SHIPMENT CONSOLIDATION AND DISTRIBUTION MODELS IN THE INTERNATIONAL SUPPLY CHAIN

A Thesis presented to

the Faculty of the Graduate School

at the University of Missouri

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy

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by

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May 2013

The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled:

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ACKNOWLEDGMENTS

The Ph.D. training in the Department of Industrial and Manufacturing Systems Engineering at the University of Missouri has been a challenging, precious, and enjoyable experience for me, and it would not have been possible to achieve the Ph.D. without the support and help that I received from many people.

First of all, I would like to express my deepest gratitude to my advisor Dr. Wooseung Jang for his invaluable guidance, consistent encouragement and long-term support. I have been working as a research assistant under his supervision for about five years. He was always patient in teaching me how to think things through and how to conduct research. I thank him a lot for his ideas and advice, which I shall strive to follow in the future.

I would also like to thank Dr. Cerry Klein, Dr. James Noble, Dr. Mustafa Sir and Dr. Timothy Matisziw for serving on my committee and providing helpful suggestions and feedbacks.

I am grateful to Dr. Luis Occeña and Dr. Cheng-Hsiung Chang for providing me many great opportunities and good advice on the development of my career. I am grateful to administrative staff members Ms. Paula McDonald and Ms. Jonni Sutton in the Department of Industrial and Manufacturing Systems Engineering who were always happy to help and gave me lots of kind assistance during my Ph.D. study.

I am thankful to my friends and colleagues Zhongwei Yu, Gaohao Luo, Phichet Wutthisirisart, Rung-Chuan Lin, Mahmood Pariazar, Rana Afzali Baghdadabadi for their friendship, support and company.

Last but not least, I wish to thank my family: my parents, my husband Dongdong and my 10-month-old son Jayden. My parents gave me unconditional love and support. And they encouraged and helped me at each stage of my life. Without their love I could not have accomplished my degree. I cannot thank my husband Dongdong enough for his support and encouragement during my 5-year Ph.D. study. He was always there when I met difficulties. And he has always been the source of my strength and courage in my life. I could not achieve the degree without his deep love and support. Finally, I want to thank my son Jayden, who has made my life colorful and enjoyable.

This research was supported in part by the National Science Foundation under Grant No. IIP-0815195.

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ABSTRACT

With the increasing competition in global trade, many US companies purchase parts and finished products overseas in a just-in-time and low-inventory operation. Therefore, buying and transporting items efficiently are critical and challenging problems for many companies. The objective of this study is to design a cost-effective consolidation and distribution method to transport shipments in a global network.

In the dissertation, we investigate an integrated consolidation problem in the international supply chain, where a US manufacturing company buys multiple items from China. A proactive order consolidation strategy is proposed to improve the performance of the supply chain. Different from current practices, our approach consolidates items at the early stage in China considering inland transportation to final destinations in US. This strategy is modeled to minimize the total costs by effectively loading items into an ocean container considering subsequent inland transportation cost and handling cost given container capacity and packing constraints. Two difficult combinatorial optimization problems, such as a mode selection problem and a three-dimensional bin packing problem, are combined into the model. Due to the problem complexity, approximation algorithms are proposed to solve the model. The basic model is extended to consider the inland multi-stop delivery and multi-period planning horizon. Several solution methodologies are developed and evaluated to solve large-scale problems. Based on the numerical results, it is observed that our proposed methods could achieve up to 30% cost savings compared with the current shipping practices. The algorithms we developed could obtain the good implementable solution in a reasonable time for real-world problems.

This research provides new insights into the global supply chain management area. The methodologies developed not only provide practical solutions, but also the theoretical research in the area.

Chapter 1

Introduction

1.1 Background

1.1.1 The Effect of Globalization on Supply Chain

With the rapid development of the world-wide transportation systems and the fast growth of global trades, many companies are being more international than ever before. They have suppliers, manufacturing plants, warehouses and customers in several different countries. By building manufacturing factories overseas and utilizing offshore sourcing from low-cost countries, especially in some Asian countries, companies improve their competitive advantages and make more profits thanks to bigger foreign markets and cheaper labor and material resources.

However, being international not only brings opportunities, but also challenges. In the international network, raw materials, parts and semi-products are moved between suppliers, manufacturing plants, and distribution centers in different countries of the world, which increases the cost of a supply chain significantly. These costs are driven by multiple factors. Long-distance movement of a flow of goods by using multiple transportation modes increases transportation cost. The continually increasing fuel price is another critical factor in the rise of logistics costs. Besides, more handling costs incur since shipment flows are transferred multiple times among multiple carriers, port authorities and consolidators from origin to destination. Furthermore, the variability and uncertainty from a longer supply chain, such as delayed or incomplete shipments, lead to higher inventory buffers and freight expedition expenses. All of these factors result in the increase of logistics cost, being an obstacle to revenue growth. According to the IBM 2005 Industry-Week Value-Chain Survey(Vinas (2005)), a half of the survey respondents say their logistics costs are 10 percent or more of sales revenues.

The global supply chains that most companies deal with nowadays are more difficult to manage than domestics models (Dornier et al. (1998); Wood et al. (2002); MacCarthy and Atthirawong (2003); Meixell and Gargeya (2005)). There are lots of complex decision activities involved in every function of a supply chain, such as procurement, replenishment, inventory policy, production, distribution, and transportation planning. All of them are intertwined to each other and any bad decision on one function would influence the performance of an entire supply chain (measured by the total cost). Besides, two critical characteristics of an international supply chain, such as long lead time and high transocean transportation cost, are needed to consider for any strategic, tactical and operational decisions.

A decision on the oversea outsourcing, in particular, has a series of impacts on other functions of the supply chain, such as inventory, transportation, cargo loading, packing, and the overall performance of the supply chain. Figure 1.1 and the following descriptions illustrate the relationships of these functions.

- An inventory policy is important for outsourcing overseas. An inventory policy consists of order quantity and order frequency. In practice, a full-container-load ordering strategy will lead to a high inventory level and a long cycle time, but

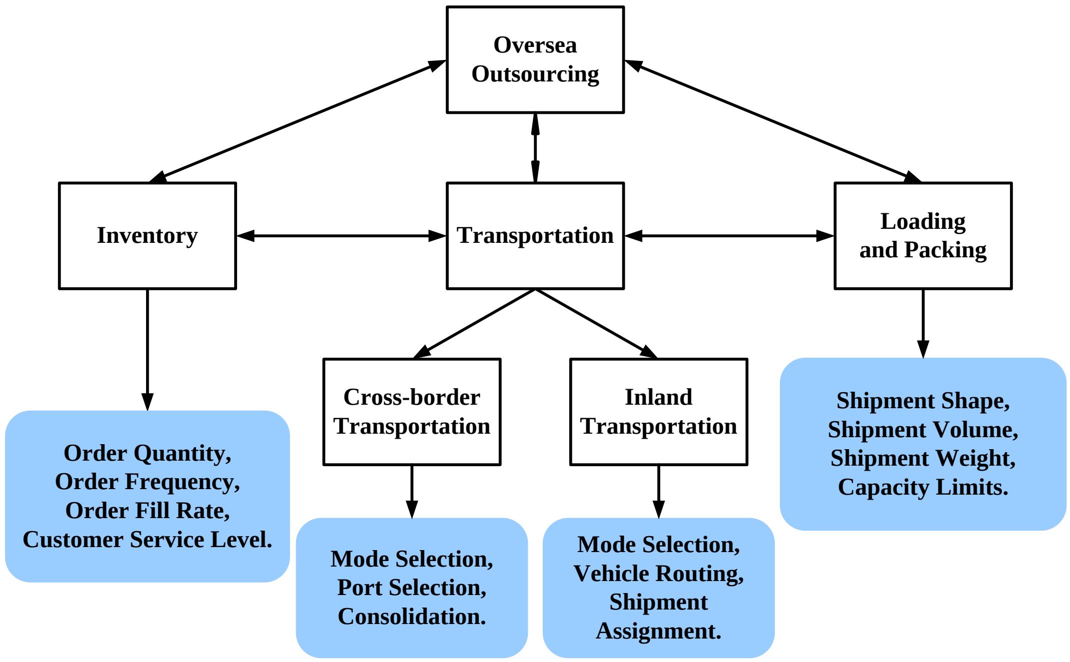


Figure 1.1: Oversea sourcing example

less ordering and transocean transportation costs. Small volume purchasing strategy will bring less inventory and shorter cycle time, but more frequent ordering and higher transocean transportation cost. Hence, any decisions on ordering policy affect inventory cost and transportation cost.

- For international shipments, at least two transportation modes are needed from an origin to a destination. With regard to cross-border transportation, air and marine are two commonly used modes. The marine transportation has a long transit time with a lower rate. The air transportation is fast, but has high cost. Thus, if the marine transportation is chosen, a high inventory buffer needs to be set to provide good customer service due to the long lead time-subsequently leading to a high inventory cost. The inland transportation mode is determined by order quantity and characteristics. For heavy and large size shipments, Full-Truck-Load is more economical than Less-than-Truckload. Otherwise, Less-than-Truckload is more advantageous. In addition, other operational decisions on the inland transportation, such as routing vehicles, assigning shipments to vehicles, also need to be taken into account to reduce cost.

- Issues, such as a shipment's geometric shape, container capacity limits and loading patterns, need to be considered when planning for cargo loading and packing. Good loading techniques not only maximize the utilization of containers, but also save subsequent inland distribution costs.

Given from the examples above, it is clear that global supply chain management involves complex systems engineering. Its overall performance is influenced by many interdependent decisions involved in the supply chain. Therefore, it is essential to study and design an effective, efficient and scientific decision-making tool aimed at helping companies identify cost-effective alternatives when designing their supply chain. Using such a tool, companies can better provide the desired customer service with minimal costs. To date, many practitioners and academics have emphasized two innovative practices in global supply chain design - the integration and consolidation of decisions across the supply chain (Meixell and Gargeya (2005)). Our work, consistent with the topics, is to explore potential cost-saving opportunities by integrating transportation, packing and inventory through order consolidation in the international supply chain.

In this chapter, Section 1.1.2 provides a general introduction to supply chain and logistics management. Section 1.1.3 introduces consolidation strategies. Section 1.1.4 presents the integrated inventory and transportation strategy. Section 1.1.5 describes various transportation modes and their economical pricing on intermodal, Full-Container-Load (FCL), Less-than-Container-Load (LCL), Full-Truck-Load (TL) and Less-than-Truckload (LTL) transportation. Section 1.2 presents an overview of the research problem. Section 1.3 discusses the motivations for this research while the objective of the research is given in Section 1.4. Section 1.5 summarizes the contribution of the dissertation. The last section shows the organization of the dissertation.

1.1.2 Supply Chain and Logistics Management

A supply chain is a system of facilities and activities that functions to procure, produce, and distribute goods to customers (Shen (2007)). According to the Council of Supply Chain Management Professionals (CSCMP), supply chain management encompasses the planning and management of all activities involved in sourcing, procurement, conversion, and logistics management. Its main objective is to enhance the operational efficiency, profitability and competitive position of a firm and its supply partners by best-planned movements of goods within the supply chain (Min and Zhou (2002), Shen (2007)). The performance of supply chain can be measured by three main factors: system-wide costs, cycle (transit) time and customer service level.

Logistics deals with the planning and control of material flows and related information in organizations, both in the public and private sectors. Its mission is to get the right materials to the right place at the right time, while optimizing a given performance measure (e.g. minimizing total operating cost) and satisfying a given set of constraints (Ghiani et al. (2004)). According to the Council of Logistics Management, logistics management activities typically include inbound and outbound transportation management, fleet management, warehousing, materials handling, order fulfillment, logistics network design, and inventory management of third party logistics service providers.

Logistics is one of the most important activities in modern societies. Based on the 2010 State of Logistics report of CSCMP, logistics costs, which includes inventory, transportation, and logistics administration costs, are equal to about 1.1 trillion dollars in 2009, representing 7.7 percent of the gross domestic' product (GDP) (Gilmore (2010)). Figure 1.2 shows the trend of logistics costs as a percentage of GDP between the years 2000 to 2009.

The cost reduction from 2000 to 2003 is explained by the fact that Just-in-Time initiatives were adopted by many US companies during that period of time. The

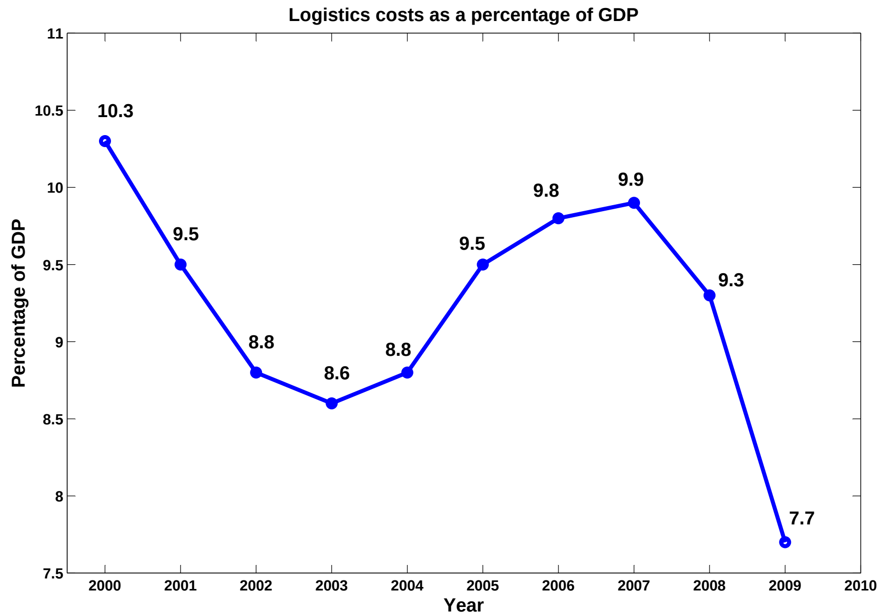


Figure 1.2: The trend of logistics costs as a percentage of GDP

raise after 2003 is primarily due to increasing inventory and transportation costs. At that time, lots of companies changed their warehousing strategies from central, mega-warehousing to a large number of smaller distribution centers across country in an effort to improve delivery times and reliability. The increase in transportation cost was also caused from rising gas and diesel costs (Cooke (2006)). However, the big drop from 2007 to 2009 was due almost entirely to the recession. The economy had a negative impact on the two main components of logistics costs, such as inventory and transportation cost. Low interest rates pushed down inventory carrying cost significantly. Low volumes and increased fuel price caused transportation cost to decrease a lot.

Among the cost components, transportation cost accounts for a big proportion (62%) of the logistics costs, and inventory cost represents about 32% (Cooke (2006)), shown in Figure 1.3. Therefore, it is crucial to control these two key cost components to reduce overall logistics cost.

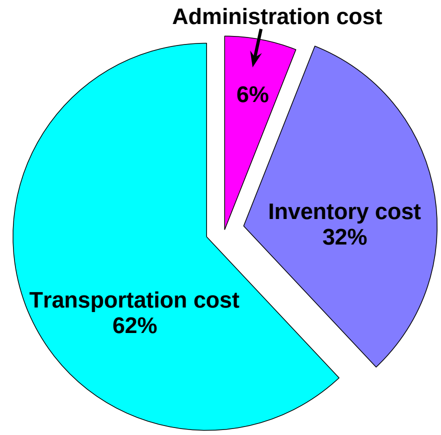


Figure 1.3: Breakdown of logistics costs

1.1.3 Consolidation

Consolidation, as an innovative and important industrial practice, can achieve considerable transportation cost savings by taking advantage of economies of scale in transportation (Ghiani et al. (2004)). Bowersox (1978) illustrates the concept "shipment consolidation" as

> "A significant opportunity existing in all logistical operations is the potential for reducing transportation expenditures as a result of shipment consolidation. Quantity discounts are provided in the published rate structures of common carriers. Generally speaking, the larger the shipments, the lower the freight rate per hundredweight."

This practice has been applied for more than three decades since the 1980s. In a survey by Jackson (1985), 100% of the firms indicated that freight consolidation is important (16%) or very important (84%) as a competitive tool in terms of cost, while 77% of the responding firms indicated freight consolidation is an important competitive tool in terms of service. With regard to cost, by comparing rate structures of Less-than-Container-Load (LCL) with Container-Load (CL), and Less-than-Truckload(LTL) with Truck-Load (TL), the findings indicate that per unit freight rate decreases as the shipment size increases. If the shipments to the same destination can fill up a single container or truck, it is more economical to aggregate them into CL or

TL instead of multiple separate LCLs or LTLs. Besides, freight consolidation could reduce shipments damages. Forwarding small shipments separately will have a higher risk of damage due to more transshipping and handling from origin to destination. Another advantage of consolidation is reliability. Generally speaking, the transit time of CL and TL has a smaller variance than that of LCL and LTL.

According to existing literature (Hall (1987); Higginson and Bookbinder (1994); Ghiani et al. (2004)), consolidation strategies could be achieved in three ways. The first one is a vehicle or multi-stop consolidation (over stops), where small load shipments are picked up and dropped off along the multi-stop route by the same vehicle so that combined big loads could maximize the capacity of the container or truck. For this problem, some operational issues, such as how to route trucks and how to assign shipments into trucks or containers, need to be taken into account. The second one is inventory or temporal consolidation (over time), where the current shipments are held to wait for future shipments. By waiting for one period or multiple periods, the total combined load could be shipped using one container or one truck so as to save multiple separate LCL or LTL costs. Two fundamental operational issues in this area are (1) when to dispatch a vehicle so that service requirements are met, and (2) how large the dispatch quantity should be so that the scale of economies are realized (Cetinkaya (2005)). The third consolidation strategy is terminal or facility consolidation (over space), where the small shipments among several facilities are transported over long distances to the transshipment center to consolidate into larger shipments. For this problem, some tactical and operational decisions on hub locations, hub service areas and vehicle routing are needed to optimize for better system performance.

Consolidation strategies have already been widely applied in ground, sea and air transportation (Tyan et al. (2003)). For example, LTL trucking, liner cargo shipping and airline optimize their logistics network through consolidation strategies to save costs. Usually, shipments are transported in their pre-established transportation network, where there are fixed hubs, hub service areas, and transportation frequency. Cargo or passengers from different origins are consolidated in the hubs, and then shipped to some intermediate hubs, and/or finally to destinations. Vendor Managed Inventory (VMI) practice is another application of freight consolidation. Vendors manage inventory of downstream warehouses or customers, their deliveries, and their own inventory. By consolidating inbound and outbound shipments, transportation cost can be reduced significantly. In addition, several big companies mimic the procedures of LTL trucking companies and third party freight forwarders to redesign their own distribution network and optimize the loading plan, which might be more beneficial because companies know more and better about their own problems.

1.1.4 The Integration of Transportation and Inventory

Substantial geographical distances on the international level not only raise transportation costs, but also increase inventory costs due to the long lead time. In general, inventory control involves decisions on ordering quantity and frequency. If the sizes of orders are too big, they would reduce fixed ordering cost, but tie up so much capital and lead to high average inventory level. Otherwise, it would reduce average inventory level, but increase fixed ordering and transportation costs. Order quantity directly influences the way how cargoes are shipped from origin to destination, such as FCL for large volume order size, CLC or consolidated FCL for small volume purchase quantities. Thus, incorporating transportation cost into inventory replenishment decisions is important in supply chain management. The integration of transportation and inventory involves both inventory and transportation aspects of management concerns. An inventory policy relates to determinations on replenishment quantity, frequency, safety stock and inventory allocation on vehicles. In transportation planning, decisions need to be made on mode and route selection, the assignment of vehicles on the route, and the visiting sequence of customers on the route. Usually, the decisions on these two aspects are simultaneously made to minimize the total cost. Literature reviews in this field are detailed in Chapter 2.

1.1.5 Multi-modal Transportation

There are five basic transportation modes: sea, rail, road, air and pipeline. Multi-modal transportation is to use at least two transportation modes to move the shipments from origin to destination. In most international trade, transit of shipments from a sea or air mode to an inland mode is inescapable. In our work, we focus on the sea-truck transportation modes.

The use of ocean containers has been increasing for oversea transportation. Two primary sizes of ocean containers, 20- and 40-foot containers, are commonly used. Their features (Ghiani et al. (2004)) are summarized in Table 1.1. There are two types of international cargoes: LCL and FCL cargoes. LCL cargoes are used to describe the international cargoes which cannot fill an entire 20- or 40-foot ocean container. And their bookings are usually made by small companies while FCL bookings are usually from bigger firms. LCL cargoes are consolidated with shipments from other companies at the same port. Their rates are typically calculated by volume. For FCL cargoes, customers only pay the price per container and can load any shipments as long as the total weight and volume do not violate capacity limits (Ang et al. (2007)).

Type	Size (ft^3)	Tare(lbs)	Capacity (lbs)	Capacity (ft^3)
ISO 20	8*8*20	4,850	61,289	1,169
ISO 40	8*8*40	8,380	57,759	2,385

Table 1.1: Main features of the most common ocean containers

Trucking is the most important mode of road transportation, and trucks transport 71% of US freight by value and 83% by volume (Agrahari (2007)). Trucking includes both LTL and TL transportation. LTL service is for small volume shipments. LTL loads are not usually shipped directly to their destination. They are shipped to multiple transshipment hubs and then to final destination. For TL, trucks usually go to the destination directly or via one or two intermediate stops consigned by shippers to destination. Hence, in terms of transit time, TL is relatively faster and more reliable than LTL. With regard to pricing, LTL and TL have different rules. Determination of LTL rates can be very complicated in practice. Generally speaking, LTL rates depend on the delivery distance, geographic region, the shipment weight and the shipping class based on density. TL pricing is relatively simple because rates are typically structured as per-mile cost depending on the given geographic regions of origin and destination. Thus, if the volume or weight of shipments are big enough to utilize a truck container fully, it can be more economical to ship them using TL rather than multiple separate LTLs.

