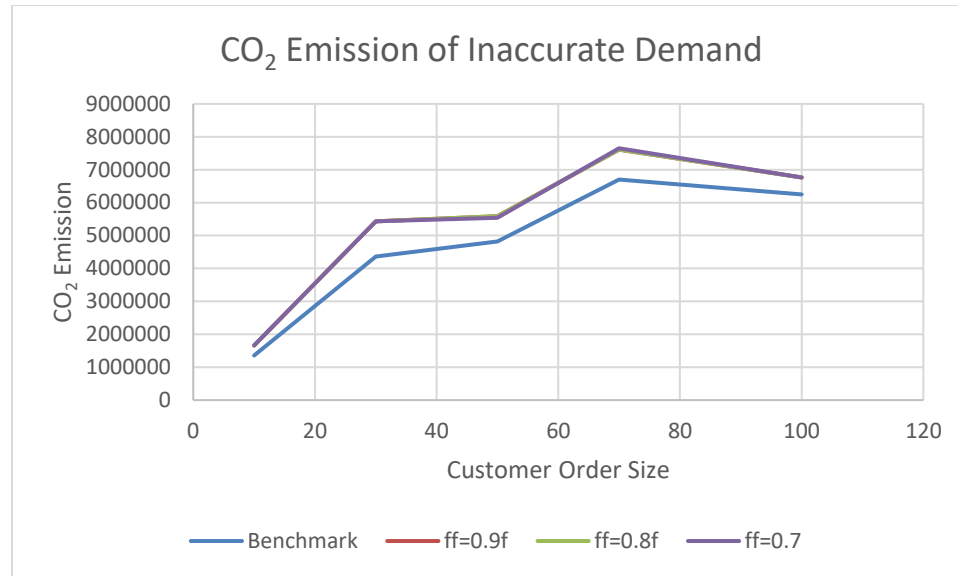
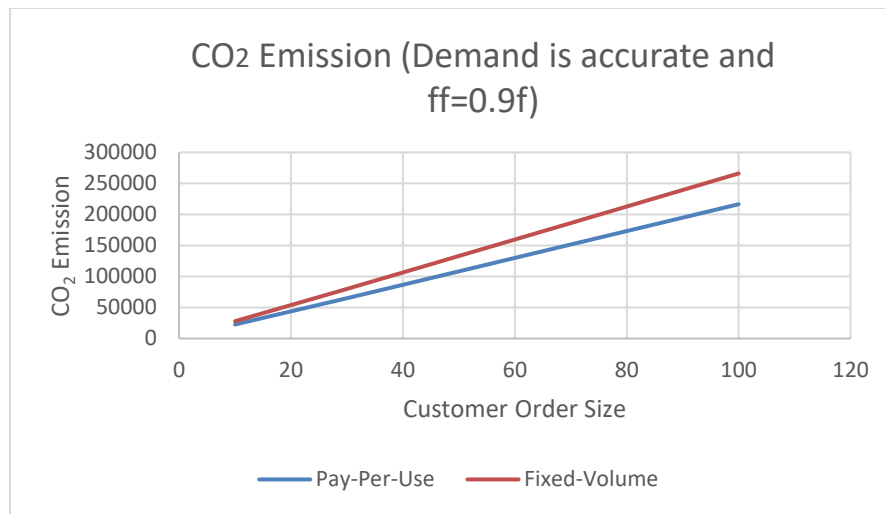**Figure 4.23 CO₂ Emissions of Inaccurate Demand**

Figure 4.24 Transportation Cost of Inaccurate Demand

Figure 4.21 through Figure 4.24, we see that CO_2 emissions of fixed volume based on different unit cost are identified. The possible reason that CO_2 emission of fixed volume based on different unit cost are identified is that the change in unit cost is small so that the solutions of models based on different unit cost didn't change. The other finding is that

transportation cost is still higher than that of benchmark by fixed-volume even though the unit transportation cost is 90% of the one of benchmark based on accurate demand. However, the transportation cost decreases if the unit transportation cost become smaller like ff=0.8f or even smaller like ff=0.7f regardless the demand is accurate or not. In the inaccurate demand cases, CO_2 emissions of fixed volume in different unit cost keeps same. Transportation costs are smaller than that of benchmark in unit transportation cost equals 80% and 70% of the one of benchmark.