1.2 Overview of the Research Problem

Our work considers a global supply chain, which consists of overseas suppliers, one overseas consolidation center, one US deconsolidation center and multiple US manufacturing plants and distribution centers. In the supply chain, a multinational company orders semi-products and finished-products overseas, and transports the international shipments into US and distributes them domestically. In order to reduce the logistics costs, several tactical and operational decision aspects across this chain are studied. With the consideration of the two most common problems in a global network, such as high inventory and high transocean transportation costs, we propose an order consolidation strategy to reduce them. A frequent and small-volume ordering policy is applied to reduce inventory and an order consolidation strategy is proposed to maximize the utilization of ocean containers. The order consolidation strategy is modeled in such a way that the total costs are minimized by effectively loading items into an ocean container considering subsequent inland transportation planning given container capacity and packing constraints. A mixed integer programming model is formulated for this problem. Then, the model is extended to consider more practical issues, such as multi-stop, and multi-period aspects and efficient heuristics algorithms. Our proposed consolidation strategy is proactive and considers the consolidation process at the early stage of the supply chain. Numerical examples show that it can achieve substantial logistics cost reduction. In addition, a coordinated replenishment policy is investigated. The optimal ordering quantity and frequency are determined with regard to the consolidation process. The whole research integrates the decisions on the transportation planning, packing, and inventory policy. The methodology discussed in this dissertation is to use mathematical models to solve practical logistics problems, and research results discuss several managerial implications, which can help logistics managers plan and adopt better supply chain operations.

1.3 Thesis Objectives

The goal of our approach is to design, model and implement a cost-effective consolidation method to transport international shipments in the global network to improve and evaluate the performance of a supply chain. Several tactical and operational decision aspects are investigated. Practical and value added cost drivers are considered by integrating decisions across transportation, packing and inventory to search for opportunities of cost reduction.

1.4 Research Motivation

Our research is motivated by four main factors.

1. A real-life logistics optimization project initiated from a US Fortune 500 manufacturing company, which operates more than 200 manufacturing factories and warehouses scattering in the wide geographic area of US. With more and more outscourcing and trade with China, the company has thousands of ocean containers enter US each month for distribution throughout US. Being faced with high inventory and high transportation costs, the company sought an optimization method to reduce their logistics costs. In this context, our research started with the integrated order consolidation strategies in a global network to explore the potential cost-saving opportunities. More issues on the integration of transportation and inventory were emerged and investigated during the project.

2. The growth in globalization and managerial challenge make our research important and necessary. We briefly discussed the growth of global trade and complex issues involved in the global supply chain in Section 1.1.1. In academia, several books (Dornier et al. (1998); Wood et al. (2002)) and papers (MacCarthy and Atthirawong (2003); Meixell and Gargeya (2005)) talk about the difficulties in managing and controlling global supply chains. Thus, it is necessary to explore some effective methods to improve its performance so that the multinational companies can benefit from it.

3. The increasing academic interests and trend on inter-functional integration of supply chain also motivate our work. There are lots of papers focusing on the integrations across different functions of the supply chain, such as procurement-production (Goyal and Deshmukh (1992); Munson and Rosenblatt (2001)), production-inventory (Yang and Wee (2002); Hwang et al. (2005); Hill and Omar (2006)), production-distribution (Chandra and Fisher (1994); Jayaraman and Pirkul (2001); Jang et al. (2002)) and transportation-inventory (Thomas and Griffin (1996); Bertazzi et al. (2005);Kang and Kim (2010)). And the

increasing trend also influences the design of the global supply chain. Some papers (Arntzen et al. (1995); Hadjinicola and Kumar (2002); Trent and Monczka (2003)) explore the value and need for integration of decisions in the global supply chain. Our study fits current research trends and is to investigate the value of integration of transportation, inventory and packing.

4. There are real industry needs, but relevant literature lacks in the proposed research area. Currently, companies are increasing global trades and outsourcing overseas. The most common problems they face are: how to transport cargoes from foreign countries to domestic destinations, and how to make replenishment more effective and efficient in terms of cost and service. Although these problems are crucial, to the best of our knowledge, there is few literature investigating the specific problem. Attanasio et al. (2007) work on the integrated shipment dispatching and packing problem in a case study. Crainic et al. (2009) firstly illustrate the concept: "proactive order consolidation" and apply bin packing model and simulation method to evaluate three strategies of the integration of inventory and transportation. However, there are several important issues which are not considered in their models, such as multi-modal transportation, the integration of transportation, packing and inventory. Our work tries to fill this gap.

1.5 Thesis Contributions

The contributions of our research are as follows:

1. We develop a series of mathematical models, which show the consolidation process in the international network with regard to several practical issues.

2. The approximation solution methodologies are proposed to solve the models.

Since all of our models combine several difficult combinatorial problems, no exact solution can be obtained even for small size problems. We propose approximation solution methodologies to disaggregate the problem into subproblems, and then to solve them iteratively. The methodologies can obtain good solutions within a satisfactory computational time.

3. The problem we investigate in the dissertation integrate many issues, such as bin packing problem, mode and route selection problem, inventory problem, which occur commonly in practice. However, there is few literature, which studies the integrated problem. Our models, methodologies and results can give some insights for academic and commercial industries.

1.6 Organization of the Thesis

The remainder of this dissertation is organized as follows. Chapter 2 gives a summarization of relevant literature. Specifically, four research areas are reviewed. They include global supply chain design models with consideration of the integration of decisions; models and algorithms for cargo loading and packing problems; models for freight consolidation strategies; and coordinated models for inventory and transportation.

Chapter 3 proposes an integrated and proactive order consolidation strategy in the global network and studies how logisticians effectively load items into ocean containers considering subsequent inland transportation planning given container capacity and packing constraints. In order to view the structure of the problem clearly, only single period and two transportation modes' direct delivery are taken into account in this chapter. A mixed integer linear programming model is formulated to minimize the total costs involved in the entire supply chain. The heuristics solution algorithms are developed and numerical examples are tested to evaluate different consolidation strategies.

Chapter 4 discusses more complicated but practical situations. In particular, we assume that shipments arrive at each time period in a finite planning horizon $t = 1, 2, \cdots, T$. The consolidation planner has some knowledge of future shipment arrival. Consequently, he has to make the consolidation and shipment dispatch plan at the beginning of the planning horizon considering future shipments in order to save costs as much as possible. A mixed integer programming model is formulated to solve the multi-period and multi-stop problem. A heuristic algorithm is developed to solve the large-scale problem.

Chapter 5 extends the model proposed in Chapter 3 and integrates TL multi-stop delivery and route selection into the model to explore further cost-saving opportunities. A modified model is proposed and the freight is consolidated into ocean containers with the consideration of subsequent inland transportation mode, route and stop selection. The objective is to minimize the total costs, including ocean container cost, handling cost, TL cost and LTL cost. The problem is constrained by ocean container capacity and freight packing.

The last chapter concludes our research and provides discussions on the future research direction.

Chapter 2

Literature Review

2.1 Introduction

Our work is to study how to improve the performance of the international supply chain through consolidation strategies. A series of issues are involved in the consolidation process, such as load planning problem, consolidation problem, packing problem, and integrated inventory and transportation problem. Hence, due to its relevance, a large amount of literature is reviewed in order to better understand the nature of the problem, the available research methodologies and solution algorithms in the field.

In this chapter, papers concerning consolidation models and strategies are introduced in Section 2.2. Section 2.3 summarizes different models and algorithms of the integrated inventory and transportation system. In Section 2.4, the literature on mode selection and routing models is reviewed. The studies considering cargo loading and bin packing problems are discussed in Section 2.4. At last, a summary is given in Section 2.5.

2.2 Consolidation Models

Consolidation is the process of combining different items, produced and used at different locations and different times, into single vehicle loads (Hall (1987)). Due to its importance and complexity, this topic has received a great deal of attention from academia and industry during the last three decades. The main motivation behind the studies is to take advantage of cost savings from economies of scale in transportation by combining several small shipments as a single load. The studies in the area are investigated in various aspects. Early research (the late 1980s and early 1990s) is primarily focused on simulations. During the period from the middle 1990s to present, a great amount of analytical papers come out. The methodologies based on mathematical models, such as mixed-integer programming and stochastic programming, are primary skills to study the problem. Different subjects of consolidation problems are explored. For example, some papers focus on order consolidation problem in the international context due to the growth of globalization. Some research has analyzed the tradeoffs between transportation and inventory costs of consolidation versus direct shipping. Some literature has investigated the optimal shipment dispatch policy through consolidation, for instance, determining the optimal dispatch quantity and timing, in the deterministic and stochastic settings. Other work discusses consolidation problems in the design of Hub-and-Spoke networks, for example, determining hub locations and assigning spokes to hubs. The following subsections summarize the work on consolidation models.

2.2.1 Initial Studies on Freight Consolidation

Initial studies on freight consolidation began in the early 1980s. Most papers use descriptive methodologies or simulation models to analyze shipment consolidation strategies and evaluate the effects of related factors with regard to the costs and service level.

Jackson (1981) studies consolidation strategies and develops a simulation approach to investigate major variables, such as the number of pool points, length of maximum holding time, and the shipment release strategies, involved in an order consolidation system. In the paper, a medium-sized national packaged goods distributor receiving daily orders with average size of 1,300 pounds is studied in a simulation experiment. A major finding of the paper is the sensitivity of order consolidation to the volume of orders, which has a big impact on the number of pool points, the holding time, and the shipment release strategies. The low-volume system has a longer and more variable order cycle. Longer cycle time leads to lower transportation costs. In addition, high volume of orders and a longer holding time make it possible to reduce transportation costs through the addition of pool points to the distribution network. However, a low volume system and short holding time cannot accumulate shipments of sufficient size to produce savings to the newly added points. For shipment release strategies, a combination of a scheduled- and weight-based policy is faster, but more costly than a schedule-based policy. The future research directions pointed out in the paper include the effects on system performance of the distribution of order weights, multiple shipping locations, inbound consolidation and international order consolidation.

Jackson (1985) surveys freight consolidation practices and illustrates the findings of a study of how and why order consolidation is practiced. A questionnaire is developed to survey fifty-three US business firms. According to the findings, cost reduction is the most important reason for engaging in consolidation. And its biggest disadvantage is more complex planning and operations. The common decisions involved in the consolidation practice include consolidated shipment dispatch rule, the number of pool points (hubs), transportation mode, the number of intermediate stops and distribution service. The combination of the choices is large and most of firms make the planning and operations manually. Thus, it is not easy to implement consolidation strategies optimally in the practice. Finally, it is mentioned that scientific and integrated approaches are needed to be developed in the future.

Hall (1987) groups the consolidation strategies into three categories which consist of inventory consolidation (over time), vehicle consolidation (over stops), and terminal consolidation (over space) and discusses the trade-offs between consolidation benefits and penalties. The main benefits are the lower transportation charges that come from larger load sizes. The penalties might include inventory costs, longer truck routes, transit time and handling costs. Common issues in the consolidation system include frequencies of vehicle dispatches, the number of stops, the number of terminals and the routing policy. It is concluded that a properly planned, rational, coordinated consolidation strategy can greatly reduce transportation costs without sacrificing quality.

Pooley and Stenger (1992b) evaluate and compare the logistical performance for a mix of multiple stop TL distribution strategy and standard LTL strategy. Five key factors, which affect logistics system performance, measured by total costs, are tested. They are mean order cycle, internal cycle time, geographic distribution of customer demand, carrier price levels, and type of network design model. Empirical data which came from two shippers are used. Results are obtained by applying a heuristic shipment consolidation algorithm, a simulation model, and a mixed integer mathematical programming model. Additionally, a 2^k full factorial experiment is designed to determine significance of the factors. Results show that LTL discount, increased internal cycle time, a larger mean order size result in lower unit costs. They also show that the geographic distribution of customer demand was relatively unimportant.

There are other papers in this period. For instance, Masters (1980) investigate the effects of freight consolidation on customer service. Cooper (1983), Closs and Cook (1987), Higginson and Bookbinder (1994) discuss consolidation problems using simulation tools. Burns et al. (1985), Blumenfeld et al. (1987) seek consolidation strategies to reduce logistics costs at General Motors.

2.2.2 International Order Consolidation

International order consolidation problems consider consolidation strategies in the international logistics network. These studies come out due to the growth of globalization and the recent trend of JIT (just-in-time) and OPT (optimized production technology) that emphasize small-quantity ordering (Popken (1994)). Most work is concerned with assigning shipments to airplanes or marine containers, selecting transportation mode and routes so that the total cost is minimized over the network.

Tyan et al. (2003) model and evaluate the freight consolidation policies in a global third party logistics network, where a global 3PL provider collects and consolidates products from a manufacturer in Taiwan and provides the door-to-door distribution service for B2B and B2C customers in US. Due to the feature of volatile demands in the build-to-order (BTO) and configuration-to-order (CTO) market, consolidation strategies are considered to reduce the total cost. Three different polices are proposed. Policy A represents the common as-is practice, where B2C orders are packed as loose cartons and B2B orders are packed as skids consisting of 40 cartoons. Policy B considers breaking skid shipments into a loose mode to increase unit-load-device (ULD) utilization. Policy C improves service level by loading the shipments which should be delivered the next day when the flight capacity is not full. Three linear programming models are developed based on these policies. Numerical analysis shows that policies B and C yield 6.7 percent of total cost savings over policy A. The service level measured by average cycle time shows that Policy B is better than Policy A by 2.4 percent, while policy C achieves a 20.2 percent better service level than policy A. The sensitivity analysis is performed on flight capacities, shipment volume, minimum ULD profit and the skid loaded ULDs load factor. The results show that the change of flight capacities affects allocations of shipments and the total costs. And the changes of shipment volume do not influence the total cost of different policies. Hence, it is implied that the selection of the consolidation policy will not be altered with volume fluctuations. Additionally, the analysis of changing ULD profit and load factor give valuable suggestions for policy A. The methodology and its managerial implications proposed in this paper are helpful for a distribution industry.

Attanasio et al. (2007) investigate a consolidation and dispatching problem when a multinational chemical company in Europe routinely decides the best way of delivering a set of orders to its customers over a multi-day planning horizon. The company makes decisions on the mode of the transportation (TL and LTL), consolidation plan, TL route and stops selection and loading plan. An integer linear programming model is developed based on the problem. Packing constraints are firstly relaxed using volume constraint, and thus a lower bound of the solution is obtained for the original problem. Infeasible solutions are pruned by feasibility checking with consideration of actual shipment packing. A constructive heuristic for two dimensional bin packing problems is proposed to pack items into truck. At last, the rolling horizon technique is used to improve the computational efficiency by reducing the problem size. The methodology proposed in the paper has been applied to solve a real-world problem. Results show that the algorithm achieves significant savings over the current manual procedure.

Crainic et al. (2009) study the proactive order consolidation strategy in the global retail supply chain. In the paper, the international procurement process, the roles and functions of merchandizing, purchasing and logistics in the supply are analyzed. Due to the disadvantages of a full-container-load (FCL) purchasing strategy, a order consolidation policy is proposed where small-volume orders are combined as FCL in order to maximize the utilization of the containers. A mathematical model for 1-BP problems is used to pack the items into the containers and a simulation approach is developed to evaluate three order strategies including a FCL ordering policy, a LCL ordering policy, and order consolidation policy. Results show that order consolidation policy is the most favorable policy, which achieves 4.6 percent cost savings over the second policy, and 7.5 percent savings over the first policy even though it has more ordering costs. In addition, the results also implies a FCL ordering policy is a bad choice for slow moving products.

2.2.3 Consolidation for Optimal Order Dispatch

Research on order dispatch through consolidation investigates the methods for determining the optimal quantity and timing of order dispatch. When shipments or customer orders arrive randomly, how long should they be held and/or what quantity should be accumulated before a consolidated load is released (Higginson and Bookbinder (1994))? When they are held, it is more possible for small shipments to aggregate into a larger load which can benefit from lower transportation cost per unit weight. However, inventory and customer waiting cost will incur and increase when more shipments are delayed. Thus, there exist a tradeoff between inventory and dispatch cost. This consolidation method is known as temporal (inventory) consolidation (Hall (1987); Higginson and Bookbinder (1995); Bookbinder and Higginson (2002); Cetinkaya and Bookbinder (2003); Ghiani et al. (2004)), and it is also implemented in VMI (Vendor Managed Inventory) practice which considers inbound inventory policy and outbound shipment dispatch.

Bookbinder and Higginson (2002) apply probabilistic approaches to the dispatch of vehicles in freight consolidation by private carriage. Stochastic clearing theory is employed to study a time-and-quantity policy. Under this policy, the shipments are dispatched based on two factors: a pre-determined shipping date and the accumulation of a fixed weight or volume. If the latter occurs first, the orders are dispatched before the specified release date. Otherwise, they are shipped on time. It is assumed that order weight is Ga-distributed and the arrivals form a Poisson process. This paper firstly recognize (via probability) a possible inability to obtain the target load in an acceptable time. Then a four-graph nomograph is developed to discuss the relationships between the optimal consolidation quantity, the acceptable cycle time, the probability and the cost structure. And nomograph is a simple tool to evaluate the impact of altering any factors.

Cetinkaya and Bookbinder (2003) develop stochastic models for the dispatch of consolidated shipments and derive the optimal solutions under two dispatch policies and two carriers, respectively. One dispatch policy is to send the combined load which are accumulated to a fixed weight (quantity policy), the other one is to ship them every fixed cycle (time policy). Two carriers consist of private carrier (shipments are moved in trucks owned or leased by the shipper) and commercial carrier (a commercial trucking company is hired). In their model, renewal theory is applied to obtain the optimal target weight or the optimal cycle length by minimizing the total cost including transportation cost and inventory cost. Some examples are developed assuming that shipment' arrival and the weight follow a Poisson process and exponential distribution, respectively. For private carriage, key results show that the expected dispatch quantity under time policy is larger than the optimal critical weight, but smaller than the mean load dispatched under the quantity policy. And quantity policy has a mean cycle length longer than that of the corresponding optimal time policy. So the time policy offers superior service to customers. For common carriage, the approximate solutions under time policy and quantity policy are summarized. And key results show that it is not necessary to consolidate shipments for some optimal quantity policy and time policy.

Chen et al. (2005) investigate an integrated inventory replenishment and temporal shipment consolidation problem in context of VMI. A vendor controls its own inventory according to (R, Q) inventory replenishment policy, and fulfills customer orders based on one of two policies: time-based and quantity-based consolidation policies. The objective of this study is to compare the two order-dispatch policies and find which one is cost-effective. The total cost consists of four cost component: cost of replenishing inventory, cost of dispatching shipment to customers, inventory carrying cost and customer waiting cost. The results of numerical experiment show the quantity-based policy always outperforms the time-based policy because the time-based policy will result in higher customer waiting costs. Other papers, such as Gupta and Bagchi (1987), Cetinkaya and Lee (2000), Cetinkaya (2005),Cetinkaya et al. (2006), and Mutlu and Cetinkaya (2010), also work on this topic. Readers can refer to these papers for extensive understanding.

2.2.4 Network and Other Consolidation Models

Network consolidation problems study consolidation strategies in the Hub-and-Spoke network. Research in this subject concerns how to locate hubs and how to assign spokes to hubs so that the total cost of transporting shipments from origin to destination is minimized. This problem has wide applications in air transportation, LTL transportation, and telecommunications. O'Kelly (1986a,b, 1987) begin the studies in this area and investigate single-hub and two-hub network using mathematical models in airline passenger networks. Powell and Sheffi (1989) explored loading planning problem, such as how to route the shipments from origin to intermediate hubs to destination, in the LTL transportation industry. Campbell (1992, 1994a,b, 1996) and Campbell et al. (2005a,b) present a series of models for hub location problems.

In other studies, Popken (1994) studies an inbound freight consolidation problem at transshipment points in a multi-commodity and multi-attribute flow network where commodities are shipped between origin and destination through a maximum of one transshipment terminal. Each commodity has three attributes: weight, volume, and inventory holding cost. And each vehicle has weight and capacity constraints. A non-linear programming model is developed. And the objective is to determine the vehicle and commodity flows that minimize vehicle and inventory holding costs, while satisfying demand requirements. Service level considerations are included via inventory holding costs. Since the nonlinear structure of cost function results in multiple local optima, a heuristic algorithm is presented to make local improvements for a local optimum. The algorithm is evaluated by comparing the solutions with those from MINOS mathematical programming software, and results show that the proposed algorithm could obtain good solutions. At last, a series of numerical examples are created to test the benefits of the multi-attribute (weight and volume constraints) formulation compared with a formulation only considering weight constraints. The results indicate a significant relative advantage in using a technique that considers both weight and volume constraints in achieving a solution; the change of inventory holding cost have little effect on the relative advantage of the multi-attribute method. With the average weight per commodity flow increase, the advantage decreases.

2.3 Integrated Inventory and Transportation Models

The integration of inventory and transportation is critical to improve the performance of supply chain. The research on this integration concerns two aspects of the joint decisions. One is from inventory policy, and the other one is from transportation policy. Inventory policy involves the determinations on replenishment quantity, frequency, safety stock and inventory allocation on vehicles. For transportation policy, decisions need to be made on mode and route selection, the assignment of vehicles on the route, and the visiting sequence of customers on the route. Usually, the decisions on the two aspects are simultaneously made to minimize the total cost. Among reviewed literature, some studies (Cetinkaya and Lee (2000, 2002); Chen et al. (2005); Moon and Park (2008); Moon et al. (2011)) deal with the problems on the replenishment of inbound shipments and the dispatch of outbound orders, which have applications in the VMI practice. Some papers (Qu et al. (1999); Kang and Kim (2010); Moin and Salhi (2007)) focus on inventory routing problems, where the inventory allocation and vehicle routing are solved.

Qu et al. (1999) investigate an integrated inventory-transportation approach for an inbound material-collection problem with multi-items, multi-suppliers and stochastic demand over a time horizon. They consider the network which consists of a central warehouse (where all stock are kept) and several geographically dispersed suppliers. The central warehouse makes the replenishment by dispatching vehicles to collect the goods from vendors. And the vehicles with unlimited capacity make round trips which start from the warehouse and end there. The total cost incurred consists of the transportation cost, which includes stopover and routing costs, and the inventory cost, which includes ordering, holding and backlog costs. Based on the problem, a mathematical model is formulated to determine optimal periodic inventory policy and vehicles routing patterns that enables the warehouse to meet its demand at minimum long-run total cost per unit time. The solution method for the model is to decompose the model into two parts: an inventory problem as a master problem, and a transportation problem as a subproblem. An inventory problem is solved item by item and a transportation problem is solved period by period. And the overall model is solved by iterating between these two problems. The lower bounds for the original problem and the special case when each supplier provide exactly one item are constructed to evaluate the effectiveness of the heuristic solution algorithm. The results of numerical examples demonstrate that the solution method could achieve satisfactory results. At last, large scale problems are tested using the method. The computational results show that the heuristic method is more effective when there are more items in the system with a given number of suppliers. They also conclude that their method could applies to practical problems.

Cetinkaya and Lee (2002) present an optimization model for coordinating inventory and transportation decisions at an outbound distribution warehouse that needs to fulfil the orders of downstream supply chain members in a given area. The warehouse keeps all the inventory and downstream customers carries zero inventory. With the knowledge of deterministic customer demands and the motivation of cost-savings, the warehouse need to make decisions on the replenishment policy and freight consolidation simultaneously. In their work, two questions are addressed: (1) how often to dispatch a truck so that transportation scale economies are realized and timely delivery requirements are met. (2) how often, and in what quantities, the stock should be replenished at the warehouse. In order to solve these two questions effectively, a mathematical model is developed with the objective of minimizing the total cost, including inventory replenishment cost, inventory carrying cost, customer waiting cost and outbound transportation cost. An approximate and exact algorithms are presented for computing the policy parameters for both the uncapacitated and finite cargo capacity problems. Numerical examples are generated to compare the approximate and the exact algorithm. Some insights about the sensitivity of the other optimal solution parameters to the model are also discussed.

Moon et al. (2011) explore a multi-item joint replenishment and freight consolidation problem for a third party warehouse. The warehouse order multiple (n different types) item from multiple suppliers and then fulfill customer' order. This paper addresses three questions: (1) what is the basic replenishment cycle for the warehouse? (2) what is the replenishment cycle for each item? (3) what is the cycle for outbound delivery schedule for each item? Two delivery policies are discussed. Under stationary policy, customer orders are delivered on a fixed interval. The quasi-stationary policy is where the successive interval is changed over time. Four heuristic algorithms are developed to obtain the near optimal decisions for these two policies. Numerical examples are tested to evaluate the performance of the heuristic algorithms and two policies. Experimental results illustrate that the quasi-stationary policy is better than the stationary policy due to cheaper transportation cost while not affecting customer service. Besides, the proposed algorithm gives better solutions than the common cycle approach.

Kang and Kim (2010) work over the integrated inventory and transportation managements in a two-level supply chain which consist of a single supplier and multiple retailers. In the network, the supplier manage the inventory of retailers, and dispatch trucks to make replenishment for retailers. Each dispatched truck has to visit multiple retailers in a single trip. Thus, the supplier has to determine the replenishment quantities and the frequencies for each retailer as well as the quantity delivered to the retailers by each vehicle. The objective is to minimize total cost, including fixed vehicle cost, retailer-dependent material handling cost, and the inventory cost of the whole supply chain. A mixed integer programming model is formulated and two-phrase heuristic algorithms are developed for solving the problem. In the first phrase, the replenishment quantities are determined, and eight solution algorithms, such as lot sizing algorithms of Wagner and Whitin (1958), Silver and Meal (1973), Lambert and Luss (1982) and etc., are applied. In the second phrase, the shipments of the replenishment quantities are assigned to the vehicles, and a modified FFD algorithm for 1-BP problems are used for shipment assignments. Numerical examples are tested to evaluate the performance of the heuristic algorithm suggested in the study. The results show that the algorithms provide good solutions in a reasonable time.

2.4 Mode Selection and Routing Models

Since in the Chapter 4, the mode and route selection are integrated in our consolidation model, some relevant papers are reviewed. Research on this topic seeks an optimal strategy to deliver shipments from a single source (central warehouse) to local customers by two alternative transportation modes, TL and/or LTL, with the objective of minimal total cost. The decisions involved in the problem include TL/LTL mode selection, assignment of shipments to TL, and TL route selection. Most heuristic algorithms in the reviewed literature apply and modify the savings algorithm of Clarke and Wright (1964).

Pooley and Stenger (1992a) presents a heuristic algorithm to solve the problem of selecting mode between a multiple-stop TL and LTL, assigning a shipment to a TL vehicles, and sequencing the stops for a TL vehicle, where TL is one-way delivery from origin to local customers. It is proved in the paper, due to combinatorial complexity, this problem is more difficult to solve than a basic vehicle routing problem (VRP). The heuristic algorithm proposed is based on the savings algorithm of Clarke-Wright. For the characteristic of the specific problem, three modifications on the Clarke-Wright method are made. (1) the proposed algorithm is based on cost analysis instead of original distance measurement. (2) saving formula is changed. (3) processing logic is altered. In the multiple-stop TL versus LTL problem, the algorithm needs to test if the shipper's consolidation savings from a multiple-stop TL vehicles exceed its cost. While in the original method, a routed truck needs to visit all the destinations, and only the sequence of visiting need to be decided. The algorithm is beneficial for the companies which deliver their most shipments using LTL and much more efficient than manual generated shipping pattern. Pooley (1993) applies a simulation to explore the effect of LTL pricing discounts on the LTL versus multiple-stop TL carrier selection decision. Results from the study show that the discount of LTL can result in the increase of LTL loads.

Chu (2005) studies the problem of mode selection between LTL and TL for outbound shipments. For TL mode, private trucks are used to customers for delivery, and then back to the warehouse (a round-trip delivery). For LTL mode, a outsider carrier is used. The objective is to develop a heuristic algorithm to route the private trucks and to select LTL by minimizing a total cost. The mixed integer programming model and the algorithm are proposed based on the problem. The algorithm is also based on the Clarke and Wright's savings algorithm. The modifications include cost criterion and saving calculation. The main steps of the heuristic algorithm are: (1) select customers served by LTL. (2) construct the initial routes for TL using modified Clarke and Wright's savings algorithm. (3) use local improvement heuristic to improve the solution. The results of computational results show that the heuristic algorithm obtains the optimal or near-optimal solutions.

Bolduc et al. (2007) investigate the same problem with Chu (2005). He proposes a more efficient and effective algorithm. Different from the algorithm of Chu (2005), he constructs two initial solutions by implementing sequentially and parallelly the modified Clarke-Wright algorithm, respectively, and then make local improvements by using 4-opt heuristic for both initial solutions, and at last choose the better solution as final solutions among improved solutions. Computational results show the algorithm performs well in terms of time and accuracy.

2.5 Bin-Packing Models and Algorithms

Since our work concerns packing constraints in our model, the general area of bin packing problems is relevant. Below, we provide brief literature review on bin packing models and algorithms. Bin packing models is to solve the problems, where given a set of items and an unlimited number of identical bins with finite capacity, how are items allocated into the bins so that the number of required bins is minimized. They can be classified into three categories according to the number of parameters needed to characterize an item and bin (Ghiani et al. (2004)).

1. One-dimension packing (1-BP) problem. It deals with weight-oriented (high-

density) or volume-oriented (low-density) items, where weight or volume is binding. For example, if loading weight-oriented items into containers or trucks, items can be characterized just by their weight, without any considerations with their length, width and height, and vice versa for volume-oriented items.

2. Two-dimension packing (2-BP) problem. In this case, items and bin are only characterized by length and width. And it is about to load a set of rectangular items to larger rectangular standardized bin by minimizing the waste. It has the industrial applications in wood or glass industries, warehousing and newspapers paging (Lodi et al. (2002)). It is also applied in cargo loading when loading pallets with items having the same height (Ghiani et al. (2004)).

3. Three-dimension packing (3-BP) problem. It deals with loading three-dimensional rectangular items into identical three-dimensional bins. It has applications in container/ truck loading and packaging design. In many cases, it arises as a subproblem. Our work focuses on three-dimension packing problem.

All the bin packing problems are strongly NP-hard problems (Martello et al. (2000); Lodi et al. (2002)). The mathematical model for 1-BP problem is formulated as follows. Take loading weight-oriented items into container as an example. Given I items, each item $i \in I$ with a weight f_i, and J (or an upper bound on the number of containers) containers, each $j \in J$ with weight capacity F. The decision variable is $x_{ij}, i \in I, j \in J$, which is a binary variable and equal to 1 when the item i is allocated into the container j, and 0 otherwise. And $y_j, j \in J$ is a binary variable and equal to 1 when the bin j is used, and 0 otherwise.

Minimize

$$\sum_{j \in J} y_j \tag{2.1}$$

subject to:

$$\sum_{j \in J} x_{ij} = 1, \qquad \forall i \in I \tag{2.2}$$

$$\sum_{i \in I} f_i x_{ij} \leq F y_j, \qquad \forall j \in J \tag{2.3}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J \tag{2.4}$$

$$y_j \in \{0, 1\}, \qquad \forall j \in J \tag{2.5}$$

The objective function (2.1) is to minimize the number of required bins. Constraints (2.2) state that each item is assigned to exactly one container. Constraints (2.3) ensure that the item i cannot be loaded into the container j unless it is used and the total weight carried in the container must not exceed its weight capacity F. Constraints (2.4) and (2.5) guarantee x_{ij} and y_j are binary variables.

A lower bound $\underline{z}$ on the number of bins in any 1-BP solutions is $\underline{z} = \lceil \sum_{i \in I} f_i / F \rceil$. 1-BP problem is a NP-hard problem (Karp (2010); Coffman Jr. et al. (1997)). Lots of papers use heuristic algorithms to get approximate solutions efficiently. Two of the fastest heuristics are First-Fit Decreasing (FFD) and Best-Fit Decreasing(BFD) greedy algorithms, which have been shown to use at most 22.2 percent more bins than required by the optimal solution (Martello and Toth (1990); Ben-Khedher and Yano (1994)). In the FFD algorithm, the items are sorted by weight in a non-increasing order, and iteratively are assigned to the bin where its residual capacity is greater than or equal to the item's weight, and if the item will not fit into any non-empty bin, a new bin is started. BFD algorithm is similar to FFD, and the only difference is in BFD, item is inserted to the bin with a residual capacity greater and much closer to the item's weight (best fit).

For 2-BP problems, the lower bound $\underline{z}$ on the number of bins is $\underline{z} = \lceil (l_1 w_1 + l_2 w_2 + \cdots + l_m w_m) / LW \rceil$, given L and W, l_i and w_i are the length and width of bins and items, respectively. Currently 2-BP problems are well-studied. Lots of papers investigate the exact and approximate algorithms. Lodi et al. (2002) summarize the mathematical models, classical approximation algorithms, recent heuristic and metaheuristic methods and exact enumerative approaches. Most algorithms are based on the idea of forming layers of items inside the bins. The width of each layer is W, equal to the width of the bin, and the length of each layer is the longest length of the item in that layer. Berkey and Wang (1987) study two approaches for 2-BP problems. One is finite first fit algorithm (FFF), the other is finite bottom-left (FBL) algorithm. FFF is to sort the items by length in a non-increasing order, and then sequentially assign the item into the left-bottom of first layer of the first bin, and create a new layer if the current layer cannot fit the items, and start a new bin if no layer can be used in current bins. In FBL, the items are sorted by non-increasing length and assigned to the bin in the lowest and leftmost position, and a new bin is started if no such bin exists. Chung et al. (1982) propose a two-phase approach to solve 2-BP problems. In the first phrase, it is assumed that items are packed in one bin with the width W and infinite length. And items are packed into the bin using modified FFF algorithm in order to minimize the length of the bin. So at the end of the first phrase, the bin is composed of layers with the same width and different length. In the second phrase, each layer is considered as a big item, and FFD algorithm for 1-BP problems is applied to provide the solution for 2-BP problems.

For 3-BP problems, the simple continuous lower bound $\underline{z}$ on the number of bins is $\underline{z} = \lceil (l_1 w_1 h_1 + l_2 w_2 h_2 + \cdots + l_m w_m h_m)/LWH \rceil$, given L, W and H, l_i, w_i and h_i are the length, width and hight of bins and items, respectively. Chen et al. (1995) use the exact method to solve 3-BP problems in container loading. In his paper, a mixed integer programming model is developed and numerical examples are tested to validate the model. Martello et al. (2000) investigate an exact and approximation algorithms for 3-BP problems. The exact algorithm is two-phrased. During the first phrase, the items are assigned into bins without considering their actual position using a branch-and-bound algorithm. Under the second phrase, the algorithm to fill a single bin is applied to determine the position of items. Lodi et al. (2002, 2004) introduce a Tabu search framework for 3-BP problems and provide a unified Tabu search code for two- and three-dimensional bin packing problems. Ghiani et al. (2004) discuss a two-phrase heuristic algorithm for this problem. In the first phrase, items are firstly sorted by volumes in a non-increasing order. And then items are assigned into bins according to the algorithms for 2-BP problems characterized by the hight and width of items and bins. The floor of the first layer is the surface ($W \times H$) of the bin. The floor of subsequent layer in the bin is equal to the length of the largest item. In the second phrase, 1-BP problem associate with the floors is solved.

2.6 Summary

In this chapter we review and summarize a large amount of literature related to our topic. The consolidation problem investigated in this dissertation integrates several issues, such as freight consolidation, transportation mode selection, routing, bin packing and inventory management. Hence, the relevant literature reviewed is classified into four categories, consolidation models, integrated inventory and transportation models, mode selection and routing models and bin packing models and algorithms.

Initial consolidation studies focus on descriptive methodologies and simulations to identify the value of consolidation strategies and evaluate the related factors which affect cost and service level, such as the length of holding time, shipment release strategies and the type of network. The current literature has mostly focused on mathematical models to study the problem. Some papers concern order consolidation problem in the international network; Some literature discusses the optimal shipment release strategies during consolidation; Other research has investigated the optimization of distribution network design, for example, determining the optimal number of hubs and assigning spokes to hubs.

The literature on integrated inventory and transportation models studies effects of joint decisions on the system performance. Most papers work on the inbound material-collection and outbound freight distribution problems. The joint decisions includes how to determine replenishment quantity, frequency, safety stock, transportation mode and routing selection and the sequence of customer visiting, and etc. The common methodologies among the literature are mathematical models and heuristic algorithms.

Research on mode selection and routing models seeks an optimal strategy to deliver shipments from a single source (central warehouse) to local customers and then go back to warehouse by two alternative transportation modes, TL and/or LTL, with the objective of minimal total cost. The decisions involved in the problem include TL/LTL mode selection, assignment of shipments to TL, and TL route selection. Most heuristic algorithms in the reviewed literature are based on the savings algorithm of Clarke-Wright, and some more efficient algorithms are also proposed.

Bin packing models are used to evaluate problems, where items are to be allocated into identified bins so that the number of required bins is minimized. Bin packing problems include one-, two- and three-dimensional bin packing problems based on dimensions considered while packing. Bin packing problems are known to be strongly NP-hard problems. Therefore, only small-size problems can be solved exactly. As such, much research has focused on heuristic and meta-heuristic algorithms to solve the problems.

By reviewing through the relevant literature, we find that the integrated problem of consolidation, three-dimensional, mode and route selection and inventory management, are rarely studied although some aspects of the problem have been mentioned. In the following chapters, we will present the models and algorithms to better integrate these planning aspects.

Chapter 3

An Integrated Consolidation Model for Single Period and Direct Delivery

3.1 Introduction

In this chapter, an integrated multi-commodity consolidation problem is considered in the global supply chain network, which consists of overseas suppliers, one overseas consolidation center, one US deconsolidation center and multiple US manufacturing plants and distribution centers. In the network, a US manufacturing company operates more than 200 manufacturing factories and warehouses, called branches, scattered around the wide geographic area from east coast to west coast. Each branch purchases parts or finished products from China according to a frequent and small-volume replenishment policy to keep low inventory. The parts and finished products are not homogeneous and have different sizes and shapes. The commodities ordered by each branch are collected and consolidated into ocean containers in the overseas consolidation center. They are then shipped to the US deconsolidation center, where the commodities are broken down and are delivered to their final destinations by road transportation. Two alternative road transportation modes, such as LTL and TL, are taken into account. Different modes are chosen according to the shipment's quantity, size and cost. In this chapter, we consider LTL and TL direct delivery without stops during a trip. The decisions to be made for this problem include:

1. the number of ocean containers used

2. the assignment of multi-commodities to the ocean containers

3. the TL and LTL mode selection for final delivery

The goal of our approach is to develop a cost-effective consolidation method to transport international shipments in the global network. Thus, the objective in the model is to minimize the total costs involved in the global supply chain, including ocean container costs, handling costs, TL and LTL costs. Ocean container costs are the costs of shipping containers from China to US. Handling costs are incurred during unloading/loading shipments from containers onto the trucks. A fixed handling cost incur for shipments to the same destinations in the same container. Inland transportation costs consist of both TL costs and LTL costs. The TL mode is often preferable if the shipments to the same destination are heavy or big. Otherwise, it may be more economical to choose LTL for delivery.

The proposed method in this chapter is a proactive consolidation strategy, which makes consolidation planning at the early stage of the supply chain. Commodities to different branches are effectively grouped and loaded into ocean containers considering final destinations before they are shipped to US. Consequently, once ocean containers arrive at US, commodities already grouped in China could be directly reloaded into trucks for final delivery based on the predetermined distribution plan. No additional sorting or storage procedures are needed during the US deconsolidation. This saves transit time and ensures timely delivery to the final destinations. Furthermore, it eliminates handling and storage costs, which could be significant at the expensive

US deconsolidation sites. If shipments are randomly loaded without a consolidation planning, and handling/ sorting processes in China , the road transportation costs in US will significantly increase due to more frequent LTL deliveries. Therefore, an effective order consolidation in a proactive way could achieve significant cost savings compared to other strategies. In Section 3.5, some examples and numerical analysis show the comparison results for different consolidation planning strategies.

The concept of "proactive order consolidation" is introduced by Crainic et al. (2009). In their paper, a one-dimensional bin packing model is used to effectively group the orders from several suppliers and a simulation approach is developed to compare order consolidation strategies with a full-container ordering strategy. They conclude that an order consolidation strategy could save substantial costs on inventory and transportation. Attanasio et al. (2007) investigate the integrated shipment dispatching and packing problems in a case study. In their model, TL & LTL selection and bin packing constraints are considered. A cutting plane method and a constructive heuristic are developed for the packing problem. A rolling horizon technique is also used to reduce the problem size. The methodology proposed in the paper has been applied to solve a real-world problem. Results show that the algorithm achieves significant cost savings over the current manual procedure. Tyan et al. (2003) model and evaluate the freight consolidation policies in global third party logistics network, and discuss the managerial implications from the proposed policies.

Our method also integrates the problem of selection between LTL and TL mode. Selecting right mode to transport shipments might bring significant cost savings to the company. However, there is little research in this area. Pooley and Stenger (1992b); Pooley (1993) investigates the problem on LTL VS. multi-stop and one-way TL problem. He analyzes the differences between this problem with a general routing problem, and modifies Clarke and Wright vehicle routing algorithm to solve the problem. Chu (2005) works on a problem of LTL & TL routing problem, presents a mathematical model and a heuristic algorithm to solve the mode selection problem. Results show that his algorithm obtains the optimal or near-optimal solutions in an efficient way in terms of time and accuracy. Bolduc et al. (2007) study the same problem with Chu (2005), and improve their algorithm and get better performance. Côté and Potvin (2009) apply a Tabu search heuristic to solve the vehicle routing problem with private fleet (TL) and common carrier (LTL).

There is other literature concerning consolidation problems in the different aspects. For example, some papers (O'Kelly (1986a,b, 1987); Klincewicz (1991); Campbell (1996), Campbell et al. (2005a,b); Yoon and Current (2008); Cunha and Silva (2007); Wagner and Whitin (1958); Alumur and Kara (2008)) discuss the consolidation problem in a Hub-and-Spoke network, where hub location problem, hub arc location problem and node assignments are mostly explored and optimized. Other papers (Higginson and Bookbinder (1995); Bookbinder and Higginson (2002); Cetinkaya and Bookbinder (2003); Cetinkaya (2005); Chen et al. (2005)) work on the optimal shipments dispatch strategy for the consolidation problem. Time-based consolidation policies, quantity-based consolidation policies, and hybrid consolidation policies are investigated to determine the tradeoffs between the inventory costs and transportation costs.

Our work is different from existing research in three aspects. First, the consolidation problem is studied in the international and multi-modal logistics network. In our study, marine and road (TL and LTL) transportation modes are used to transport freight from China to multiple destinations in US, while other studies consider only single transportation mode. For example, Tyan et al. (2003), Attanasio et al. (2007) and Crainic et al. (2009) investigate the international consolidation problem with air, road and marine transportation mode, respectively. Second, more issues are integrated into our mathematical model, such as mode selection, three-dimensional bin packing problem and handling operations. The integrated issues can help explore more potential opportunities for cost reduction and real-world logistics problems. Third, we consider the multi-commodity shipment flows in our model. The attributes of commodities include: weight, shape (length, width and height), and corresponding LTL transportation cost. In addition, a CzarLite software is used for the estimation of LTL rate rather than an assumed LTL rate.

The remainder of this chapter is organized as follows. Next, in Section 3.2, a mixed integer program formulation for our problem is developed. In Section 3.3, we make the model approximation. In Section 3.4, model complexity is analyzed. In Section 3.5, a special case based on the original problem is presented. In Section 3.6, general algorithm is proposed for large scale problem. In the last section, some examples are tested to evaluate different strategies and compare the cost savings.

3.2 Mathematical Model

In this section, a mathematical formulation of the problem is presented. The objective in the model is to minimize the total costs including ocean container shipping cost, handling cost and inland transportation cost, such as TL and LTL cost. In addition, the container capacity constraints and shipments packing constraints are considered. The total weight of shipments in each container must not exceed the container capacity. And also the shipments in each container must be feasibly (non-overlapping) packed into a loading space of length L, width W and height H. Definitions of variables and a mathematical model are presented in the next subsections.

3.2.1 Variables and Parameters Definitions

In order to develop a mathematical model, the notations for variables and parameters are given as follows.