Figure 4.25 through Figure 4.36 are the performances based on different unit transportation cost. If the discount of unit cost of fixed-volume is 90% or $ff = 0.9f$ comparing to the original cost, the fixed-volume subscription has no advantage regardless of whether the forecasting of demand is accurate or not. Both CO2 emissions and transportation costs of discount of unit cost for $ff = 0.9f$ are larger than those of benchmark. In other words, the impact of unit cost is larger than the impact of demand accuracy. However, if the discount of unit cost of fixed-volume is $ff = 0.8f$, the total transportation cost is much smaller for the fixed-volume subscription based on accurate forecasting (total demand is close to prepay capacity). Although the emissions are still larger in the fixed-volume subscription, it has achieved some economic benefit by saving some transportation cost. Even in the worst case, such as inaccurate forecasting, we see that the fixed-volume subscription still has less total transportation costs in some cases. If the discount of unit cost of fixed-volume is $ff = 0.7f$, the difference between fixed-volume subscription and benchmark become larger in transportation cost in both accurate demand data and inaccurate demand data. Fixed-volume subscription still has more CO_2 emission. In sum, from an environmental view, the fixed-volume subscription may be not

a good option, but from an economic view, it may be a better option for some logistic companies. If we choose the fixed-volume subscription, we can increase our negotiation power with the contractor and thus lower our unit transportation costs. Once we know the future demand accurately based on useful forecasting models, we can prepay our transportation capacity and make sure that all the prepaid capacity is been fully used. Thus, our total transportation cost will be lower than for a pay-per-use subscription. However, from an environmental view, we did not change much to ensure that prepay modes will cause less CO_2 emissions. We cannot guarantee that the modes that we prepay will discharge less CO_2 emissions than those of pay-per-use. Thus, the potential environmental benefit of fixed-volume is not clear based on our tests.