Parameters definitions:

I: a set of shipments;

J: a set of available containers;

K: a set of destinations;

e_i: the volume of shipment $i \in I$;

f_i: the weight of shipment $i \in I$;

(s_i^l, s_i^w, s_i^h): length, width and height of shipment i;

E: the volume capacity of a standard ocean container;

F: the weight capacity of a standard ocean container;

(L, W, H): length, width and height of a standard ocean container;

$d_{ik} = 1$: if shipment $i \in I$ is assigned to destination $k \in K$, and 0 otherwise;

C^{OC}: unit ocean container cost from China to US;

C^H: handling cost for shipments to one destination within a container;

C_k^{TL}: TL transportation cost from the US deconsolidation center to destination $k \in K$;

$C_k^{LTL}(v, w)$: LTL transportation cost from the US deconsolidation center to destination k for a shipment with volume v and weight w;

M: an arbitrary large number;

Decision variables:

x_{ij}: a binary type having a value equal to 1 if shipment $i \in I$ is loaded into container $j \in J$, and 0 otherwise;

y_j: a binary variable equal to 1 if container $j \in J$ is used, and 0 otherwise;

z_{jk}: a binary variable equal to 1 if handling cost to destination $k \in K$ is incurred in container $j \in J$, and 0 otherwise;

u_{jk}: a binary variable equal to 1 if using TL to deliver the shipments which are in container $j \in J$ and to destination $k \in K$, and 0 otherwise;

v_{jk}: the volume of the shipments in container $j \in J$ to destination $k \in K$, which are transported by LTL.

w_{jk}: the weight of the shipments in container $j \in J$ to destination $k \in K$, which are transported by LTL.

(cx_i, cy_i, cz_i): continuous variables indicating the coordinates of the front-left bottom corner of box $i \in I$;

$a_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the left of the shipment $i' \in I$, and 0 otherwise;

$b_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the right of the shipment $i' \in I$, and 0 otherwise;

$c_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the behind of the shipment $i' \in I$, and 0 otherwise;

$o_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the front of the shipment $i' \in I$, and 0 otherwise;

$p_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the below of the shipment $i' \in I$, and 0 otherwise;

$q_{ii'}$: a binary variable equal to 1 if the shipment $i \in I$ is on the above of the shipment $i' \in I$, and 0 otherwise;

3.2.2 Model Formulation

The integrated shipment consolidation and dispatch problem with container capacity and packing restrictions can be formulated as:

Minimize

$$\sum_{j \in J} C^{OC} y_j + \sum_{j \in J} \sum_{k \in K} C^H z_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{TL} u_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{LTL}(v_{jk}, w_{jk}) \qquad (3.1)$$

Subject to:

$$\sum_{j\in J} x_{ij} = 1, \qquad \forall i \in I \tag{3.2}$$

$$x_{ij} \leq y_j, \qquad \forall i \in I, \quad \forall j \in J \tag{3.3}$$

$$\sum_{i\in I} x_{ij} f_i \leq F, \qquad \forall j \in J \tag{3.4}$$

$$cx_i + s_i^l \leq cx_{i'} + (1 - a_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.5}$$

$$cx_{i'} + s_{i'}^l \leq cx_i + (1 - b_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.6}$$

$$cy_i + s_i^w \leq cy_{i'} + (1 - c_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.7}$$

$$cy_{i'} + s_{i'}^w \leq cy_i + (1 - o_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.8}$$

$$cz_i + s_i^h \leq cz_{i'} + (1 - p_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.9}$$

$$cz_{i'} + s_{i'}^h \leq cz_i + (1 - q_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.10}$$

$$a_{ii'} + b_{ii'} + c_{ii'} + o_{ii'} + p_{ii'} + q_{ii'} \geq x_{ij} + x_{i'j} - 1, \quad \forall i, i^{'} \in I, i < i^{'}, \quad \forall j \in J \tag{3.11}$$

$$cx_i + s_i^l \leq L, \qquad \forall i \in I \tag{3.12}$$

$$cy_i + s_i^w \leq W, \qquad \forall i \in I \tag{3.13}$$

$$cz_i + s_i^h \leq H, \qquad \forall i \in I \tag{3.14}$$

$$Mz_{jk} \geq \sum_{i\in I} x_{ij} d_{ik}, \qquad \forall j \in J, \quad \forall k \in K \tag{3.15}$$

$$Mu_{jk} + v_{jk} \geq \sum_{i\in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \tag{3.16}$$

$$Mu_{jk} + w_{jk} \geq \sum_{i\in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \tag{3.17}$$

$$x_{ij}, y_j, z_{jk}, u_{jk} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J, \forall k \in K \tag{3.18}$$

$$a_{ii'}, b_{ii'}, c_{ii'}, o_{ii'}, p_{ii'}, q_{ii'} \in \{0, 1\}, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{3.19}$$

$$v_{jk}, w_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{3.20}$$

$$cx_i, cy_i, cz_i \geq 0, \qquad \forall i \in I \tag{3.21}$$

In this formulation, the objective function (3.1) minimizes the total costs which include the ocean container shipping cost, handling cost and inland transportation cost. The first term in (3.1) is a linear ocean container shipping cost where $\sum_{j\in J} y_j$ is the total number of ocean containers used. The second term in (3.1) is handling cost. The handling cost occurs proportionally to the number of destinations shipped in each container. The last two terms in (3.1) are inland transportation costs. The company has two alternatives for delivering a set of shipments, such as TL and LTL modes. TL pricing is relatively simple because its rate is typically given as per-mile cost depending on the given geographic regions of origin and destination. So C_k^{TL} is used as the fixed TL cost from the US deconsolidation center to destination k. On the other hand, the LTL pricing is very complicated in practice. Generally speaking, LTL rate depends on the delivery distance, geographic region, the shipment weight and its determined class based on density. Hence, in our objective function, $C_k^{LTL}(v_{jk}, w_{jk})$ represents the LTL cost of shipments with volume v_{jk} and weight w_{jk} delivered to destination k.

Constraints (3.2) state that each shipment is assigned to exactly one container. Constraints (3.3) ensure that shipment i cannot be loaded into container j unless it is selected for use. Constraints (3.4) guarantee that the total weight carried in the container must not exceed its weight capacity F. Constraints (3.5)$\sim$(3.14) are three dimensional packing constraints. For the sake of simplicity, we assume the shipments in the container cannot rotate or translate and are placed in a fixed orientation. If more orientations are considered, nine new decision variables need to be added (Chen et al. (1995)). Specifically, Constraints (3.5)$\sim$(3.10) stipulate that any two shipments in the same container must not overlap each other. Constraints (3.11) shows that the placement relationship between any two shipments only exists if they are loaded into the same container. Constraints (3.12)$\sim$(3.14) ensure that all the shipments loaded in a container don't violate the geometric dimensions (length, width and height) of the container. Constraints (3.15) ensure the conditions of handling cost incurred. Because shipments to the same destination are grouped together as one batch, the handling procedure is needed only once (i.e., $z_{jk} = 1$) as long as there are shipments in container j to destination k, and 0 otherwise. Constraints (3.16)∼(3.17) select the inland transportation mode such as TL and LTL. These two transportation modes are mutually exclusive for given shipments with destination k in container j. If TL mode is selected (i.e., $u_{jk} = 1$), then both volume and weight variables (v_{jk} and w_{jk}) become zero to minimize the total cost. On the other hand, if LTL mode is selected, v_{jk} and w_{jk} represent appropriate volume and weight, respectively, of shipments with destination k in container j. Constraints (3.18)∼(3.21) define the types of decision variables.

3.3 Model Complexity Analysis

The mathematical model (3.1)∼(3.21) is a non-linear mixed integer programming model, which optimally solves the three dimensional packing problem and the mode selection problem together in the international consolidation context. Its size complexity, which indicates how large a problem is, depends on the number of decision variables and constraints in the problem. For example, for the case of 100 shipments, 4 ocean containers, and 5 final destinations, there are 100×4 variables for x_{ij}, 4 for y_j, 4×5 for z_{jk}, u_{jk}, v_{jk} and w_{jk}, 100 for cx_i, cy_i and cz_i, and $(99 + 98 + \cdots + 1)$ variables for $a_{ii'}$, $b_{ii'}$, $c_{ii'}$, $d_{ii'}$, $p_{ii'}$ and $q_{ii'}$. Hence, there are $30,144$ binary variables and 340 continuous variables. In total, there exist $2^{30,144} (\approx 10^{9,074})$ possible integer solutions. In addition, there are $51,264$ constraints. For a general case with m shipments, n containers, and k destinations, there are $3m^2 + mn + 2nk + n - 3m$ binary variables, $2nk + 3m$ continuous variables, $\frac{1}{2}m^2n + 3m^2 + \frac{7}{2}mn + 3nk - 2m$ constraints. The number of possible integer solutions is $2^{3m^2+mn+2nk+n-3m}$, which increases exponentially as m, n and k increase. Thus, in the worst case, it takes exponential time to find an optimal solution using enumerative techniques.

Currently, several commercial software packages exist to solve mixed integer programming models, such as CPLEX, Gurobi, and LINGO. CPLEX uses the branch-and-cut algorithm with some pre-solving techniques, cutting planes, search strategies, and heuristic techniques to solve mixed integer programming models (MIP). Gurobi is a high-performance optimization software package for linear programming, quadratic programming and mixed-integer programming. It uses multi-core processors and parallel processing, and could solve difficult problems fast. Gurobi Optimizer uses cutting planes and heuristics algorithms to solve MIP. LINGO uses the branch and bound algorithm to find solutions for MIP. Usually, it takes much longer time to find solutions than CPLEX and Gurobi. According to Mittelmann benchmark tests on various MIP solvers, including Gurobi 3.0.1, CPLEX 12.2, and other commercial and non-commercial solvers, Gurobi is the fastest solver. However, not all MIP models can be solved by commercial software packages. Moreover, their computational times depend on the specific characteristics of models.

Our model includes two combinatorial optimization problems, such as a mode selection problem and a three-dimensional bin packing problem. It has been proved that three-dimensional packing problems are strongly NP-hard, and extremely difficult to solve in practice (Martello et al. (2000, 2007), Lodi et al. (2004)). Chen et al. (1995) develop a mixed integer programming for this problem and a small instance with only 6 items is solved optimally using an MIP solver in around 15 minutes. Based on the research of Martello et al. (2000, 2007) and Fuellerer et al. (2010), several instances with less than 50 items cannot be solved to optimality using an exact branch-and-bound algorithm. Because the actual number of items need to be packed into a container in our problem is much larger than 50, it would be hard to solve it in a reasonable time. Thus, in the next section, approximate solution methods are proposed to get good solutions.

3.4 Approximation Solution Approaches

The problem presented in the previous section is an integration of mode selection and three-dimensional bin packing problems. According to the complexity analysis in the previous section, we find that the three-dimensional packing problem significantly increases the number of constraints and decision variables. For example, the case of 100 shipments, 4 ocean containers, and 5 final destinations results in $30,144$ binary variables, 340 continuous variables, and $51,264$ constraints. However, if three-dimensional packing constraints (3.5-3.14) are eliminated, there would be only 444 binary variables, 40 continuous variables and 564 constraints in total. The decrease in the number of decision variables and constraints can largely reduce the computational difficulty. Hence, in our approximation method, we loosely disaggregate the problem to two parts such as mode selection / consolidation and bin packing and solve them iteratively. That is, the mode selection / consolidation problem is first solved with relaxed three-dimensional packing constraints. The packing feasibility of the initial solution is subsequently evaluated. If the solution is feasible, it is optimal. Otherwise, the initial problem is modified to tighten the volume capacity, and the procedure is repeated. In the following subsections, the relaxation method of packing constraints, the algorithms for packing feasibility check, and detailed approximation algorithms are discussed.

3.4.1 Packing Constraints Relaxation

In order to relax packing constraints (3.5-3.14), a volume load factor α is introduced into the model. The load factor α_j, $0 < \alpha_j \leq 1$, represents the utilization of the volume capacity of container j. Its value depends on shipments' characteristics such as shipment shape and size. In most cases, α_j can be set between 0.5 to 1. The larger shipments' sizes are or the more odd the shapes are, the lower α is. In this situation, it is possible that a container could not be filled any more based on its geometric dimensional limits, although the volume capacity has not been reached at all. Hence, α_j can be set lower to represent the low volume utilization of the container. On the other hand, if most of shipments are small-sized, α_j could be set to the value close to 1, because container volume could be fully utilized. In practice, logistics manager can estimate the value of α_j well based on the knowledge of shipment contents and past experiences. In our work, we introduce an algorithm to determine right α_j values by solving problems iteratively.

Based on the above arguments, the packing constraints (3.5-3.14) are substituted by new constraints

$$\sum_{i \in I} x_{ij} e_i \leq \alpha_j E, \forall j \in J \tag{3.22}$$

where α_j is the volume load factor for container j, e_i is the volume of shipment i, and E is the volume capacity of the standard ocean container. The constraints state that the total volume of the shipments loaded into container j cannot violate a certain percentage of container volume limit determined by α_j values. The original model is now rewritten as follows.

Minimize

$$\sum_{j \in J} C^{OC} y_j + \sum_{j \in J} \sum_{k \in K} C^{H} z_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{TL} u_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{LTL}(v_{jk}, w_{jk}) \tag{3.23}$$

Subject to:

$$\sum_{j \in J} x_{ij} = 1, \qquad \forall i \in I \tag{3.24}$$

$$x_{ij} \leq y_j, \qquad \forall i \in I \tag{3.25}$$

$$\sum_{i \in I} x_{ij} f_i \leq F, \qquad \forall j \in J \tag{3.26}$$

$$\sum_{i \in I} x_{ij} e_i \leq \alpha_j E, \qquad \forall j \in J \tag{3.27}$$

$$M z_{jk} \geq \sum_{i \in I} x_{ij} d_{ik}, \qquad \forall j \in J, \quad \forall k \in K \tag{3.28}$$

$$M u_{jk} + v_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \tag{3.29}$$

$$M u_{jk} + w_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \tag{3.30}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J \tag{3.31}$$

$$y_j \in \{0, 1\}, \qquad \forall j \in J \tag{3.32}$$

$$z_{jk} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall k \in K \tag{3.33}$$

$$u_{jk} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall k \in K \tag{3.34}$$

$$v_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{3.35}$$

$$w_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{3.36}$$

This relaxed model can solve the problem optimally if α_j is selected well by managers or items are small and well-shaped. However, in general, the solution from the relaxed model may or may not load into containers when geometric shapes of shipments are considered. Hence, it might be necessary to check the feasibility of loading for each container. The next section describes algorithms used for this purpose.

3.4.2 Algorithms for Packing Feasibility Check

As discussed in Section 3.3, the three-dimensional bin packing problem is NP-hard in the strong sense. That is, an optimal solution cannot be found in a reasonable time for many instances. Because the packing feasibility check, as a subproblem in our model, is performed repeatedly, the computational efficiency and effectiveness are two key factors to consider during algorithm development. Hence, heuristics rather than exact methods are suggested in our algorithm to check the packing feasibility within a short time. There are multiple methods that can be used to check the packing feasibility (see Martello et al. (2000); Lodi et al. (2002, 2004); Ghiani et al. (2004)), but we use a two-step algorithm as follows. Given shipments assigned to each container from (3.22-3.35), in the first step, the lower bound of the number of containers needed is determined based on the three-dimensional bin packing algorithm in Martello et al. (2000). If any lower bound is larger than one, the current shipment assignment is infeasible. On the other hand, if the lower bound is one for every shipment assignment, we apply another three-dimensional packing algorithm called TSpack (Lodi et al. (2004)) to make sure the packing feasibility. If the shipment assignment is feasible according to TSpack, we accept the current solution. If the assignment is infeasible in either step, the current solution is modified and the feasibility test is run again. We next briefly explain two three-dimensional bin packing algorithms used in our work.

1. Packing algorithm 1. Martello et al. (2000) propose lower bounds L_1 and L_2 for three-dimensional bin packing problems.

The simple continuous lower bound for this problem is $L_0 = \lceil \frac{\sum_{i \in I} e_i}{E} \rceil$, where e_i is the volume of shipment i, and E is the volume capacity of the container, respectively. However, L_0 produces a tight value when item sizes are small respect to the container size, and it is not appropriate for large-sized shipments. Because large-sized shipments might need more containers than small-sized ones do, even though they are within volume limits. The paper shows the worst-case performance ratio of lower bound L_0

is $\frac{1}{8}$, which means a heuristic algorithm could produce a feasible solution requiring 8 times the L_0 value.

Lower bound L_1

L_1 is obtained based on the lower bound L_{1BP} for one-dimensional bin packing problems (Boschetti (2004)). Given a set of items I with volume e_i for shipment i, and container capacity E, one-dimensional bin packing problem is to find the minimum number of container to fill all the items. L_{1BP} is calculated according to the following theorem.

Theorem 1. Given any integer p, such that $1 \leq p \leq \frac{1}{2}E$, let $S_1 = \{j \in S : e_j > E - p\}$, $S_2 = \{j \in S : \frac{1}{2}E < e_j \leq E - p\}$ and $S_3 = \{j \in S : p \leq c_j \leq \frac{1}{2}E\}$. A valid lower bound on the optimal one-dimensional bin packing solution value is

$$L_{1BP}(S,E) = max_{1 \leq p \leq \frac{1}{2}E}\{max\{L_\alpha(p), L_\beta(p)\}\} \tag{3.37}$$

where

$$L_\alpha(p) = |S_1 \bigcup S_2| + max\{0, \lceil \frac{\sum_{j \in S_3} e_j + \sum_{j \in S_2} e_j}{E} - |S_2| \rceil\}, \tag{3.38}$$

$$L_\beta(p) = |S_1 \bigcup S_2| + max\{0, \lceil \frac{|S_3| - \sum_{j \in S_2} \lfloor \frac{E - e_j}{E} \rfloor}{\lfloor \frac{E}{p} \rfloor} \rceil\} \tag{3.39}$$

Base on this theorem, the lower bound L_1 is proposed for three-dimensional bin packing problem. Given L, W and H, l_i, w_i and h_i are the length, width and hight of bins and items, respectively, let $J^{WH} = \{j \in J : w_j > \frac{W}{2}$ and $h_j > \frac{H}{2}\}$. Hence,

$$L_1 = max\{L_1^{WH}, L_1^{WD}, L_1^{HD}\} \tag{3.40}$$

where

$$L_1^{WH} = |\{j \in J^{WH} : d_j > \frac{D}{2}\}| \tag{3.41}$$

$$+max_{1 \le p \le \frac{D}{2}}\{\lceil \frac{\sum_{j \in J_s(p)} d_j - (|J_l(p)|D - \sum_{j \in J_l(p)} d_j)}{D} \rceil, \tag{3.42}$$

$$\lceil \frac{|J_s(p)| - \sum_{j \in J_l(p)} \lfloor \frac{D-d_j}{p} \rfloor}{\lfloor \frac{D}{p} \rfloor} \rceil\}, \tag{3.43}$$

$$J_l(p) = \{j \in J^{WH} : D - p \ge d_j > \frac{D}{2}\}, \tag{3.44}$$

$$J_s(p) = \{j \in J^{WH} : \frac{D}{2} \ge d_j \ge p\}. \tag{3.45}$$

L_1^{WD} (resp. L_1^{HD}) is obtained from (3.40-3.44) by interchanging h_j (resp. w_j) with d_j and H (resp. W) with D. The overall lower bound can be computed in $o(n^2)$.

Lower bound L_2

The lower bound L_2 is calculated as follows. Given any pair of integers (p, q), such that $1 \le p \le \frac{1}{2}W$ and $1 \le q \le \frac{1}{2}H$, let

$$K_1(p, q) = \{j \in J : w_j > W - p, h_j > H - q\}, \tag{3.46}$$

$$K_2(p, q) = \{j \in J \backslash K_1(p, q) : w_j > \frac{1}{2}W, h_j > \frac{1}{2}H\}, \tag{3.47}$$

$$K_3(p, q) = \{j \in J \backslash (K_1(p, q) \bigcup K_2(p, q)) : w_j \ge p, h_j \ge q\}. \tag{3.48}$$

Hence,

$$L_2^{WH} = L_1^{WH} + max_{1 \le p \le (1/2)W, 1 \le q \le (1/2)H}\{max\{0, \lceil \frac{\sum_{j \in K_2 \cup K_3} e_j + \sum_{j \in K1} d_j WH}{E} - L_1^{WH} \rceil\}\} \tag{3.49}$$

The lower bound L_2 is:

$$L_2 = max\{L_2^{WH}, L_2^{WD}, L_2^{HD}\} \tag{3.50}$$

Where L_2^{WD} (resp. L_2^{HD}) is obtained from (3.45-3.48) by interchanging h_j (resp. w_j) with d_j and H (resp. W) with D. The overall lower bound can be computed in $o(n^2)$.

It has been proved that L_1 doesn't dominate L_0, but L_2 dominates L_0 and L_1. And numerical experiments show that the average deviation of new lower bounds to the optimal solution is 9.6%, while the deviation of L_0 is 28.4%.

2. Packing algorithm 2. TSpack (Lodi et al. (2004)) implements the general Tabu search technique and provides a unified search code to solve three-dimensional bin packing problems with the objective of minimizing the number of bins used. The inputs of the algorithm include number of items (n), length (l_i), width (w_i), and height (h_i) for item i, and length (L), width (W), and height (H) for containers. The outputs of the algorithm are the number of containers used, and the assignment plan of items and the coordinates of packing in each container.

In the algorithm, the continuous lower bound L_0 is first calculated. And then the modified classical hybrid next fit algorithm (Johnson (1973)) as an inner heuristic is applied to get the initial upper bound. If the lower bound and the upper bound are equal, the algorithm terminate and the optimal solution is obtained. Otherwise, local improvement based on Tabu search is implemented.

The filling in each container is first calculated based on the filling function

$$\varphi(S_i) = \alpha \frac{\sum_{j \in S_i} e_j}{E} - \frac{|S_i|}{n} \tag{3.51}$$

Where S_i denote the set of items currently packed into container i, e_j the volume of shipment $j \in S_i$, E the volume of container, and α a user-specified positive value.

The container with the minimum filling is selected as target container, say t. One item, say j, in container t is removed. And then item j and the contents of k other containers, where k defines neighborhood size, consist of a subset S. By repacking S

and the items $\{1, 2, \cdots, n\} \backslash S$, the new solution is obtained. If the overall number of containers are not more than the previous solution, the move is accepted. In other words, they try to move item j out of container t without creating extra containers.

The neighborhood size k, which defines the size of the neighborhood and works as a tool of intensification/diversification, is changed as follows. If the move doesn't increase the previous solution, the move is accepted and $k = k - 1$. If the move increase the previous solution by more than one unit, this move is penalized and the penalty is infinity. If the move increase the previous solution by only one unit, $k = k + 1$, and this move is penalized according to the penalty formula.

The key aspect of the overall framework is the switch between neighborhoods of different size. Experiments show this algorithm produces better solutions compared with simple heuristics. This algorithm is easy to be implemented and a time limit could be set as a stopping conditions according to real problems. In TSpack, we set a time limit to be 100 seconds. The procedure for packing feasibility check is summarized as follows.

Procedure for Packing_Check

STEP 1: Apply packing algorithm 1 to each container. If any lower bound is larger than one, the current shipment assignment is infeasible. Otherwise, go to **STEP 2**.

STEP 2: Apply packing algorithm 2 to each container. If any container needed is larger than one, the current shipment assignment is infeasible.

3.4.3 Approximation Algorithms

In this section, three algorithms solving the original integrated model (3.1-3.21) are proposed. They are called General Capacity Reduction Algorithm, Simplified Capacity Reduction Algorithm and Shipment Reduction Algorithm because the solution is sought by reducing either available capacity of containers or assigned shipment size iteratively. The performance of these algorithms is evaluated in the next section.

We use two parameters such as α_j and $\hat{\alpha_j}$, $0 \leq \alpha_j, \hat{\alpha_j} \leq 1$, in these algorithms to represent the available and the actual usage of capacity/volume of container j. Specifically, α_j, an input parameter for each mathematical optimization iteration, represents how much portion of container j can be used to load shipments. The potential amount of shipments assigned to a container can be controlled by this parameter. The smaller value of α_j will reduce the shipment volume, which is appropriate for large and odd-shaped shipments. On the other hand, $\hat{\alpha_j}$, an output after each mathematical optimization iteration, represents actual volume used in container j. It is calculated by using the formula $\hat{\alpha_j} = \frac{\sum_i x_{ij} e_i}{E}$, where x_{ij} is a binary type with a value equal to 1 if shipment i is loaded into container j, and 0 otherwise; e_i is the volume of shipment i; and E is the volume capacity of a container. Next, we explain three algorithms in detail.

General Capacity Reduction Algorithm

This algorithm solves the integrated consolidation problem by iteratively tightening the available capacity of containers. The method starts with solving the relaxed model (3.22-3.35) with $\alpha_j = 1, \forall j \in J$ to obtain an initial solution. If the solution is feasible after applying the packing feasibility check for all containers, it is optimal, and the algorithm terminates. Otherwise, α_j values for infeasible containers are decreased by a step size Δ. The relaxed model (3.22-3.35) is solved again with updated α_j values and the packing feasibility is checked subsequently. The procedure is repeated iteratively until all the containers become feasible.

A container is determined to be infeasible if it holds too many items in terms of the container's physical dimensional (length, width and height) constraints, although the items' total volume and weight are still within the given container volume and weight capacities. Hence, some items have to be taken out from an overloaded infeasible container, which is achieved by decreasing α_j value. The amount of removed items depends on the step size Δ. If Δ is small enough, a near-optimal solution can be found with potentially very long computational time due to the large number of iterations. On the other hand, a large Δ finds a feasible solution quickly. Appropriate Δ values will be experimentally obtained in our work.

Besides, we note that, if we only change α_j values to do mathematical optimization, certain dead loops might appear in the algorithm. One of the ways to avoid them is to add the following constraints to fix certain loads in infeasible containers for each iteration while updating α_j.

$$x_{ij} = 1 \tag{3.52}$$

where i represents a shipment in a set of TL loads and j denotes an infeasible container. In the algorithm, if there exist TL loads in an infeasible container, we fix one TL load with the largest volume which can be feasible for packing in the container during each iteration. Because the idea behind our model is try to group the shipments to the same destination in the same container and ship them using TL, the procedure by adding constraints do not affect the performance of the model. If there are no any TL loads in an infeasible container, we fix one LTL load with the smallest volume during each iteration, because it is more possible for small-volume shipments for LTL delivery no matter what containers they are loaded.

A procedure "SortShipments" is used in this algorithm. It is to sort the shipments in an infeasible container according to a defined rule. The output of the procedure is a sorted list. The sorting rule is described as follows.

Procedure for SortShipments

For an infeasible container:

Scenario 1. If the shipments in it are all LTL loads,

group the shipments by destination and sort each destination's volume in non-increasing order.

Scenario 2. If the shipments in it are the mixes of TL and LTL loads,

group the TL shipments by destination and sort each destination's shipments by volume in non-decreasing order.

Scenario 3. If the shipments in it are all TL loads,

group the TL shipments by destination first and sort each destination's shipments by volume in non-decreasing order.

The specific steps of the algorithm are as follows:

STEP 0: Initialize $\alpha_j = 1$, $\forall j \in J$.

STEP 1: Solve the relaxed model (3.23-3.36). Let N be the number of containers used, A_j be the set of shipments assigned to container j, and $\hat{\alpha_j}$ be the volume utilization of container j in the solution obtained.

STEP 2: Call procedure PackingCheck for each container. If all the containers are feasible, accept the current solution and STOP. Otherwise, go to **STEP 3**.

STEP 3: For infeasible container(s), set new $\alpha_j = \alpha_j - \Delta$. For feasible container(s), set α_j to its value of last step.

STEP 4: Call procedure SortShipments for infeasible containers. Pick one set of shipments from the top of the sorted list. Add constraints $x_{ij} = 1$ for these shipments to the relaxed model (3.23-3.36). Go to **STEP 1**.

Simplified Capacity Reduction Algorithm

In practice, General Capacity Reduction Algorithm can be modified to a simpler version. In the simplified algorithm, α_j's are assumed to be the same regardless of container j. In each iteration, all α_j's are decreased by Δ if there is any infeasible container. The simplified algorithm is easier to implement and very effective for small-sized shipments. Because small-sized items are easy to be packed in the container and the container could become feasible from infeasible status just by removing a small amount of items. The detailed steps of the algorithm are as follows.

STEP 0: Initialize $\alpha_j = 1$, $\forall j \in J$.

STEP 1: Solve the relaxed model (3.23-3.36). Let N be the number of containers used, A_j be the set of shipments assigned to container j, and $\hat{\alpha_j}$ be the volume utilization of container j in the solution obtained.

STEP 2: Call procedure PackingCheck for each container. If all the containers are feasible, accept the current solution and STOP. Otherwise, go to **STEP 3**.

STEP 3: Set new $\alpha_j = \alpha_j - \Delta, 1 \leq j \leq N$. Go to **STEP 1**.

Shipment Reduction Algorithm

This algorithm removes assigned items to make containers feasible instead of adjusting the capacity of infeasible containers. In the algorithm, the relaxed model (3.23-3.36) is first solved with $\alpha_j = 1, \forall j \in J$ to obtain an initial solution. If the solution is feasible for all containers, the current solution is accepted and the algorithm terminates. Otherwise, items are removed one by one from infeasible containers until they become feasible. For containers of which status is from infeasible to feasible, they are tagged "finished". Items in "unfinished" containers and removed items are re-optimized using the relaxed model (3.23-3.36), and then the entire procedure is repeated until all the containers are tagged "finished".

The performance of the algorithm depends on the method to remove items. It becomes an NP problem to remove items optimally. In our algorithm, we use a greedy-type method to reach a feasible solution quickly. A procedure "SortShipments" (shown in the following) is also used in this algorithm but in a different rule.

Procedure for SortShipments2

For an infeasible container:

Scenario 1. If the shipments in it are all LTL loads,

sort the volume in non-decreasing order.

Scenario 2. If the shipments in it are the mixes of TL and LTL loads,

sort LTL shipments by volume in non-decreasing order. Group the TL shipments by destination first and sort each destination's shipments by volume in non-decreasing order. Then sort the shipments to the same destination by volume in non-decrasing order.

Scenario 3. If the shipments in it are all TL loads,

group the TL shipments by destination first and sort each destination's shipments by volume in non-decreasing order. Then sort the shipments to the same destination by volume in non-decreasing order.

The specific steps of the algorithm are described as follows.

STEP 0: Initialize $\alpha_j = 1, \forall j \in J$.

STEP 1: Solve the relaxed model (3.23-3.36). Let N be the number of containers used, A_j be the set of shipments assigned to container j, and $\hat{\alpha_j}$ be the volume utilization of container j in the solution obtained.

STEP 2: Call procedure PackingCheck for each container. If all the containers are feasible, accept the current solution and STOP. Otherwise, go to **STEP 3**.

STEP 3: Call procedure SortShipments2 for infeasible containers.

STEP 4: Remove One shipment from the top of the sorted list.

STEP 5: Apply procedure PackingCheck for this container. If the container is feasible, tag it "finished". Go to **STEP 6**. Otherwise, go to **STEP4**.

STEP 6: Remove the shipments in the "finished" containers from the original order list. And then go to **STEP 1**.

3.5 Computational Experiments

The objectives of our computational experiments are to evaluate the performances of three approximation algorithms on the basis of solution quality and time, and to validate the value of our integrated model in comparison to a traditional strategy. A traditional strategy is an uncoordinated strategy where the original problem is optimized in two separate phases, such as a shipment-loading phase and an inland transportation-planning phase.

Three approximation algorithms in this section are abbreviated using the notation GCRA for General Capacity Reduction Algorithm, SCRA for Simplified Capacity Reduction Algorithm and SRA for Shipment Reduction Algorithm.

3.5.1 Data

Our examples are generated based on the international logistics network of a US Fortune 500 manufacturing company. Data were obtained from the company, but were modified substantially to avoid revealing any proprietary information. The tested network consists of one overseas consolidation center, one US deconsolidation center and 15 US branches. Based on the actual business operations with China in the company, Shanghai, China serves as a consolidation center in China, and Los Angeles, CA as a deconsolidation center in US.

We test multiple-commodity flows, which include a wide range of commodity classes from light to heavy shipments. The scheme of Popken (1994) is applied to generate shipment types. It is assumed there are ten commodity classes (listed in 3.1), which are mostly typical in manufacturing companies. The light commodities stand for foam products, fabric, and light plastic components with less-than-10 lb/ft^3 density. The medium density commodities represent machinery parts, furniture components, and building materials with density in the range of 10 to 50 lb/ft^3. The density of heavy commodities, such as heavy metal, is more than 50 lb/ft^3.

Shipment sizes in our examples are similar to instances of Pisinger (2002), where he investigates container loading problems and generates box types to reflect typical characteristics of industrial loading problems. However, we add some bigger-size shipments to accurately represent the problem of our industry partner (shown in 3.1).

We test cases with 5 and 10 branches selected from 15 target branches, and each

Type	Weight (lb)	Volume (ft^3)	Density (lb/ft^3)
1	40.00	1.00	40.00
2	20.00	2.00	10.00
3	20.00	4.00	5.00
4	5.00	5.00	1.00
5	1,000.00	10.00	100.00
6	400.00	20.00	20.00
7	50.00	25.00	2.00
8	1,500.00	30.00	50.00
9	40.00	40.00	1.00
10	80.00	60.00	1.33

Table 3.1: Commodity class

Dataset 1					**Dataset 2**				
Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)	Average Weight (lb)	Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)	Average Weight (lb)
1	5	1,395	3.61	58.42	21	5	181	33.29	340.61
2	5	995	3.75	73.62	22	5	172	32.09	345.12
3	5	1,025	3.79	71.61	23	5	171	24.53	216.08
4	5	1,018	3.74	65.23	24	5	193	32.25	324.82
5	5	1,075	3.66	70.14	25	5	168	27.74	570.24
6	5	1,125	3.54	68.80	26	5	243	31.32	530.62
7	5	1,225	3.58	64.82	27	5	150	31.87	565.07
8	5	1,490	3.38	33.83	28	5	175	31.31	520.91
9	5	1,400	3.38	41.71	29	5	165	34.42	676.12
10	5	1,540	3.49	31.92	30	5	225	34.84	646.22
11	10	925	3.94	142.54	31	10	260	31.37	651.65
12	10	1,205	4.27	196.06	32	10	233	32.55	640.56
13	10	850	3.46	78.59	33	10	250	30.22	674.52
14	10	1,260	3.29	44.01	34	10	401	28.82	600.67
15	10	1,450	3.44	39.93	35	10	331	27.80	579.97
16	10	1,660	3.35	37.65	36	10	289	26.00	574.22
17	10	1,770	3.31	19.60	37	10	260	27.42	499.15
18	10	1,630	3.64	29.82	38	10	301	25.95	477.01
19	10	1,670	3.85	15.05	39	10	305	25.41	518.36
20	10	1,270	3.88	14.69	40	10	320	27.03	517.81

Table 3.2: Details on the instance generation

branch orders two types of commodities chosen from the listed commodities. The purchase quantity of each branch is feasible for one ocean container since we focus on small-quantity order consolidation problem.

Two data sets have been generated, each containing 20 instances. The first set was used to test the performance of algorithms on small-size shipments, which are selected from type 1 to type 5 in Table 3.1. The other set includes shipments, which are big items from type 6 to type 10 in Table 3.1. The corresponding instances in these two datasets consider the same destinations. Their statistical characteristics are summarized in Table 3.2.

3.5.2 Model Parameters

The following parameters are used in our examples.

1. Ocean container cost: The cost of shipping one 40-foot ocean container from Shanghai, China to Los Angeles, CA is set as $2,000 dollars per container. It is estimated according to the logistics market snapshot (Siplon (2011)).

2. Handling cost: The fixed handling cost is incurred for each set of the shipments to the same destination in the same container. The default value is $80, but its sensitivity effect is tested.

3. TL rate: The value is $1.5 per mile, estimated based on Flatbed Truckload Market Price Index(Group and Freight Audit Services (2012)).

4. LTL rate: In our analysis, we use actual LTL rates used in practice. The value is computed as follows. According to the SMC^3 white paper (2009), CzarLite, one of the most widely used and accepted LTL rates, is used by nearly half of the Fortune 500 including our industry partner and more than 2,000 shippers, including some of the largest US logistics service providers. It computes LTL

base rate based on zip codes of origin and destination, shipment weight, and class. We use LTL base rate and 60% discount to estimate the actual LTL rate in practice.

5. Ocean container capacity: According to ISO standards for international containers, a 40-foot ocean container has a weight capacity (excluding tare weight) of 59,000 lbs, and a volume capacity of 2,560 ($40 \times 8 \times 8$) cubic feet.

3.5.3 Results

The proposed three algorithms have been coded in MatLabR2009a and run on a computer with Intel Core 2 Duo CPU L7500 1.60GHz processor and 1GB RAM under Windows 32. The optimization solver embedded in the algorithms is Gurobi 4.0.1.

Numerical results for performance comparison of three algorithms are summarized in Table 4.4. The first column of Table 4.4 gives the instance identifier. The characteristics of each instance are described in Table 3.2. The values such as UB_{GCRA}, UB_{SCRA} and UB_{SRA} are provided by implementing the algorithms GCRA, SCRA and SRA, respectively. Associated runtimes are also recorded upon termination. The best upper bound (UB_{best}) is the minimum of UB_{GCRA}, UB_{SCRA} and UB_{SRA}. We employ a stopping criteria of 3600 seconds time limit for Gurobi solver in each iteration for $k = 10$ and no time limit for $k = 5$. The step size Δ in GCRA and SCRA is set to 0.1. The optimality gap is calculated as $100 \times (UB - LB)/LB$, where UB is the objective function value of the corresponding approximation solution, and LB is the lower bound.

It is known that it is extremely hard to solve our original model directly, hence it is difficult to use exact solutions as benchmark solutions to evaluate the quality of the solutions obtained by our algorithms. Here we provide a method to compute the lower bound. The lower bound (LB) is calculated as the sum of optimal container cost, handling cost and in-land transportation cost. The optimal number of containers needed is obtained by implementing a three-dimensional bin packing algorithm (TSpack), which is introduced in Section 3.4.2. Thus, the product of the optimal number of containers and unit container cost is the optimal container cost. The optimal handling cost depends on optimal container cost. If the optimal container cost is the same with the container cost of implementing any one algorithms such as GCRA, SCRA and SRA, the optimal handling cost is the handling cost of the algorithm. If the optimal container cost is the same with the container cost of two or three algorithms, the optimal handling cost is the minimum among them. Otherwise, the optimal handling cost is determined according to the loading pattern under the optimal packing. The optimal in-land transportation cost is the minimum cost of delivering the shipments from US consolidation center to their destinations after deconsolidating. The LTL and TL costs to each destination are computed separately, and the cheaper one is chosen.

In terms of solution quality GCRA is clearly superior to SCRA and SRA. For the instances of Dataset1, which represent small-size shipments, GCRA performs always better than SRA except in one case (instance 4). GCRA always finds slightly better solutions than SCRA. And its average of percentage gap is 2.16%, which is lower by 1.36% and 11.68% than that of SCRA and SRA, respectively. Similar phenomenon is observed in Dataset 2, which are large items, GCRA outperforms SCRA and SRA in 18 out of 20 instances. In the remaining two instances, SRA produces better solutions compared to those obtained by SCRA and SRA. In respect to average percentage gap, GCRA still achieves the lowest percentage gap (2.82%), followed by SCRA (7.05%) and SRA (8.27%). From Table 4.4, we observe that if these three algorithms are used together and the best results are chosen, the solution quality could be improved.

With respect to different CPU speeds, GCRA takes less time to find the best

	GCRA		SCRA		SRA				% Gap			
Instance No.	UB_{GCRA} (\$)	Runtime (*seconds*)	UB_{SCRA} (\$)	Runtime (*seconds*)	UB_{SRA} (\$)	Runtime (*seconds*)	UB_{best} (\$)	LB (\$)	GCRA	SCRA	SRA	Best
Dataset 1												
1	20,501.28	82.82	20,501.28	245.10	24,810.18	2,595.49	20,501.28	20,501.28	0.00	0.00	21.02	0.00
2	18,501.28	1.24	18,501.28	1.25	18,501.28	3.33	18,501.28	18,501.28	0.00	0.00	0.00	0.00
3	20,501.28	23.42	20,501.28	132.53	22,308.92	321.74	20,501.28	18,741.28	9.39	9.39	19.04	9.39
4	20,501.28	25.72	20,501.28	216.14	19,336.45	92.76	19,336.45	18,501.28	10.81	10.81	4.51	4.51
5	21,761.19	24.74	21,761.19	175.06	23,568.83	325.21	21,761.19	20,001.19	8.80	8.80	17.84	8.80
6	21,761.19	27.67	21,761.19	149.10	24,461.31	598.94	21,761.19	20,001.19	8.80	8.80	22.30	8.80
7	21,761.19	42.96	24,169.50	266.17	24,381.31	2045.04	21,761.19	21,761.19	0.00	11.07	12.04	0.00
8	21,978.49	105.76	24,169.50	2,121.21	28,423.59	3,730.46	21,978.49	21,761.19	1.00	11.07	30.62	1.00
9	19,400.70	45.07	19,400.70	355.84	23,180.80	2,716.68	19,400.70	19,400.70	0.00	0.00	19.48	0.00
10	19,544.92	376.14	21,400.70	2,264.85	21,597.40	3,027.06	19,544.92	19,400.70	0.00	0.74	11.32	0.00
11	37,802.83	181.46	37,802.83	175.44	37,802.83	192.24	37,802.83	36,202.83	4.42	4.42	4.42	4.42
12	37,802.83	40.63	37,802.83	123.13	42,276.10	1,505.46	37,802.83	37,802.83	0.00	0.00	11.83	0.00
13	35,802.83	21.27	35,802.83	12.54	36,226.09	1,684.35	35,802.83	35,802.83	0.00	0.00	1.18	0.00
14	37,802.83	48.99	37,802.83	262.75	43,779.62	2,365.15	37,802.83	37,802.83	0.00	0.00	15.81	0.00
15	37,802.83	73.14	37,802.83	1,107.58	41,634.51	3,767.61	37,802.83	37,802.83	0.00	0.00	10.14	0.00
16	37,802.83	387.43	39,802.83	1,147.39	42,508.59	4,477.99	37,802.83	37,802.83	0.00	5.29	12.45	0.00
17	37,802.83	1,155.77	37,802.83	295.17	41,401.28	503.92	37,802.83	37,802.83	0.00	0.00	9.52	0.00
18	38,709.49	484.80	39,802.83	987.06	47,393.82	3,882.31	38,709.49	38,709.49	0.00	0.00	19.07	0.00
19	37,344.90	423.31	37,344.90	1,220.52	44,612.61	5,202.65	37,344.90	37,344.90	0.00	0.00	19.46	0.00
20	35,344.90	77.73	35,344.90	318.66	40,580.80	2,314.03	35,344.90	35,344.90	0.00	0.00	14.81	0.00
AVG	29,011.59	182.50	29,489.01	578.87	32,439.31	2,067.62	28,953.35	28,604.18	2.16	3.52	13.84	1.85
Dataset 2												
21	22,146.47	15.08	24,424.19	17.15	24,283.64	49.35	22,146.47	22,066.47	0.36	10.68	10.05	0.36
22	21,688.56	10.58	22,236.53	48.38	21,848.56	20.70	21,688.56	21,688.56	0.00	2.53	0.74	0.00
23	21,440.01	8.31	21,440.01	13.64	22,235.16	45.24	21,440.01	21,440.01	0.00	0.00	3.71	0.00
24	24,362.86	38.02	24,562.10	20.32	23,612.22	36.82	23,612.22	22,362.86	8.94	9.83	5.59	5.59
25	21,497.50	24.40	21,497.50	10.12	23,854.19	47.25	21,497.50	21,497.50	0.00	0.00	10.96	0.00
26	24,501.28	116.39	33,850.48	1,297.06	26,354.00	145.86	24,501.28	24,501.28	0.00	38.16	7.56	0.00
27	24,169.21	24.85	24,169.21	5.40	24,100.78	30.09	24,100.78	22,169.21	9.02	9.02	8.71	8.71
28	26,207.50	77.81	27,432.05	27.37	26,631.12	40.15	26,207.50	25,304.56	3.57	8.41	5.24	3.57
29	25,498.27	15.01	27,370.36	66.24	29,210.13	23.19	25,498.27	25,304.56	0.77	8.16	15.43	0.77
30	27,224.56	31.77	27,766.02	32.93	29,446.04	56.14	27,224.56	27,224.56	0.00	1.99	8.16	0.00
31	44,578.41	4,966.42	44,658.41	759.33	45,161.41	37.77	44,578.41	42,578.41	4.70	4.89	6.07	4.70
32	40,067.70	435.42	40,067.70	435.42	40,469.32	62.09	40,067.70	40,067.70	0.00	0.00	1.00	0.00
33	41,904.55	1,274.25	41,984.55	1,139.84	42,426.54	60.70	41,904.55	39,904.55	5.01	5.21	6.32	5.01
34	50,586.90	7,881.61	52,974.87	6,394.15	58,999.62	187.99	50,586.90	47,962.83	5.47	10.45	23.01	5.47
35	47,802.83	8,574.94	50,357.14	4,048.24	51,324.15	97.95	47,802.83	45,802.83	4.37	9.94	12.05	4.37
36	43,798.34	5,255.82	43,798.34	270.39	46,861.74	104.81	43,798.34	41,798.34	4.78	4.78	12.11	4.78
37	42,752.40	2,095.29	44,752.40	1,170.70	44,288.67	68.69	42,752.40	42,752.40	0.00	4.68	3.59	0.00
38	45,658.68	1,208.68	45,738.68	1,326.52	46,303.03	78.42	45,658.68	43,658.68	4.58	4.76	6.06	4.58
39	45,658.68	10,894.37	45,904.43	1,077.00	47,195.02	104.20	45,658.68	43,658.68	4.58	5.14	8.10	4.58
40	46,063.96	4,854.80	47,011.28	3,640.14	50,930.76	84.66	46,063.96	45,914.49	0.33	2.39	10.93	0.33
AVG	34,380.43	2,395.19	35,599.81	1,090.02	36,276.80	69.10	34,339.48	33,382.92	2.82	7.05	8.27	2.64