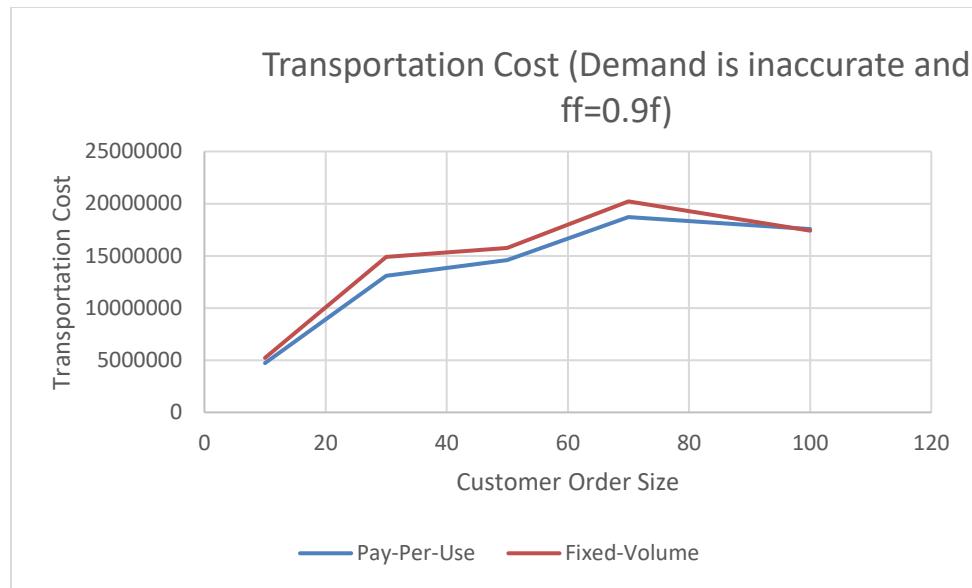**Figure 4.25 CO_2 Emissions of Accurate Demand Based on ff=0.9f**
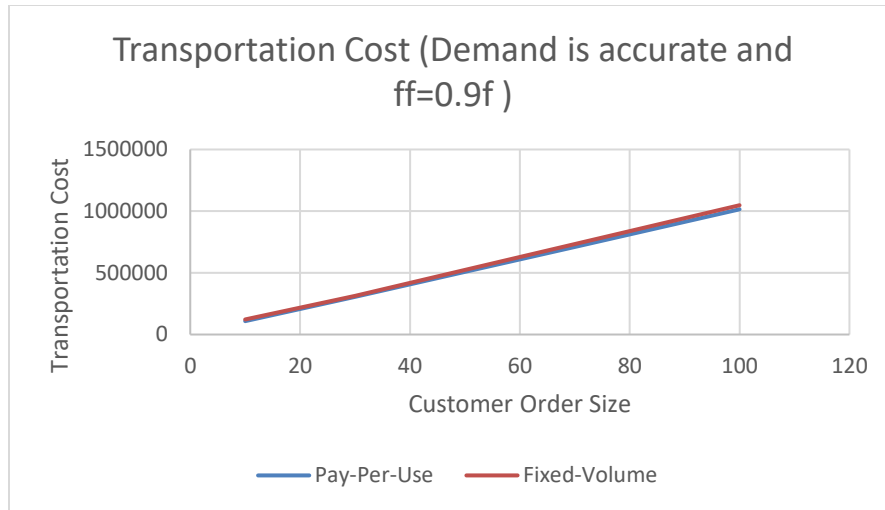
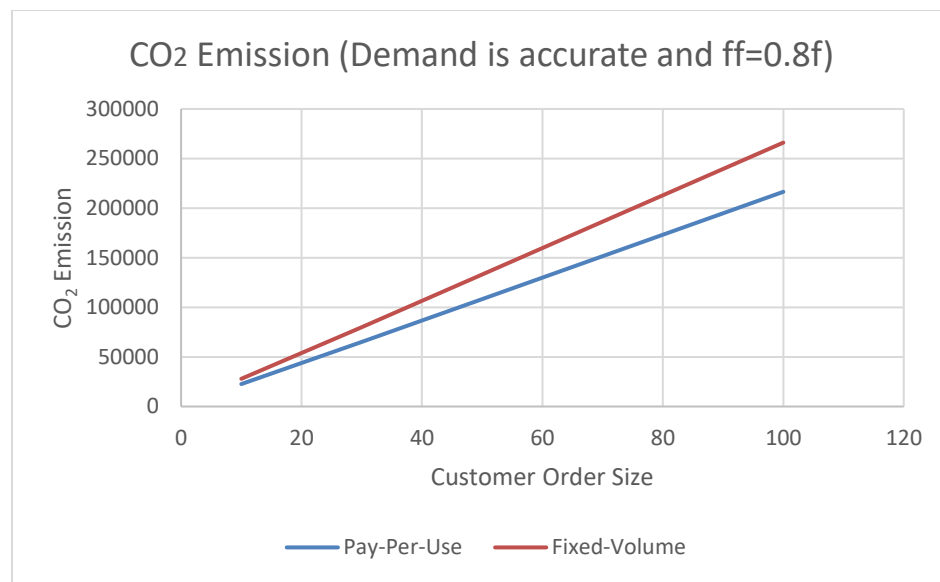**Figure 4.26 Transportation Cost of