Table 3.3: Performance comparison for three proposed algorithms

solutions for the instances of Dataset1, while SRA is much more efficient for instances of Dataset2. The main reason is that SRA achieves final solutions by removing assigned items in infeasible containers. The shipments in Dataset2 are all of large size, thus it takes shorter time to remove items to make the container from a infeasible status to a feasible one. Based on that, SRA might identify final solutions in one iteration, whereas GCRA might need more iterations to obtain solutions. The average computation time of GCRA for Dataset1 is 182.50 seconds (about 3 minutes), which is two times faster than that for SCRA (578.87 seconds), and ten times faster than that for SRA (2067.62 seconds). In Dataset2, SRA achieve solutions within an average computation time of 69.10 seconds (about 1 minute). By observing Table 4.4, we can conclude that the three algorithms are able to solve all the instances with up to 1770 items within a moderate computing time. For these algorithms, the time for solving the instances of $k = 10$ is much longer than those of $k = 5$, that's because the number of decision variables and constraints grows largely with the increase of k and n, which makes the solution time going up.

Therefore, based on the results of Table4.4, we conclude that GCRA performs the best both in terms of solution quality and computational time for small-size shipments. For large-volume shipments, GCRA provides the best solution quality. However, SRA is a good alternative in this case because it can generate satisfactory solutions within very short computational time. Besides, we also notice that SCRA does not have significant advantages in terms of computational time and solution quality compared to other two algorithms. But its solution quality and time are also at acceptable levels.

We tested whether small step size Δ could improve the solution quality of GCRA and SCRA, as seen in Table 3.4. The tested Δ values are 0.1 and 0.01. By observing Table 3.4, we find that a small step size improves the solutions in most cases. And the solution improvement of SCRA is bigger that that of GCRA.

Dataset 1										
	$\Delta = 0.1$				$\Delta = 0.01$				Improvement	
	GCRA		SCRA		GCRA		SCRA			
Instance No.	UB_{GCRA} (\$)	Runtime (*seconds*)	UB_{SCRA} (\$)	Runtime (*seconds*)	UB_{GCRA} (\$)	Runtime (*seconds*)	UB_{SCRA} (\$)	Runtime (*seconds*)	GCRA %	SCRA %
1	20,501.28	82.82	20,501.28	245.10	20,501.28	98.22	20,501.28	624.54	0.00	0.00
2	18,501.28	1.24	18,501.28	1.25	18,501.28	1.22	18,501.28	3.13	0.00	0.00
3	20,501.28	23.42	20,501.28	132.53	20,501.28	122.60	20,501.28	186.95	0.00	0.00
4	20,501.28	25.72	20,501.28	216.14	18,501.28	21.34	20,501.28	187.72	9.76	0.00
5	21,761.19	24.74	21,761.19	175.06	21,761.19	85.70	21,761.19	548.38	0.00	0.00
6	21,761.19	27.67	21,761.19	149.10	21,761.19	95.65	21,761.19	227.05	0.00	0.00
7	21,761.19	42.96	24,169.50	266.17	21,761.19	84.10	21,761.19	223.93	0.00	9.96
8	21,978.49	105.76	24,169.50	2,121.21	21,761.19	116.22	21,761.19	832.08	0.99	9.96
9	19,400.70	45.07	19,400.70	355.84	19,400.70	57.83	19,400.70	479.22	0.00	0.00
10	19,544.92	376.14	21,400.70	2,264.85	19,400.70	345.12	21,400.70	2,155.58	0.74	0.00
11	37,802.83	181.46	37,802.83	175.44	37,802.83	195.37	37,802.83	197.64	0.00	0.00
12	37,802.83	40.63	37,802.83	123.13	37,802.83	80.86	37,802.83	189.84	0.00	0.00
13	35,802.83	21.27	35,802.83	12.54	35,802.83	32.06	35,802.83	25.03	0.00	0.00
14	37,802.83	48.99	37,802.83	262.75	37,802.83	41.25	37,802.83	356.45	0.00	0.00
15	37,802.83	73.14	37,802.83	1,107.58	37,802.83	68.06	37,802.83	1,404.84	0.00	0.00
16	37,802.83	387.43	39,802.83	1,147.39	37,802.83	706.20	37,802.83	678.23	0.00	5.02
17	37,802.83	1,155.77	37,802.83	295.17	37,802.83	283.13	37,802.83	719.88	0.00	0.00
18	38,709.49	484.80	39,802.83	987.06	37,802.83	631.25	39,802.83	1,244.09	2.34	0.00
19	37,344.90	423.31	37,344.90	1,220.52	37,344.90	1,337.57	37,344.90	11,032.21	0.00	0.00
20	35,344.90	77.73	35,344.90	318.66	35,344.90	35.42	35,344.90	1,298.14	0.00	0.00
AVG	29,011.59	182.50	29,489.01	578.87	28,848.18	221.96	29,148.18	1,130.75	0.69	1.25
Dataset 2										
21	22,146.47	15.08	24,424.19	17.15	22,146.47	37.05	22,146.47	128.06	0.00	9.33
22	21,688.56	10.58	22,236.53	48.38	21,688.56	38.25	22,007.04	29.45	0.00	1.03
23	21,440.01	8.31	21,440.01	13.64	21,440.01	18.83	21,440.01	65.91	0.00	0.00
24	24,362.86	38.02	24,562.10	20.32	24,442.86	126.97	24,999.82	70.18	-0.33	-1.78
25	21,497.50	24.40	21,497.50	10.12	21,497.50	23.11	21,497.50	45.27	0.00	0.00
26	24,501.28	116.39	33,850.48	1,297.06	24,501.28	108.73	24,501.28	258.30	0.00	27.62
27	24,169.21	24.85	24,169.21	5.40	24,169.21	28.68	24,169.21	13.44	0.00	0.00
28	26,207.50	77.81	27,432.05	27.37	25,728.17	98.71	27,687.04	164.13	1.83	-0.93
29	25,498.27	15.01	27,370.36	66.24	25,418.27	126.04	25,498.27	187.29	0.31	6.84
30	27,224.56	31.77	27,766.02	32.93	27,224.56	38.31	27,224.56	21.42	0.00	1.95
31	44,578.41	4,966.42	44,658.41	759.33	42,578.17	286.48	42,738.41	717.44	4.49	4.30
32	40,067.70	435.42	40,067.70	435.42	39,907.70	178.19	39,907.70	19.53	0.40	0.40
33	41,904.55	1,274.25	41,984.55	1,139.84	39,824.55	9.78	41,904.55	4,260.53	4.96	0.19
34	50,586.90	7,881.61	52,974.87	6,394.15	50,586.30	57,086.3	50,955.07	23,056.38	0.00	3.81
35	47,802.83	8,574.94	50,357.14	4,048.24	46,719.43	19,048.02	48,023.83	15,551.86	2.27	4.63
36	43,798.34	5,255.82	43,798.34	270.39	42,578.41	295.99	43,798.34	2,216.22	2.79	0.00
37	42,752.40	2,095.29	44,752.40	1,170.70	42,592.40	2,881.00	42,752.40	4,608.88	0.37	4.47
38	45,658.68	1,308.68	45,738.68	1,326.52	43,738.68	779.50	45,738.68	1,222.64	4.21	0.00
39	45,658.68	10,894.37	45,904.43	1,077.00	45,658.68	27,024.58	45,824.43	8,572.75	0.00	0.17
40	46,063.96	4,854.80	47,011.28	3,640.14	46,063.96	11,300.80	48,627.56	4,133.72	0.00	-3.44
AVG	34,380.43	2,395.19	35,599.81	1,090.02	33,925.30	5,976.77	34,572.11	3,267.17	1.06	2.93

Table 3.4: The effect of step size

We have so far shown the performance comparison of the proposed three algorithms. We next investigate the value of our integrated model compared with an uncoordinated strategy, which solves the cargo loading and inland transportation planning separately. During the process of the cargo loading and packing, only the physical dimensions of the shipments are considered. The three-dimensional bin packing algorithm (TSpack) is implemented to obtain good packing pattern. The subsequent inland transportation planning are determined based on the packing pattern in the last process. Each container is unpacked and shipped by TL or LTL directly according to cost after arriving at the deconsolidation center. Dataset1 and Dataset2 are still used for numerical experiments. Our model is solved by three algorithms GCRA, SCRA and SRA.

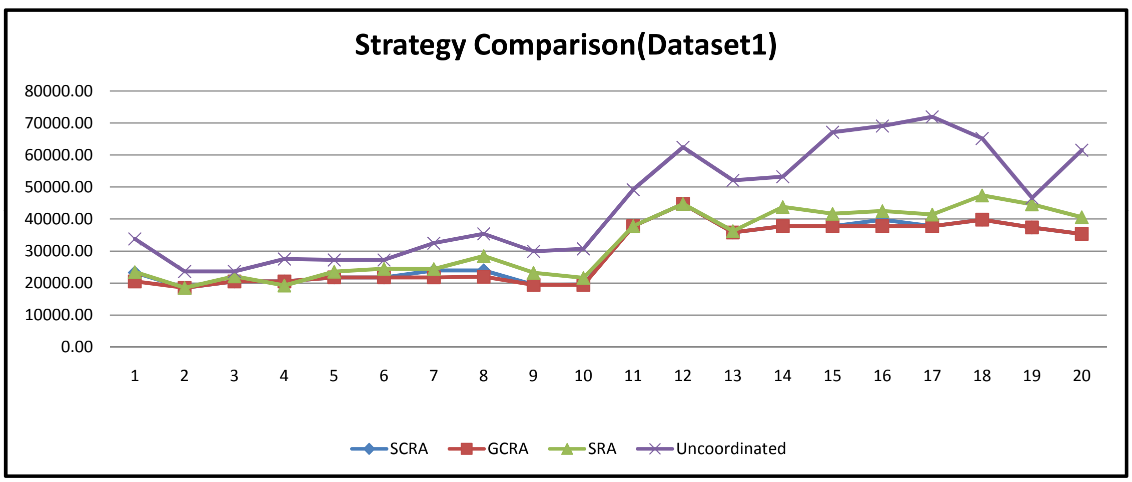


Figure 3.1: Strategy comparison for dataset1

Table 3.1 and Table 3.2 demonstrate the comparison of our strategy and uncoordinated one. Based on the figures, we find that our method performs quite well compared with uncoordinated one. The cost savings of our method for dataset1 are much bigger than those for dataset2. Table 3.5 displays the results in detail. The first column refers to the problem instance identifier. The second to fourth column report the corresponding solutions (UB) of three algorithms, measured by total cost. The

Instance No.	Coordinated GCRA	Coordinated SCRA	Coordinated SRA	Coordinated Best	Uncoordinated	% Cost decrease GCRA	% Cost decrease SCRA	% Cost decrease SRA	% Cost decrease Best
Dataset 1									
1	20,501.28	20,501.28	24,810.18	20,501.28	33,781.00	39.31	39.31	26.56	39.31
2	18,501.28	18,501.28	18,501.28	18,501.28	23,626.32	21.69	21.69	21.69	21.69
3	20,501.28	20,501.28	22,308.92	20,501.28	23,626.32	13.23	13.23	5.58	13.23
4	20,501.28	20,501.28	19,336.45	19,336.45	27,501.84	25.46	25.46	29.69	29.69
5	21,761.19	21,761.19	23,568.83	21,761.16	27,243.52	20.12	20.12	13.49	20.12
6	21,761.19	21,761.19	24,461.31	21,761.19	27,243.52	20.12	20.12	10.21	20.12
7	21,761.19	24,169.50	24,381.31	21,761.19	32,486.00	33.01	25.60	24.95	33.01
8	21,978.49	24,169.50	28,423.59	21,978.49	35,390.58	37.90	31.71	19.69	37.90
9	19,400.70	19,400.70	23,180.80	19,400.70	29,901.31	35.12	35.12	22.48	35.12
10	19,544.92	21,400.70	21,597.40	19,544.92	30,690.06	36.32	30.27	29.63	36.32
11	37,802.83	37,802.83	37,802.83	37,802.83	49,189.09	23.15	23.15	23.15	23.15
12	37,802.83	37,802.83	42,276.10	37,802.83	62,463.76	39.48	39.48	32.32	39.48
13	35,802.83	35,802.83	36,226.09	35,802.83	52,069.56	31.24	31.24	30.43	31.24
14	37,802.83	31,002.83	43,779.62	37,802.83	53,257.77	29.02	29.02	17.80	29.02
15	37,802.83	37,802.83	41,634.51	37,802.83	67,156.77	43.71	43.71	38.00	43.71
16	37,802.83	39,802.83	42,508.59	37,802.83	69,063.78	45.26	42.37	38.45	45.26
17	37,802.83	37,802.83	41,401.28	37,802.83	71,947.90	47.46	47.46	42.46	47.46
18	38,709.49	39,802.83	47,393.82	38,709.49	65,196.93	40.63	38.95	27.30	40.63
19	37,344.90	37,344.90	44,612.61	37,344.90	46,592.24	19.85	19.85	4.25	19.85
20	35,344.90	35,344.90	40,580.80	35,344.90	61,500.87	42.53	42.53	34.02	42.53
AVG	29,011.59	29,489.01	32,439.31	28,953.35	44,496.45	32.23	31.02	24.61	32.44
Dataset 2									
21	22,146.47	24,424.19	24,283.64	22,146.47	25,848.32	14.32	5.51	6.05	14.32
22	21,688.56	22,236.53	21,848.56	21,688.56	25,344.67	9.14	9.14	5.77	9.14
23	21,440.01	21,440.01	22,235.16	21,386.08	23,597.50	9.14	9.14	5.77	9.14
24	24,362.86	24,562.10	23,612.22	23,612.22	26,926.30	9.52	8.78	12.31	12.31
25	21,497.50	21,497.50	23,854.19	21,497.50	28,533.80	24.66	24.66	16.40	27.19
26	24,501.28	33,850.48	26,354.00	24,501.28	37,501.97	34.67	9.74	29.73	34.67
27	24,169.21	24,169.21	24,100.78	24,100.78	29,073.51	16.87	16.87	17.10	17.10
28	26,207.50	27,432.05	26,631.12	26,207.50	30,361.26	13.68	9.64	12.29	13.68
29	25,498.27	27,370.36	29,210.13	25,498.27	32,625.81	21.85	16.11	10.47	21.85
30	27,224.56	27,766.02	29,446.04	27,224.56	38,473.69	29.24	27.83	23.46	29.24
31	44,578.41	44,658.41	45,161.41	44,578.41	46,080.76	3.26	3.09	2.00	3.26
32	40,067.70	40,067.70	40,469.32	40,067.70	44,377.81	9.71	9.71	8.81	9.71
33	41,904.55	41,984.55	42,426.54	41,904.55	44,376.02	5.57	5.39	4.39	5.57
34	50,586.90	52,974.87	58,999.62	50,586.90	66,202.72	23.59	19.98	10.88	23.59
35	47,802.83	50,357.14	51,324.15	47,802.83	55,156.70	13.33	8.70	6.94	13.33
36	43,798.34	43,798.34	46,861.74	43,281.68	48,364.51	9.44	9.44	3.11	9.44
37	42,752.40	44,752.40	44,288.67	42,752.40	46,511.89	8.08	3.78	4.78	8.08
38	45,658.68	45,738.68	46,303.03	45,658.68	50,150.63	8.96	8.80	7.67	8.96
39	45,658.68	45,904.43	47,195.02	45,658.68	51,628.76	11.56	11.08	8.59	11.56
40	46,063.96	47,011.28	50,930.76	46,063.96	56,011.00	17.76	16.07	9.07	17.76
AVG	34,380.43	35,599.81	36,272.80	34,339.48	40,357.38	14.98	11.83	10.68	15.13

Table 3.5: Performance comparison for coordinated and uncoordinated strategies

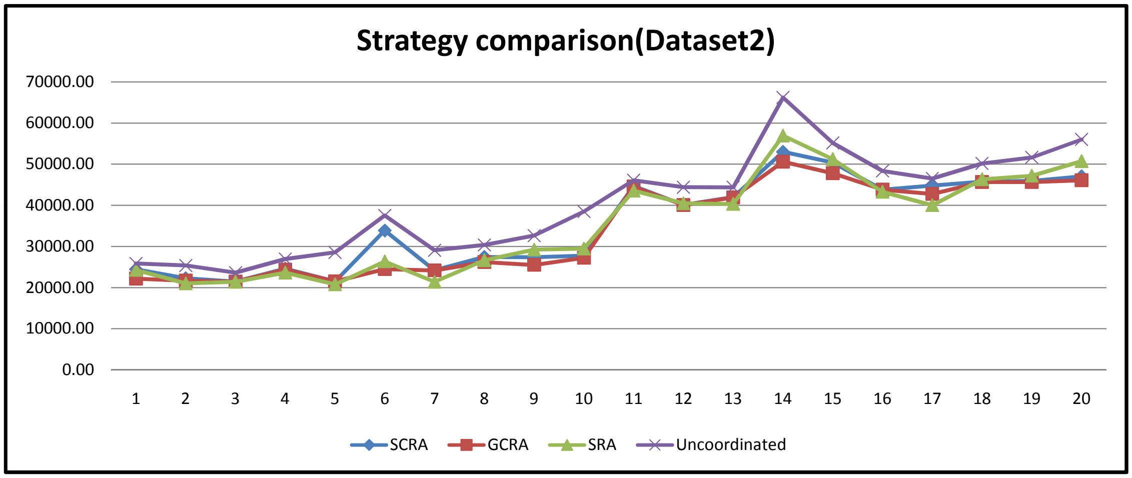


Figure 3.2: Strategy comparison for dataset2

fifth column shows the best solution of three algorithms. The sixth column presents the total cost (z) of the uncoordinated strategy, which is the sum of optimal packing cost and inland transportation cost, computed separately. The optimal packing cost is obtained by implementing TSpack, which was introduced in Section 3.4.2. The next four columns give the percentage cost decrease between two strategy, computed as $100(z - UB)/z$.

By observing Table 3.5, we find that our integrated strategy always performs significantly better than the uncoordinated strategy. For the instances of Dataset1, the average costs of integrated model, produced by GCRA, SCRA and SRA, are \$29,011.59, \$29,489.01 and \$32,439.31, respectively, which are lower by 32.23%, 31.02% and 24.61% than the uncoordinated strategy. For the instances of Dataset2, the maximal cost savings could achieve 14.98%. By comparing the results of Dataset1 and Dataset2, we observe that the cost savings of integrated model for small-size shipments are bigger than those for large-size ones. That's because small-size shipments are easily packed into containers, hence those of the same destination could be packed in one container as much as possible so that handling cost and subsequent inland transportation cost could be decreased. But for large-size shipments, due to their physical dimensions, it is more likely that those of the same destination are separated into different containers, which will make the total cost go up.

Table 3.6 presents the cost components' comparison of our integrated method and the uncoordinated one. The solution of our method in Table 3.6 is obtained by implementing GCRA.

By looking through the cost components, we observe that ocean container cost of our integrated model is slightly more than that of the uncoordinated strategy. Because the uncoordinated strategy always optimize the packing procedure, which makes it use the minimum number of containers, while our method focuses on the overall cost. In terms of handling cost, the uncoordinated strategy produces about twice more cost than our approach on average. Under our approach, the shipments to the same destination are grouped and loaded into the same containers as much as possible instead of separate several containers, which reduces handling cost. The uncoordinated strategy only consider the packing optimization and capacity limits while loading shipments. Thus, its loading patterns might need more handling procedures.

Concerning inland transportation cost, it is a dominant influencing factor for total cost because LTL expenditures can be more expensive than TL. That's why we consider the joint decisions on loading and inland distribution, which can create proper loading patterns to obtain more economical distribution plan. Our joint strategy should have a high value if inland transportation cost is high. This hypothesis is supported by the results in the Table 3.6, which shows that the total inland transportation cost, as the sum of TL and LTL cost, accounts for about 70% of total cost on average. Our strategy could yield about 30%, 15% savings for Dataset1 and dataset2 over the uncoordinated one on road transportation. The most cost savings are obtained by TL mode selection. Although the uncoordinated strategy also considers the economical delivery plan, it is only optimal for the second phase rather than the whole process. Hence, it still spends more money on LTL. We believe that the

Dataset 1								
Instance	Coordinated(GCRA)				Uncoordinated			
No.	Container	Handling	Road	Total	Container	Handling	Road	Total
1	6,000.00	400.00	14,101.28	20,501.28	6,000.00	880.00	26,901.00	33,781.00
2	4,000.00	400.00	14,101.28	18,501.28	4,000.00	640.00	18,986.32	23626.32
3	6,000.00	400.00	14,101.28	20,501.28	4,000.00	640.00	18,986.32	23,636.32
4	6,000.00	400.00	14,101.28	20,501.28	4,000.00	640.00	22,861.83	27,501.84
5	6,000.00	400.00	15,361.19	21,761.19	4,000.00	640.00	22,603.52	27,243.52
6	6,000.00	400.00	15,361.19	21,761.19	4,000.00	640.00	22,603.52	27,243.52
7	6,000.00	400.00	15,361.19	21,761.19	6,000.00	720.00	25,766.00	32,486.00
8	6,000.00	480.00	15,498.49	21,978.49	6,000.00	800.00	28,590.58	35,390.58
9	6,000.00	400.00	13,000.70	19,400.70	6,000.00	800.00	23,101.31	29,901.31
10	6,000.00	480.00	13,064.92	19544.92	6,000.00	800.00	23,890.06	30,690.06
11	6,000.00	800.00	31,002.83	37,802.83	4,000.00	1,200.00	43,989.09	49,189.09
12	6,000.00	800.00	31,002.83	37,802.83	6,000.00	1,440.00	55,023.76	62,463.76
13	4,000.00	800.00	31,002.83	35,802.83	4,000.00	1,360.00	46,709.56	52,069.56
14	6,000.00	800.00	31,002.83	37,802.83	6,000.00	1,280.00	45,977.77	53,257.77
15	6,000.00	800.00	31,002.83	37,802.83	6,000.00	1,600.00	59,556.70	67,156.70
16	6,000.00	800.00	31,002.83	37,802.83	6,000.00	1,600.00	61,463.78	69,063.78
17	6,000.00	800.00	31,002.83	37,802.83	6,000.00	1,680.00	64,267.90	71,947.90
18	8,000.00	800.00	29,909.49	38,709.49	8,000.00	1,680.00	55,516.93	65,196.93
19	8,000.00	800.00	28,544.90	37,344.90	8,000.00	1,840.00	36,752.24	46,592.24
20	6,000.00	800.00	28,544.90	35,344.90	6,000.00	1,680.00	53,820.87	61,500.87
AVG	5,900.00	604.00	22,396.73	29,011.59	5,500.00	1,128.00	37,868.45	44,496.45
Dataset 2								
21	8,000.00	560.00	13,586.47	22,146.47	8,000.00	800.00	17,048.32	25,848.32
22	8,000.00	480.00	13,208.56	21,688.56	8,000.00	880.00	16,464.67	25,344.67
23	8,000.00	480.00	12,960.01	21,440.01	8,000.00	1,040.00	14,557.50	23,597.50
24	10,000.00	400.00	13,962.86	24,362.86	8,000.00	800.00	18,126.30	26,926.30
25	8,000.00	480.00	13,017.50	21,497.50	8,000.00	960.00	19,573.80	28,533.80
26	10,000.00	400.00	14,101.28	24,501.28	10,000.00	1,120.00	26,381.97	37,501.97
27	8,000.00	480.00	15,689.21	24,169.21	6,000.00	1,200.00	21,873.51	29,073.51
28	8,000.00	560.00	17,647.50	26,207.50	8,000.00	1,040.00	21,321.26	30,361.26
29	8,000.00	560.00	16,938.27	25,498.27	8,000.00	1,040.00	23,585.81	32,625.81
30	10,000.00	400.00	16,824.56	27,224.56	10,000.00	1,120.00	27,353.69	38,473.69
31	14,000.00	880.00	29,698.41	44,578.41	12,000.00	1,840.00	32,240.76	46,080.76
32	10,000.00	960.00	29,107.70	40,067.70	10,000.00	1,760.00	32,617.81	44,377.81
33	12,000.00	880.00	29,024.55	41,904.55	10,000.00	1,920.00	32,456.02	44,376.02
34	18,000.00	960.00	31,626.90	50,586.90	16,000.00	2,160.00	48,042.72	66,202.72
35	16,000.00	800.00	31,002.83	47,802.83	14,000.00	2,080.00	39,076.70	55,156.70
36	14,000.00	960.00	28,838.34	43,798.34	12,000.00	1,920.00	34,444.51	48,364.51
37	12,000.00	1,040.00	29,712.40	42,752.40	12,000.00	1,840.00	32,671.89	46,511.89
38	14,000.00	880.00	30,778.68	45,658.68	12,000.00	1,920.00	36,230.63	50,150.63
39	14,000.00	880.00	30,778.68	45,658.68	12,000.00	1,840.00	37,788.76	51,628.76
40	14,000.00	960.00	31,103.96	46,063.96	14,000.00	2,000.00	40,011.00	56,011.00
AVG	11,200.00	700.00	22,480.43	34,380.43	10,300.00	1,464.00	28,593.38	40,357.38

Table 3.6: Cost component comparison for coordinated and uncoordinated strategies

value of our proposed joint strategy under the most conditions can be significantly high.

3.6 Summary

In this chapter, we investigate a shipment consolidation problem in a global supply chain network, which is a common practice seen in the international companies, especially in the context of globalization. More and more US companies are purchasing parts or finished products from China in a Just-in-Time (JIT) and low-inventory fashion, which makes consolidation be a cost-effective strategy to transport shipments in the global network. We propose a proactive consolidation strategy, which makes consolidation planning at the early stage of the supply chain. That is, shipments are consolidated overseas, and transported to US as a whole, and then distributed separately to their destinations by TL or LTL. A mathematical formulation is developed to model the procedure with the objective of minimizing the total costs involved in the international network, as the sum of ocean container costs, handling costs, and TL and LTL costs. Our model considers multi-commodity flows, and combines two difficult combinatorial optimization problems, such as a mode selection problem and a three-dimensional bin packing problem. These two problems are extremely hard to get exact solutions in practice. Hence, an approximation methodology is proposed to solve the model.

In the methodology, three-dimensional packing constraints are first relaxed in the original model. A volume factor α_j, which represents the utilization of the volume capacity of container j, is introduced into the model. The relaxed model can solve the problem optimally if α_j is chosen well. Thus, three algorithms are developed to solve the original problem by effectively determining good α_j values. They are called General Capacity Reduction Algorithm (GCRA), Simplified Capacity Reduction Algorithm (SCRA) and Shipment Reduction Algorithm (SRA) because the solution is sought by reducing either available capacity of containers or assigned shipment size iteratively. A simple three-dimensional packing heuristic is applied during each iteration to check whether the solution is feasible for containers.

Our computational study with two different data sets representing varying shipment sizes evaluates the performance of three algorithms on the basis of solution quality and time. The results show that GCRA performs the best both in terms of solution quality and solution time for small-size shipments. And SRA is an effective and efficient approach for big-volume shipments. SCRA is a simple version of GCRA and it is easily implemented.

In addition, we also validate the value of our integrated model in comparison to a traditional strategy in the computational experiments. It is observed that our method performs significantly better than the traditional strategy, especially for small-size shipments. The biggest cost savings could reach about 30%.

Chapter 4

An Integrated Consolidation Model for Multi-Period and Single-Stop Delivery

4.1 Introduction

The integrated consolidation problem for single period was studied in the last chapter. The problem provided valuable insights on the shipment consolidation, but it did not reflect the value of a long-term planning. Hence, we investigate the effect of the time factor on the consolidation problem in this chapter and develop the multi-period consolidation model.

The problem is described as follows. Consider a finite planning horizon $t = 1, 2, \cdots, T$. Each time period may represent one day, one week, or one month and shipments arrive at each time period. These shipments have to be consolidated and shipped within a given finite planning horizon T. For example, those arriving in the last time period T have to be shipped in the same period. The consolidation planner knows all of the shipment information at the beginning of the planning horizon, such as the number, size and destination of every shipment in each time period. Consequently, he or she can make the consolidation plan at the beginning of the planning horizon to decide what shipments need to be shipped and what shipments need to be stored to ship later in order to minimize the total cost of the entire planning horizon.

The shipments could be shipped at the period in which they are arriving or delayed to any following period until the end of a planning horizon. If shipments are delayed, waiting costs, which are proportional to the waiting periods, will incur. However, if additional shipments with the same destination arrive later, it may be advantageous to postpone current shipments and combine them with future shipments to reduce handling and shipping costs. Note that it may reduce inland transportation costs, because, for example, using one TL instead of two separate LTLs often saves costs. Therefore, the consolidation planner has to balance different types of operation costs while considering the container capacity and packing constraints.

The objective of our research is to minimize the total costs in the entire planning horizon including waiting costs, ocean container costs, handling costs, and inland transportation costs (TL and LTL costs). Waiting costs are the inventory costs which are positively correlated to the value of the shipments and waiting periods. Ocean container costs are the costs of shipping containers from China to the US. Handling costs are incurred when unloading/loading shipments from containers onto the trucks after they arrive at the deconsolidation center or warehouses in the US. It is assumed that the shipments to the same destination in the same container can be handled together and that the handling cost is fixed regardless of the shipment size and destination. Inland transportation costs consist of TL costs and LTL costs. Different transportation modes are chosen according to shipments' quantity and size. TL rate is typically given as per-mile costs, which are dependent on distance between origin and destination. LTL rate depends on the distance between origin and destination as well as the shipment weight and volume. The decisions considered in this chapter include

1. the number of ocean containers used at each period,
2. the assignment of shipments to ocean containers at each period, and
3. the TL and LTL mode selection for each shipment

4.2 Mathematical Modeling

In this section, we develop a mathematical model for the multi-period and single-stop consolidation problem. We seek to minimize the total cost in a multi-period planning horizon subject to container capacity and packing constraints. In order to present the mathematical formulation, some notations are introduced as follows.

Parameters:

T: the number of time periods $\{1, 2, \cdots, t, \cdots, T\}$;

I_t: a set of shipments arriving at period t;

I: a total set of shipments where $I = I_1 \bigcup I_2 \cdots \bigcup I_t \cdots \bigcup I_T$;

J_t: a set of ocean containers which are available at time period t;

J: a total set of available ocean containers where $J = J_1 \bigcup J_2 \cdots \bigcup J_t \cdots \bigcup J_T$;

K: a set of destinations where $k \in K$;

e_i: the volume of shipment $i \in I$;

f_i: the weight of shipment $i \in I$;

(s_i^l, s_i^w, s_i^h): length, width and height of shipment $i \in I$;

E: the volume capacity of a standard ocean container;

F: the weight capacity of a standard ocean container;

(L, W, H): length, width and height of a standard ocean container;

$d_{ik} = 1$: if the destination of shipment $i \in I$ is $k \in K$, and 0 otherwise;

C_i^{WC}: waiting cost for shipment i per period;

C^{OC}: unit ocean container cost from China to US;

C^{H}: handling cost for shipments to one destination in a container;

C_k^{TL}: TL transportation cost from the US port to destination $k \in K$;

$C_k^{LTL}(v, w)$: LTL transportation cost from the US port to destination $k \in K$ for a shipment with volume v and weight w;

M: an arbitrary large number;

Decision variables:

x_{ij}: a binary variable equal to 1 if shipment i is loaded into container j, and 0 otherwise;

y_j: a binary variable equal to 1 if container j is used, and 0 otherwise;

z_{jk}: a binary variable equal to 1 if container $j \in J$ includes shipments to destination $k \in K$, and 0 otherwise;

u_{jk}: a binary variable equal to 1 if shipments to destination $k \in K$ in container $j \in J$ are delivered using TL, and 0 otherwise;

v_{jk}: the total volume of the shipments to destination $k \in K$ in container $j \in J$, which are transported by LTL.

w_{jk}: the total weight of the shipments to destination $k \in K$ in container $j \in J$, which are transported by LTL.

(cx_i, cy_i, cz_i): continuous variables representing the coordinates of the front-left bottom corner of shipment $i \in I$;

$a_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the left of shipment $i' \in I$, and 0 otherwise;

$b_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the right of shipment $i' \in I$, and 0 otherwise;

$c_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is positioned behind shipment $i' \in I$, and 0 otherwise;

$o_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is positioned in front of shipment $i^{'} \in I$, and 0 otherwise;

$p_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is positioned below shipment $i^{'} \in I$, and 0 otherwise;

$q_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is positioned above shipment $i^{'} \in I$, and 0 otherwise;

4.2.1 Model Formulation

The problem can be mathematically formulated as follows.

Minimize

$$\sum_{r=1}^{T-1}\sum_{t=1}^{T-r}\sum_{i\in I_t}\sum_{j\in J_{t+1}} rC_i^{WC}x_{ij} + \sum_{j\in J} C^{OC}y_j + \sum_{j\in J}\sum_{k\in K} C^{H}z_{jk} + \sum_{j\in J}\sum_{k\in K} C_k^{TL}u_{jk} + \sum_{j\in J}\sum_{k\in K} C_k^{LTL}(v_{jk}, w_{jk}) \tag{4.1}$$

subject to:

$$\sum_{j \in J_t \bigcup J_{t+1} \bigcup \cdots \bigcup J_T} x_{ij} = 1 \qquad \forall i \in I_t, t = 1, 2, \cdots, T \quad (4.2)$$

$$x_{ij} \leq y_j \qquad \forall i \in I, \forall j \in J \quad (4.3)$$

$$\sum_{i \in I} x_{ij} f_i \leq F, \qquad \forall j \in J \quad (4.4)$$

$$cx_i + s_i^l \leq cx_{i'} + (1 - a_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.5)$$

$$cx_{i'} + s_{i'}^l \leq cx_i + (1 - b_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.6)$$

$$cy_i + s_i^w \leq cy_{i'} + (1 - c_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.7)$$

$$cy_{i'} + s_{i'}^w \leq cy_i + (1 - o_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.8)$$

$$cz_i + s_i^h \leq cz_{i'} + (1 - p_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.9)$$

$$cz_{i'} + s_{i'}^h \leq cz_i + (1 - q_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.10)$$

$$a_{ii'} + b_{ii'} + c_{ii'} + o_{ii'} + p_{ii'} + q_{ii'} \geq x_{ij} + x_{i'j} - 1, \quad \forall i, i^{'} \in I, i < i^{'}, \quad \forall j \in J \quad (4.11)$$

$$cx_i + s_i^l \leq L, \qquad \forall i \in I \quad (4.12)$$

$$cy_i + s_i^w \leq W, \qquad \forall i \in I \quad (4.13)$$

$$cz_i + s_i^h \leq H, \qquad \forall i \in I \quad (4.14)$$

$$Mz_{jk} \geq \sum_{i \in I} x_{ij} d_{ik}, \qquad \forall j \in J, \quad \forall k \in K \quad (4.15)$$

$$Mu_{jk} + v_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \quad (4.16)$$

$$Mu_{jk} + w_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \quad (4.17)$$

$$x_{ij}, y_j, z_{jk}, u_{jk} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J, \forall k \in K \quad (4.18)$$

$$a_{ii'}, b_{ii'}, c_{ii'}, o_{ii'}, p_{ii'}, q_{ii'} \in \{0, 1\}, \qquad \forall i, i^{'} \in I, i < i^{'} \quad (4.19)$$

$$v_{jk}, w_{jk}, cx_i, cy_i, cz_i \geq 0, \qquad \forall i \in I, \quad \forall j \in J, \forall k \in K \quad (4.20)$$

In this formulation, the objective function (4.1) minimizes the total cost which includes waiting cost, ocean container shipping cost, handling cost and inland transportation cost. The first term $\sum_{r=1}^{T-1}\sum_{t=1}^{T-r}\sum_{i\in I_t}\sum_{j\in J_{t+1}} rC_i^{WC}x_{ij}$ in (4.1) displays waiting costs. It is assumed that waiting cost has a linear correlation with the waiting period. For example, if a shipment $i \in I$ is delayed for one period, the waiting cost is C_i^{WC}, which is dependent upon i. If it is postponed for t periods, the waiting cost would be tC_i^{WC}. Hence, if collecting all the shipments that are delayed for r periods, the waiting cost becomes $r\sum_{t=1}^{T-r}\sum_{i\in I_t}\sum_{j\in J_{t+1}} C_i^{WC}x_{ij}$, and the total waiting cost in the entire T periods is $\sum_{r=1}^{T-1}\sum_{t=1}^{T-r}\sum_{i\in I_t}\sum_{j\in J_{t+1}} rC_i^{WC}x_{ij}$. The next terms in (4.1) include the linear ocean container shipping cost, where $\sum_{j\in J} y_j$ is the total number of ocean containers used, handling cost and inland transportation cost, including TL cost and LTL cost.

Constraints (4.2) state that each shipment arriving at current period t is assigned to exactly one container, which is available at the current period or any following time period, from $t+1$ to T in the planning horizon. The remaining constraints are the same as those in the single period model in Chapter 3.

The model (4.1)$\sim$(4.20) is an extension of the single-period model of Chapter 3. Because current shipments can be delayed to ship out in the subsequent planning periods in order to minimize the total cost, it increases the flexibility, but adds the complexity of the model. Table 4.1 presents the model complexity comparison between the single-period and the multi-period model. The number of variables and constraints of the multi-period model tends to grow significantly as more periods are considered. Because the multi-period model still includes three dimensional constraints, which is a NP-hard problem, it is very difficult to solve optimally. Hence, in the next section, we propose three approximation algorithms to solve the model.

	Single-Period Model	T-Period Model
Given Parameters		
the number of shipments at period i	m_i	m_i
the number of containers at period i	n_i	n_i
the number of destinations	k	k
Model Complexities		
the number of binary variables	$3m_i^2 + m_i n_i + 2n_i k + n_i - 3m_i$	$3(m_1 + m_2 + \cdots + m_T)^2 + (n_1 + n_2 + \cdots + n_T)(m_1 + m_2 + \cdots + m_T + 1 + 2K) - 3(m_1 + m_2 + \cdots + m_T)$
the number of continuous variables	$2n_i k + 3m_i$	$2(n_1 + n_2 + \cdots + n_T)k + 3(m_1 + m_2 + \cdots + m_T)$
the number of constraints	$\frac{1}{2}m_i^2 n_i + 3m_i^2 + \frac{7}{2}m_i n_i + 3n_i k - 2m_i$	$\frac{1}{2}(m_1 + m_2 + \cdots + m_T)^2(n_1 + n_2 + \cdots + n_T) + 3(m_1 + m_2 + \cdots + m_T)^2 +$ $\frac{7}{2}(m_1 + m_2 + \cdots + m_T)(n_1 + n_2 + \cdots + n_T) + 3(n_1 + n_2 + \cdots + n_T)k - 2(m_1 + m_2 + \cdots + m_T)$

Table 4.1: Model complexity comparison of single- and T-period model

4.3 Solution Methodology

In this section, three approximation algorithms are developed to solve the multi-period model. All of them use the algorithm CRA in Chapter 3 as a basis and relax the model similarly with the volume factor α_j. The relaxed model is displayed as follows. The parameters and decision variables are the the same with those in previous chapter.

Minimize

$$\sum_{r=1}^{T-1}\sum_{t=1}^{T-r}\sum_{i\in I_t}\sum_{j\in J_{t+1}} rC_i^{WC}x_{ij} + \sum_{j\in J} C^{OC}y_j + \sum_{j\in J}\sum_{k\in K} C^H z_{jk} + \sum_{j\in J}\sum_{k\in K} C_k^{TL}u_{jk} + \sum_{j\in J}\sum_{k\in K} C_k^{LTL}(v_{jk}, w_{jk}) \tag{4.21}$$

Subject to:

$$\sum_{j \in J_t \bigcup J_{t+1} \bigcup \cdots \bigcup J_T} x_{ij} = 1 \qquad \forall i \in I_t, t = 1, 2, \cdots, T \tag{4.22}$$

$$x_{ij} \leq y_j \qquad \forall i \in I, \forall j \in J \tag{4.23}$$

$$\sum_{i \in I} x_{ij} f_i \leq F, \qquad \forall j \in J \tag{4.24}$$

$$\sum_{i \in I} x_{ij} e_i \leq \alpha_j E, \qquad \forall j \in J \tag{4.25}$$

$$M z_{jk} \geq \sum_{i \in I} x_{ij} d_{ik}, \qquad \forall j \in J, \quad \forall k \in K \tag{4.26}$$

$$M u_{jk} + v_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \tag{4.27}$$

$$M u_{jk} + w_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \tag{4.28}$$

$$x_{ij} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J \tag{4.29}$$

$$y_j \in \{0, 1\}, \qquad \forall j \in J \tag{4.30}$$

$$z_{jk} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall k \in K \tag{4.31}$$

$$u_{jk} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall k \in K \tag{4.32}$$

$$v_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{4.33}$$

$$w_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{4.34}$$

While the first algorithm seeks the solution of the entire planning periods at each iteration, the second and third algorithms focus on the solution of the current period. Specifically, the second algorithm obtains the solution by iteratively changing the volume factor α_j for the current period. In the third algorithm, a rolling horizon technique is applied and the solution of the T-period model is computed by iteratively solving the 2-period model. The three algorithms are introduced in the following subsections in detail.

4.3.1 Algorithm 1

The first algorithm starts with solving the relaxed model, and then, simultaneously evaluates the packing feasibility of all the containers for the entire planning horizon. If the solution is feasible, it is terminated. Otherwise, the initial problem is modified to tighten the volume capacity of infeasible containers, and the procedure is repeated. The specific steps of the algorithm are described as follows.