Accurate Demand Based on ff=0.9f**
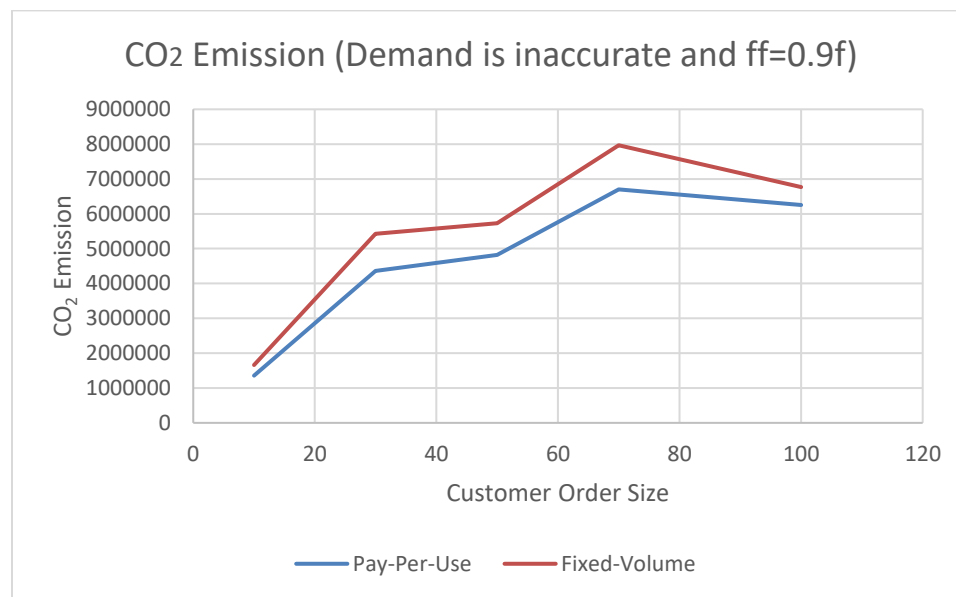
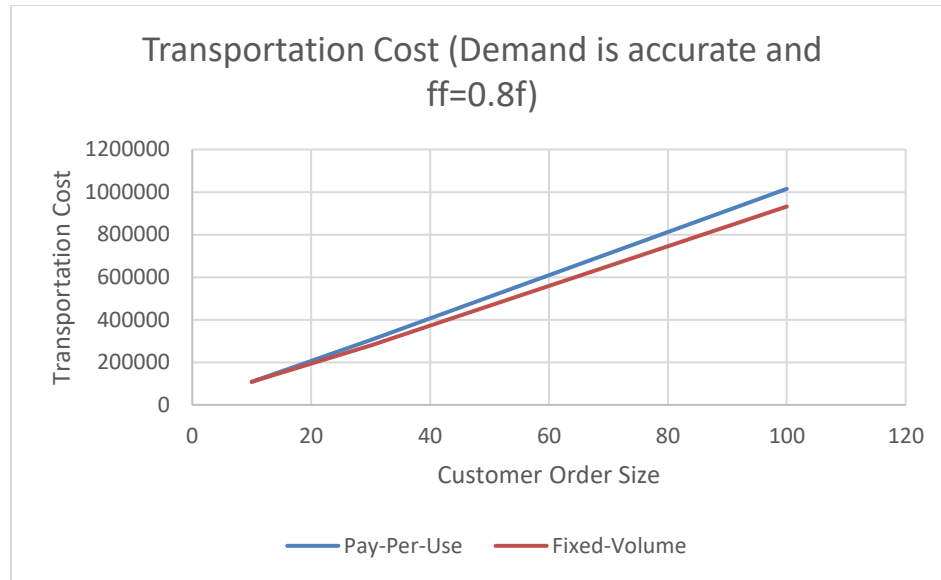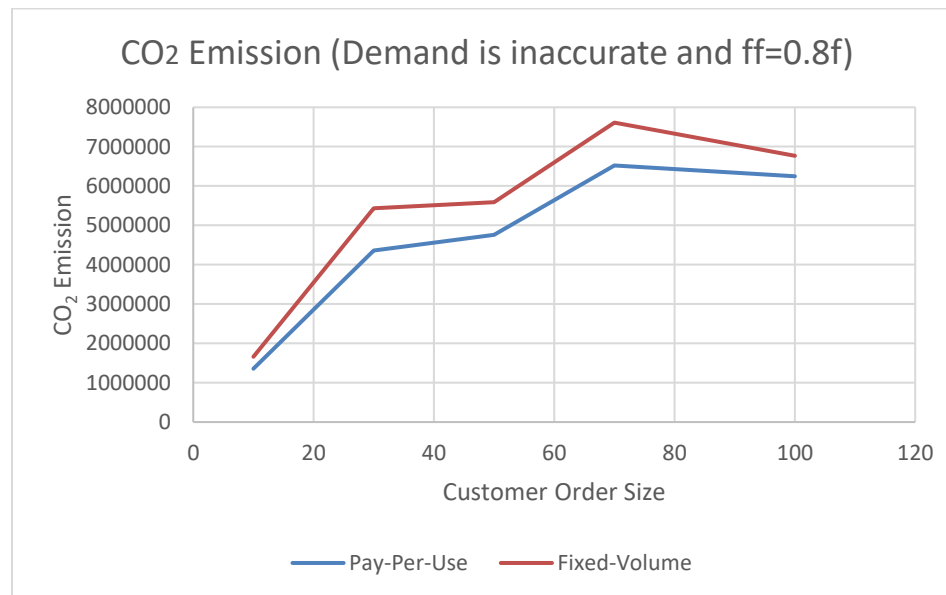**Figure 4.27 CO_2 Emissions of Inaccurate Demand Based on ff=0.9f**

Figure 4.28 Transportation Cost of Inaccurate Demand Based on ff=0.9f

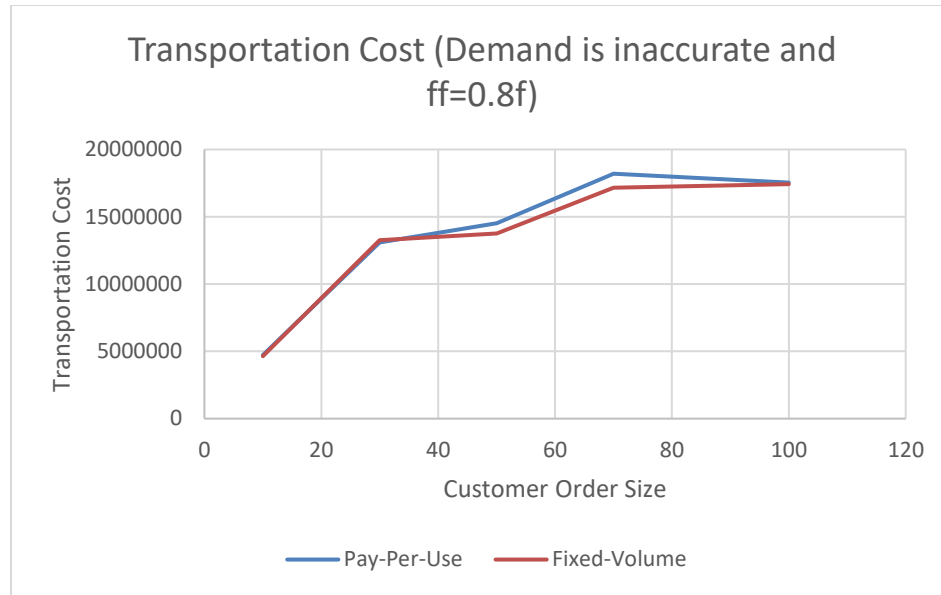**Figure 4.29 CO$_2$ Emissions of Accurate Demand Based on ff=0.8f**

Figure 4.30 Transportation Cost of Accurate Demand Based on ff=0.8f

Figure 4.31 CO_2 Emissions of Inaccurate Demand Based on ff=0.8f

Figure 4.32 Transportation Cost of Inaccurate Demand Based on ff=0.8f

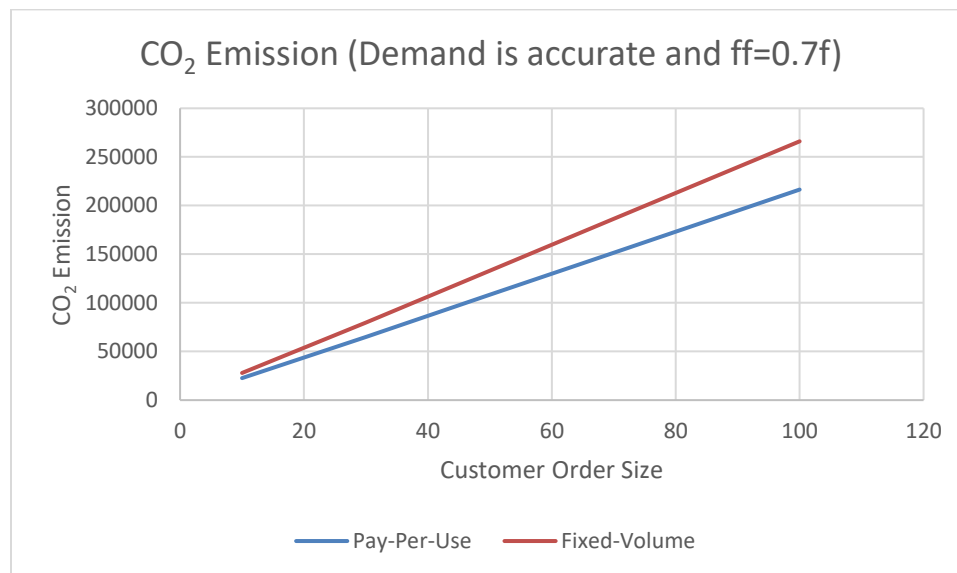**Figure 4.33 CO₂ Emissions of Accurate Demand Based on ff=0.7f**

Figure 4.34 Transportation Cost of Accurate Demand Based on ff=0.7f

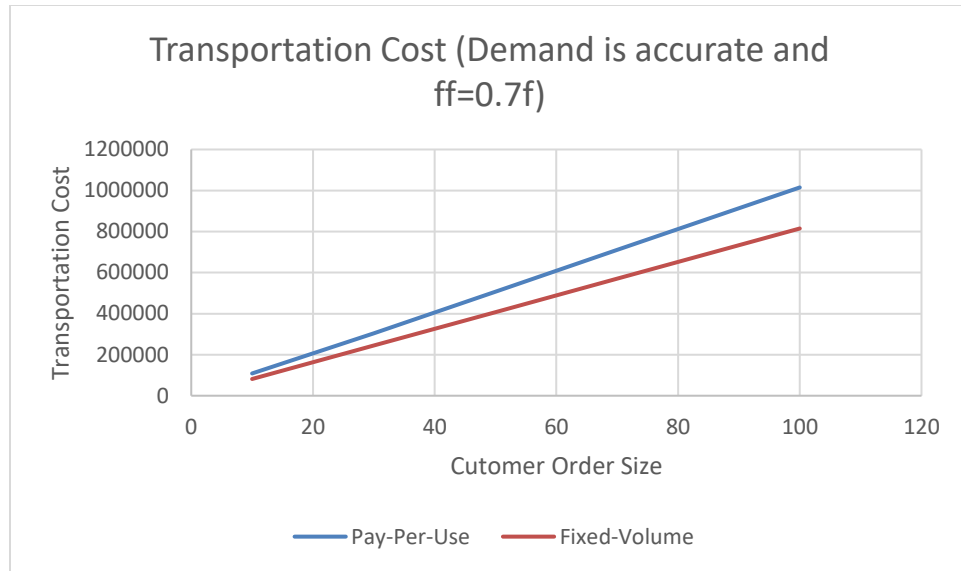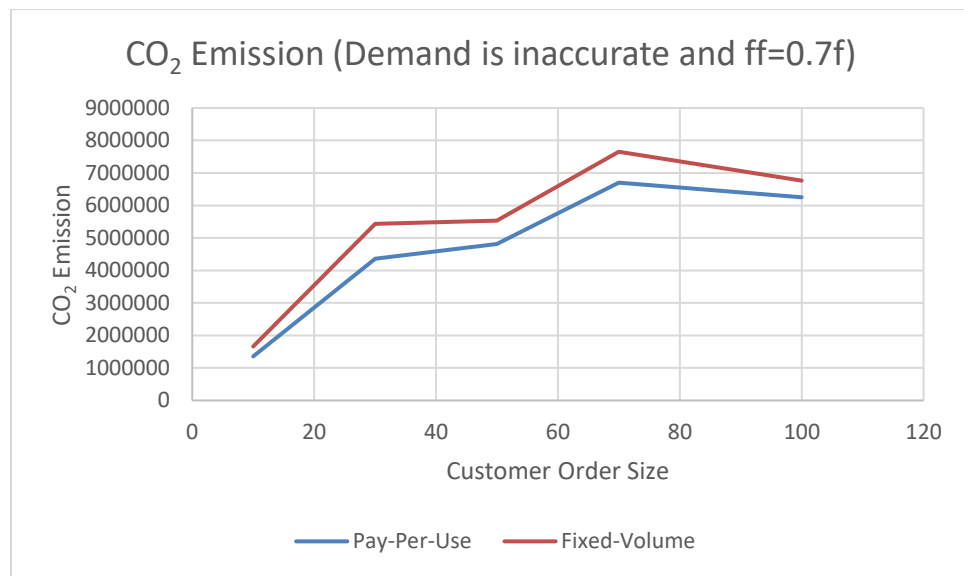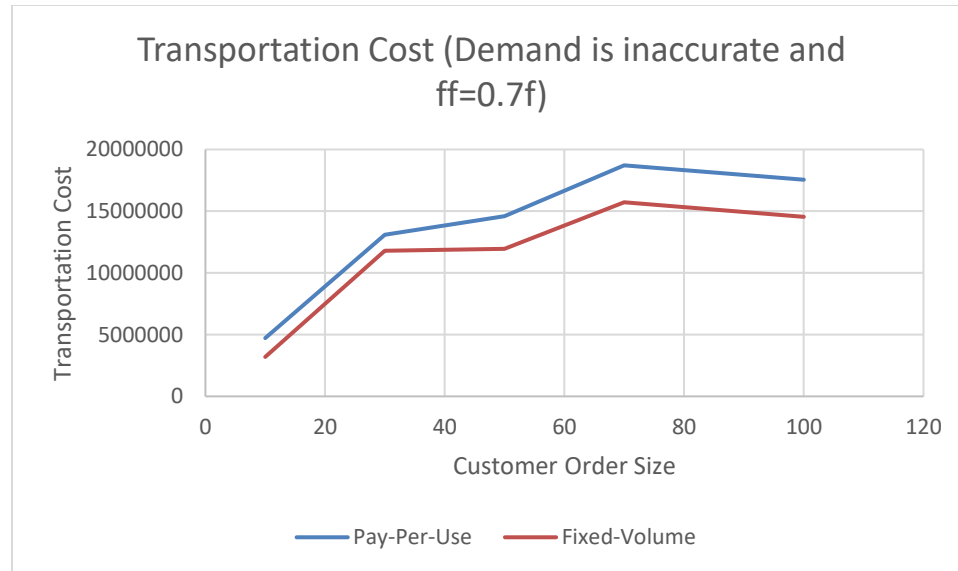**Figure 4.35 CO₂ Emissions of Inaccurate Demand Based on ff=0.7f**

Figure 4.36 Transportation Cost of Inaccurate Demand Based on ff=0.7f

4.8. Concluding Remarks

Transportation emissions total is a substantial share of total carbon emissions globally. Many governments are developing regulation mechanisms that are expected to drive down emissions. It is obvious that switching transportation modes is an effective measure to take to reduce emissions. However, it is unclear to what extent emissions will play a role in transportation mode selection or even in multimodal transportation choices. One current trend is having more logistics companies switch from truck-only to multimodal transportation. Thus, in our study, we focused on the multimodal operational planning problem for a given product based on a real infrastructure. We used a carbon emissions measurement methodology based on a multimodal transportation operational level environment. We tested the effect under different scenarios, including multimodal vs. truck-only, different capacity weight of high-speed rail, CO_2 emissions Quota, and pay-

per-use vs. fixed-volume. Specially, we focus on high-speed rail used in the Chinese high-speed rail network. Our numerical results show, first that multimodal is a better way to reduce carbon emissions. If we switch from multimodal to truck-only, the transportation cost will increase and CO_2 emissions will decrease because more expensive but environmental friendly modes will be used. Second, we believe that a high-speed rail system offers be a better solution for freight transportation no matter the unit cost or any environmental issues. As we increase the capacity weight of high-speed rail of all the modes, we find a trend that transportation cost increases and CO_2 emissions decrease. Since more high-speed rail has been used, both its economic and environmental characteristics are amplified. Third, emissions reductions can be obtained by setting a CO_2 emissions quota. Our results show that a 20% emissions reduction will cause an average of 17.3% cost increase. As the transportation carbon discharge problem will become worse at the current pace, the carbon emissions quota policy may be an optimal choice to fix the problem. Finally, fixed-volume is a potential option for the logistics companies to reduce transportation costs. Our results show that the fixed-volume subscription can lower the transportation costs under certain constraints. It is a good option from an economic perspective, but it may not help to reduce CO_2 emissions from an environmental view.

Chapter 5

Conclusion and Future Research

5.1. Conclusion

In multimodal freight, an operational planning problem, stakeholders' effect is limited. Usually we assume that the entire transportation system is run by a central department, but in practice, each player in the supply chain has its own way of dealing and sharing limited information with the others. Furthermore, these players compete. Thus, the market has become increasingly more dynamic and vibrant.

The multimodal freight transportation problems under study in this thesis are both large in problem scale, and complex in problem structure. By using a better designed model and a smarter algorithm, we can find a more accurate solution with less computational time.

In our study, we built a realistic model involving many customer orders and a set of business rules, motivated by a real-life case of Resun Co. Ltd. The capacity of each route for each mode and the attendant departure time slots were taken into consideration. We demonstrated that the problem is NP-hard by relaxing the problem to a multi-commodity integral flow problem. Because of the multiple departure times for each route of each mode, as well as the potential large number of customer order (commodities) in our problem, the NP-hard problem can be very difficult to solve. We thus proposed a Lagrangian relaxation based solution approach using a heuristic method to solve the problem. The Lagrangian problem was further decomposed into $|K|$ independent small problems. These small problems can be solved in parallel, thereby achieving significant computational benefits. We evaluated the performance of this approach by comparing it to a set of benchmark

approaches that have been commonly used in the past. Our computational experiments showed that our solution significantly outperformed the benchmark approaches. A substantial computational advantage can be achieved by solving decomposed subproblems in parallel.

Additionally, we identified a few interesting insights that can be used to assist logistics managers in making better decisions.

As mentioned in Chapter 4, government agencies are now encouraging logistics companies to switch to multimodal transportation and converting the gas discharge from shipping and logistical impacts into carbon emissions. New regulations and taxes are being created to lower carbon emissions. Our model can also be used and extended to measure impact of carbon emissions. Furthermore, switching modes is a potential option when companies are constrained by environmental goals, such as regulated quotas for carbon emissions. Specifically, we measure the financial and environmental impacts of four scenarios by simulation based on modified model we proposed in Chapter 2. We first quantify the environmental benefits of multimodal transportation, compared to truck-only transportation. Comparing to truck-only, multimodal which includes more other expensive but environmental modes can reduce the CO_2 emissions with relative high transportation cost. Second, we quantify the impacts on carbon emissions by varying usage of high-speed rail. Our numerical results showed that the potentials of high-speed rail in multimodal transportation is huge. It may be a good substitute of trucks. Third, we investigate the financial and environmental impacts on logistics companies by imposing carbon emissions quota as an operational constraint. Our results showed that an average 17.3% transportation cost increase will bring us an 20% emissions decrease. Finally, we tested pay-per-use

scheme and fixed-volume subscription. Fixed-volume may bring economic benefits to logistics companies under certain constraints but may be not a good option from an environmental view.

5.2. Future Research

This research can be extended in the following directions. First, the supply chain network model can be generalized to allow the splitting of delivery and multiple commodities at the transshipment points, which is indeed common in real life. When a logistics company runs its business, it often shares supplies with other logistics companies by sharing capacity to reduce transportation costs. Adding transshipment points to a network increases system complexity. This model is certainly one step closer to what is encountered in actual practice. In addition, we should pay more attention to commodities, such as hazardous chemical products and flammable and explosive products. A special route with strict timeframes has been designed to satisfy this requirement for shipping. In addition to minimizing the total transportation cost, another meaningful objective is delivery times. For examples, the express delivery industry offers a one-day and second-day delivery services. Minor delays in shipments are acceptable and common. However, this minor delay cannot work in the express delivery industry. Customers pay much higher fee to get the best services, a circumstance that leads to the needs with multiple objectives, such as minimizing shipping time while also minimizing total transportation cost. While minimizing operational time is not considered a primary objective in our study, it is certainly an interesting one for future studies. It would be especially useful in the express industry which focuses first and foremost on time constraints. Such a study would also

offer a new guidance for government and other logistics companies. In addition, multimodal transportation with a time priority is a good model for disaster relief operations.

Other issues that we may include in the future, for example, splitting delivery, is not allowed in the current model. Although splitting delivery is an old story, it may make the model more complex. Multiple commodities are also commonly in recent research papers. Sometimes, we could use the single item model and combine it with the current model to solve for multiple commodities, but sometimes we couldn't because of the different characteristic of the commodities. For example, hazardous chemical products and flammable and explosive products cannot be shipped as normal ones. In the past, express companies have chosen only air plus truck as their transportation modes since express freight usually is lightweight. However, we can now imagine that the express price system may be destroyed by high-speed rail since that mode can offer better service with lower rates. A multi-commodity, multimodal network flow model for disaster relief operations is the other option for a high-speed rail network system. As we know, time is the key factor during an emergency event. For example, once a hurricane strikes, the road infrastructure can be destroyed, so we need to deliver needed emergency items to the target locations as soon as possible. In such a situation, a high-speed rail system offers an even better way of delivery than air since it has more space to load more needed items unless the rail system is destroyed by the course of events (e.g., a flood). For disasters, multiple fast modes should be in place and ready to operate effectively.

We believe that our model and algorithm can provide a fast and near optimal solution for today's multimodal freight transportation problems, including those in the growing high-speed rail network environment. In practice, however, other factors may also

play a role to make the actual selected mode differ from the optimal solution to our problem. For examples, we ignored the water transportation in our model based on the data we have, but it is widely used in reality. Another example is that we assume that shipping time, demand of customer orders and shipping capacity are given as fixed parameters. However, in reality, they may be random variables or dynamic variables. In other words, we live in a dynamic system with many uncertain variables. Designing a methodology that can satisfy these optimization problems will be a challenging and fascinating task indeed. In most cases, the time variables are sensitive to commodity. For example, express industry has a high request on time. But other industries, such as normal freight delivery may not be sensitive to the time constraints. The other issue is that logistics companies may reject to offer service once they could not handle that in the peak service time. We assume that all the customer orders should be satisfied even if paying high delay penalties which is not reasonable in reality. Extending our model to include these factors would ensure that our solution is more persuasive.

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