STEP 0: Initialize $\alpha_j = 1$, $\forall j \in J$.

STEP 1: Solve the relaxed model considering a finite planning horizon from 1 to T.

STEP 2: Call procedure PackingCheck to check feasibility for each container $j \in J$. If all the containers are feasible, accept the current solution and STOP. Otherwise, go to **STEP 3**.

STEP 3: Set new $\alpha_j = \alpha_j - \Delta$ for any infeasible container $j \in J$, where Δ is a step size. Go to **STEP 1**.

Algorithm 1 seeks the solution of the entire planning period at each iteration. Hence, it is expected to generate a good solution, but take longer computational time.

4.3.2 Algorithm 2

The second algorithm focuses on the solution of current period at each iteration instead of considering the entire planning periods. If the solution is feasible at the current period, it is accepted and the next following periods planning is solved. Otherwise, the volume factor α_j for the current period is decreased, and the relaxed model is solved again. The procedure is repeated until the solutions of all periods are feasible. The detailed steps of the algorithm are as follows.

STEP 0: Initialize $\alpha_j = 1$, $\forall j \in J$. Set the current period $t = 1$.

STEP 1: Solve the relaxed model considering a finite planning horizon from t to T.
STEP 2: Call procedure PackingCheck to check feasibility for each container $j \in J_t$. If all containers are feasible, accept the solution for period t and remove shipments in container $j \in J_t$. If $t = T$, STOP. Otherwise, set $t = t + 1$ and $\alpha_j = 1$, and go to **STEP 1**. If any container is not feasible, go to **STEP 3**.
STEP 3: Set new $\alpha_j = \alpha_j - \Delta$ for any infeasible container $j \in J_t$. Go to **STEP 1**.

Since algorithm 2 seeks the solution at the current period at each iteration, it takes shorter time than algorithm 1, but sacrifices the solution quality.

4.3.3 Algorithm 3

This algorithm is based on a rolling horizon framework, where the T-period model is repeatedly solved over a 2-period moving period. More specifically, the model is solved only for the next two periods using Algorithm 2. The solution for the current period is then accepted, and the 2-period planning horizon is shifted by a period. The process is repeated until all T periods loading plans are determined. The 2-period relaxed model, which is a simpler version of (1.1) and used in the algorithm, is given below.

Minimize

$$\sum_{i \in I_1} \sum_{j \in J_2} C_i^{WC} x_{ij} + \sum_{j \in J} C^{OC} y_j + \sum_{j \in J} \sum_{k \in K} C^H z_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{TL} u_{jk} + \sum_{j \in J} \sum_{k \in K} C_k^{LTL}(v_{jk}, w_{jk}) \tag{4.35}$$

subject to:

$$\sum_{j \in J} x_{ij} = 1, \qquad \forall i \in I_1 \tag{4.36}$$

$$\sum_{j \in J_2} x_{ij} = 1, \qquad \forall i \in I_2 \tag{4.37}$$

$$\sum_{i \in I} x_{ij} f_i \leq F, \qquad \forall j \in J \tag{4.38}$$

$$M z_{jk} \geq \sum_{i \in I} x_{ij} d_{ik}, \qquad \forall i \in I, \quad \forall j \in J \tag{4.39}$$

$$M u_{jk} + v_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \tag{4.40}$$

$$M u_{jk} + w_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \tag{4.41}$$

$$x_{ij}, y_j, z_{jk}, u_{jk} \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J, \forall k \in K \tag{4.42}$$

$$v_{jk}, w_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{4.43}$$

The size complexity of single- and 2-period model is compared in Table 4.2. By observing Table 4.1 and 4.2, we find that the size (the number of binary, continuous variables and constraints) of 2-period model deceases dramatically compared with the T-period model because only two periods are considered. However, it is still more complex than single-period model because shipments delay is taken into account. Therefore, it would take shorter time to solve the 2-period model than the general T-period model, and longer time than single-period model.

	Single-Period Model	2-Period Model
Given Parameters		
the number of shipments at period i	m_i	m_i
the number of containers at period i	n_i	n_i
the number of destinations	k	k
Model Complexities		
the number of binary variables	$3m_i^2 + m_i n_i + 2n_i k + n_i - 3m_i$	$3(m_1+m_2)^2 + (n_1+n_2)(m_1+m_2) + 2(n_1+n_2)K + (n_1+n_2) - 3(m_1+m_2)$
the number of continuous variables	$2n_i k + 3m_i$	$2(n_1+n_2)k + 3(m_1+m_2)$
the number of constraints	$\frac{1}{2}m_i^2 n_i + 3m_i^2 + \frac{7}{2}m_i n_i + 3n_i k - 2m_i$	$\frac{1}{2}(m_1+m_2)^2(n_1+n_2) + 3(m_1+m_2)^2 + \frac{7}{2}(m_1+m_2)(n_1+n_2) + 3(n_1+n_2)k - 2(m_1+m_2)$

Table 4.2: Model complexity comparison of single- and 2-period model

The steps of the algorithm is given as follows.

STEP 0: Initialize $\alpha_j = 1, \forall j \in J$. Set period $t = 1$.

STEP 1: Solve the relaxed 2-period model with period t and $t + 1$.

STEP 2: Call procedure PackingCheck to check feasibility for each container $j \in J_t$. If all containers are feasible, accept the solution for period t and remove shipments in container $j \in J_t$. If $t = T - 1$, STOP. Otherwise, set $t = t + 1$, and $\alpha_j = 1$, and go to **STEP 1**. If any container is not feasible, go to **STEP 3**.

STEP 3: Set new $\alpha_j = \alpha_j - \Delta$ for any infeasible container $\jmath \in J_t$. Go to **STEP 1**.

Algorithm 3 only solves the 2-period model at each iteration, so it could obtain the solution much quicker than the previous two algorithms, but at the expense of solution quality. However, when the future shipment information is not completely available or changes dynamically in the future periods, algorithm 3 is a method to generate good solutions. Because it only considers the information for two periods, the shipment changes in the future do not affect the solution quality.

4.4 Computational Results and Analysis

In order to evaluate the performance of three algorithms, computational experiments are performed in this section. With the consideration of computational complexity, we first test three algorithms on small-scale problem instances. Based on the initial results, the efficient algorithm is selected to solve larger problems. All three algorithms were coded in MatLabR2012a and run on a computer with Intel Core i7-3520M CPU 2.90GHz processor and 8GB RAM under Windows 64. The optimization solver embedded in the algorithms is Gurobi 5.0.2.

Table 4.3 demonstrates the characteristics of the instances tested in the numerical experiments. Two datasets are generated to evaluate the performances of the algorithms to solve 3- and 5-period model ($T = 3$ and $T = 5$). Dataset 1 represents small-scale instances. It includes 6 subsets, where small- and big-size shipments, and 5 and 10 destinations are taken into account. Real-world instances are displayed in Dataset 2, where the case at each period are selected from the examples of Chapter 3. It includes 4 subsets which consider small- and big-volume shipments of 5 destinations. 10 destination cases are not included in Dataset 2 due to computational complexity.

Dataset 1: small-scale instances											
$T = 3$						$T = 5$					
Dataset	Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)	Average Weight (*lbs*)	Dataset	Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)	Average Weight (*lbs*)
Subset1	1	5	1,035	4.03	108.50	Subset4	16	5	1,520	3.94	119.88
	2	5	1,270	3.93	108.64		17	5	1,310	4.06	120.32
	3	5	615	4.02	165.98		18	5	1,025	4.02	165.98
	4	5	820	4.60	198.29		19	5	1,090	4.17	154.77
	5	5	1,060	3.49	164.95		20	5	1,310	3.84	181.60
Subset2	6	5	262	34.92	293.51	Subset5	21	5	405	34.26	340.12
	7	5	302	32.95	307.62		22	5	300	34.00	304.00
	8	5	338	34.25	297.49		23	5	342	34.12	321.11
	9	5	303	33.09	324.92		24	5	342	34.12	321.11
	10	5	300	34.00	304.00		25	5	363	34.17	328.18
Subset3	11	10	300	4.85	265.25	Subset6	26	10	500	4.85	265.25
	12	10	730	4.75	220.55		27	10	930	4.77	230.16
	13	10	1,160	4.72	208.99		28	10	1,145	4.70	216.29
	14	10	1,375	4.67	200.75		29	10	1,245	4.69	220.44
	15	10	1,160	4.72	208.99		30	10	1,345	4.82	241.80
Dataset 2: real-world instances											
Subset7	1	5	2,985	3.75	73.62	Subset9	11	5	5,625	3.54	68.80
	2	5	3,038	3.76	70.13		12	5	5,051	3.75	69.83
	3	5	3,038	3.76	70.13		13	5	5,108	3.74	70.81
	4	5	3,095	3.73	71.75		14	5	5,090	3.74	65.23
	5	5	3,065	3.72	72.40		15	5	5,375	3.66	70.14
Subset8	6	5	399	30.08	612.63	Subset10	16	5	665	28.57	624.66
	7	5	432	30.79	579.91		17	5	686	29.33	626.82
	8	5	432	30.79	579.91		18	5	686	29.33	626.82
	9	5	442	28.51	548.60		19	5	707	30.04	628.85
	10	5	462	31.95	634.29		20	5	728	30.71	630.77

Table 4.3: Instances of multi-period model

Table 4.4 summarizes the comparison of three algorithms when $T = 3$ and $T = 5$ for Dataset 1. For each instance, the total cost and runtime of the algorithms are reported. Lower bounds are obtained by solving the model (4.1)$\sim$(4.20) without considering 3D packing constraints. We compare the solution quality of three algorithms by calculating the percentage gaps between the total cost of each algorithm and lower bound, which are evaluated as $\%gap = 100(TotalCost - LowerBound)/LowerBound$. AVG1$\sim$ AVG6 give the average values of each corresponding subset. The last row shows the average values of each column.

Dataset 1: small-scale instances											
					$T = 3$						
		Lower Bound	Algorithm 1			Algorithm 2			Algorithm 3		
Dataset	Instance No.	Total cost ($)	Total cost ($)	Runtime (*seconds*)	% gap	Total cost ($)	Runtime (*seconds*)	% gap	Total cost ($)	Runtime (*seconds*)	% gap
Subset1	1	31,862	37,814	19	18.68	33,862	14	6.28	38,042	10	19.40
	2	37,522	39,965	3,725	6.51	40,320	22	7.46	41,424	22	10.40
	3	26,091	27,413	4	5.07	28,091	5	7.67	29,909	2	14.64
	4	35,941	37,793	37	5.15	37,941	22	5.56	41,750	6	16.16
	5	39,090	39,362	7	0.70	41,090	10	5.12	41,180	8	5.35
	AVG1	34,101	36,469	759	7.22	36,261	15	6.42	38,461	9.74	13.19
Subset2	6	34,348	45,379	754	32.11	42,162	287	22.75	45,656	67	32.92
	7	34,301	45,473	5,941	32.57	44,301	76	29.15	43,524	12	26.89
	8	35,924	46,817	2,257	30.32	46,373	3,141	29.08	46,969	80	30.75
	9	33,342	42,271	2,636	26.78	41,771	66	25.28	41,485	15	24.42
	10	31,531	40,332	1,202	27.91	42,171	223	33.74	43,246	67	37.15
	AVG2	33,889	44,054	2,558	29.94	43,355	758	28.00	44,176	48	30.43
Subset3	11	31,541	31,541	1	0.00	31,541	1	0.00	31,541	1	0.00
	12	52,218	52,218	5	0.00	52,218	6	0.00	55,577	2	6.43
	13	62,207	62,852	1,145	1.04	63,099	405	1.43	65,345	22	5.04
	14	62,480	63,253	4,007	1.24	63,253	1,161	1.24	71,791	119	14.90
	15	55,981	56,461	7,909	0.86	57,411	351	2.55	64,037	149	14.39
	AVG3	52,885	53,265	2,613	0.63	53,504	385	1.04	57,658	58	8.15
					$T = 5$						
Subset4	16	45,634	47,634	2,371	4.38	47,667	77	4.46	50,540	22	10.75
	17	40,613	42,073	30,149	3.59	42,073	273	3.59	48,043	18	18.30
	18	42,942	43,356	150	0.96	44,942	3,771	4.66	52,816	10	22.99
	19	46,711	46,944	88	0.50	46,944	68	0.50	54,467	4	16.60
	20	49,659	49,659	25	0.00	49,659	59	0.00	57,207	7	15.20
	AVG4	45,112	45,933	6556	1.88	46,257	850	2.64	52,614	12.25	16.77
Subset5	21	40,793	57,173	10,984	40.15	55,262	6,344	35.47	59,607	123	46.12
	22	37,576	41,522	508	10.50	45,556	10	21.24	49,660	5	32.16
	23	41,442	49,488	33,862	19.42	49,402	27	19.21	52,519	8	26.73
	24	39,700	47,230	11,297	18.97	50,050	9,095	26.07	50,801	32	27.96
	25	39,179	53,093	6,384	35.51	52,935	544	35.11	54,344	54	38.71
	AVG5	39,738	49,701	12,607	24.91	50,641	3,204	27.42	53,386	44.46	34.34
Subset6	26	48,742	48,742	11	0.00	48,742	24	0.00	52,099	1	6.89
	27	68,615	68,615	318	0.00	68,615	923	0.00	78,526	2	14.44
	28	71,914	71,914	1,024	0.00	71,914	1,101	0.00	85,516	6	18.91
	29	75,115	75,115	598	0.00	75,115	938	0.00	82,262	16	9.52
	30	78,382	78,382	1,836	0.00	78,382	2,155	0.00	85,184	71	8.68
	AVG6	68,554	68,554	757	0.00	68,554	1,028	0.00	76,717	19.29	11.69
Total	AVG	45,713	49,663	4,308	10.76	49,762	1,040	10.92	53,835	32	19.10

Table 4.4: Algorithms comparison on small problem instances

By observing Table 4.4, we find that algorithms 1 and 2 are clearly superior to algorithm 3 in terms of solution quality. The average percentage gaps of algorithms 1 and 2 are 10.76% and 10.96%, while algorithm 3 has 19.10% gaps. By looking into different subsets, it is observed that the percentage gaps of three algorithms for small-size shipments are much smaller than those for big-size shipments. For example, the average percentage gaps of three algorithms for small shipments range from 0 to 16.77%, while those for big shipments are from 24.91% to 34.34%. The reason is that the lower bound is obtained by solving the multi-period model without considering three dimensional packing constraints. Hence, the lower bound is achieved at the first iteration. The approximation solutions from three algorithms are obtained by iteratively updating α_j for infeasible containers. For large-size shipments, more iterations are required to obtain the solution because it requires more containers due to its physical dimensions. Therefore, the percentage gaps are bigger.

As expected, algorithm 3 is much faster than both algorithms 1 and 2. The average solution time is only 32 seconds, compared with algorithm 1 (4,308 seconds) and algorithm 2 (1,040 seconds). Because algorithm 3 only considers two periods per iteration, the size of the problem and computational time decrease significantly. Algorithm 1 is the slowest with several instances taking more than one hour to run, because it seeks the solution of the entire planning period at each iteration.

Therefore, based on the results of Table 4.4, we conclude that algorithm 2 provides satisfactory solutions within relative small amounts of time, and algorithm 3 is the most efficient algorithm. Although algorithm 3 performs much worse than algorithms 1 and 2 in terms of solution quality, it still performs better than single period model, as we test later. Moreover, if only limited shipment information is available, algorithms 1 and 2 may not be used.

Dataset 2: real-world instances							
$T=3$				$T=5$			
Dataset	Instance No.	Total cost ($)	Runtime (*seconds*)	Dataset	Instance No.	Total cost ($)	Runtime (*seconds*)
Subset7	1	54,891	298	Subset9	11	92,789	1,748
	2	54,899	345		12	94,249	1,161
	3	60,096	848		13	93,976	1,902
	4	56,728	809		14	96,599	1,819
	5	61,651	474		15	96,774	3,914
	AVG7	57,653	555		AVG9	94,877	2,109
Subset8	6	61,939	240	Subset10	16	93,570	1,195
	7	63,733	249		17	93,953	813
	8	54,061	459		18	92,170	631
	9	56,320	343		19	92,853	4,457
	10	59,831	90		20	96,820	429
	AVG8	59,177	276		AVG10	93,873	1505

Table 4.5: Results on real-world instances

Because algorithm 3 achieves the solution very quickly, we choose it to test real-world instances. The results are shown in Table 4.5. By observing the results, we find that algorithm 2 can obtain the solution within a reasonable time for most of cases.

Moreover, it takes more time to solve 5-period model than 3-period model, which is consistent with our complexity analysis.

We next investigate the value of our multi-period model compared with single period one. The results are given in Table 4.6. Single period addition means that single period model is applied at each period, and the total cost is the summation of the cost of each period. Only the performance of algorithm 3, which is the worst out of three algorithms, is used to validate the value of the multi-period model. The last row shows the average value of each column. According to the results of Table 4.6, we find that the multi-period model always performs significantly better than using single period model separately. The average cost savings for $T = 3$ and $T = 5$ are 11.97% and 11.03%, respectively.

Dataset 1: small-scale instances							
$T = 3$				$T = 5$			
Instance No.	Algorithm 3 Total Cost($)	Single Period Addition Total Cost($)	Cost Decrease %	Instance No.	Algorithm 3 Total Cost($)	Single Period Addition Total Cost($)	Cost Decrease %
1	38,042	45,840	17.01	16	50,540	64,978	22.22
2	41,424	51,092	18.92	17	48,043	61,380	21,73
3	29,909	42,268	29.24	18	52,816	70,447	25.03
4	41,750	54,110	22.84	19	54,467	75,448	27.81
5	41,180	49,531	16.86	20	57,207	73,465	22.13
6	38,505	43,360	11.19	21	59,607	67,068	11.12
7	43,524	46,233	5.88	22	49,660	54,112	8.22
8	46,969	54,849	14.37	23	52,519	59,294	11.43
9	41,485	49,645	16.44	24	50,801	59,294	14.32
10	43,246	51,312	15.72	25	54,344	61,886	12.19
11	31,541	35,184	10.36	26	52,099	58,640	11.15
12	55,577	57,755	3.77	27	78,526	81,211	3.31
13	65,345	80,325	18.65	28	85,516	95,147	10.12
14	71,791	94,261	23.84	29	82,262	99,899	17.65
15	64,037	82,325	22.21	30	85,184	105,673	19.39
Dataset 2: real-world instances							
1	54,891	55,504	1.10	11	102,269	108,806	6.00
2	54,900	59,504	7.74	12	94,249	98,506	4.32
3	60,096	61,504	2.29	13	93,976	98,506	4.60
4	56,728	57,503	1.35	14	96,599	102,506	5.76
5	61,650	65,284	5.56	15	96,773	102,506	5.59
6	61,939	68,107	9.06	16	93,570	94,007	0.47
7	63,733	69,293	8.02	17	93,953	97,219	3.36
8	54,061	58,266	7.22	18	92,170	95,231	3.21
9	56,320	59,830	5.87	19	92,852	96,456	3.74
10	59,831	60,076	0.41	20	96,820	97,679	0.88
AVG	51,139	58,118	11.84	AVG	74,673	83,175	11.03

Table 4.6: Results on comparison between multi- and single-period model

We also verify the effect of waiting cost on the total cost. Five different values, such as \$10, \$50, \$100, \$500 and \$10,000, are tested. When the waiting cost is very expensive, it would not save any cost by delaying shipments. Hence, the solution of multi-period model should be the same as the single period addition. By observing the results in Table 4.7, the total cost goes up as the waiting cost increases and converges to the value of single period addition. It is also noted that the multi-period model could bring cost savings as long as the waiting cost is not too expensive.

				$T = 3$		
	Single Period Addition	Algorithm 2				
Instance No.	Total Cost($)	$C^w = \$10$ Total Cost($)	$C^w = \$50$ Total Cost($)	$C^w = \$100$ Total Cost($)	$C^w = \$500$ Total Cost($)	$C^w = \$10,000$ Total Cost($)
1	45,840	33,862	44,454	43,867	44,340	45,840
2	51,092	40,320	50,085	51,092	51,092	51,092
3	42,268	28,091	40,004	41,989	42,268	42,268
4	54,110	37,941	49,079	53,189	54,110	54,110
5	49,531	41,090	46,476	47,731	47,931	49,531
6	43,361	36,477	41,307	43,091	43,361	43,361
7	46,233	44,301	45,601	48,963	46,233	46,233
8	54,849	46,373	49,663	53,607	54,769	54,848
9	49,645	41,771	44,724	47,896	49,645	49,645
10	51,312	42,171	45,436	45,994	50,090	51,312
11	35,184	31,541	35,161	35,184	35,184	35,184
12	57,755	52,218	57,755	57,755	57,755	57,755
13	80,325	63,099	78,990	80,286	80,325	80,325
14	94,261	63,253	88,722	94,081	94,261	94,261
15	82,325	57,411	76,749	80,589	82,325	82,325
			$T = 5$			
16	64,978	50,540	61,171	64,502	64,978	64,978
17	61,380	48,043	60,417	61,101	61,380	61,380
18	70,447	52,816	66,644	69,889	70,447	70,447
19	75,448	54,467	68,791	74,527	75,448	75,448
20	73,465	57,207	68,224	71,386	72,465	73,465
21	67,068	55,262	61,527	65,291	67,068	67,068
22	54,112	45,556	49,122	50,610	54,112	54,112
23	59,295	49,402	55,438	56,983	59,375	59,295
24	59,295	50,050	54,394	57,745	59,295	59,295
25	61,886	52,935	59,216	58,727	61,886	61,886
26	58,640	48,742	58,561	58,640	58,640	58,640
27	81,211	68,615	81,132	81,211	81,211	81,211
28	95,147	71,914	92,013	93,347	94,147	95,147
29	99,899	75,115	96,156	98,099	98,899	99,899
30	105,673	78,382	99,534	103,054	104,674	105,674

Table 4.7: Sensitivity analysis

4.5 Summary

In this chapter, we considered a shipment consolidation problem in a multi-period planning horizon. In contrast to Chapter 3, a long-term planning is addressed in order to explore more potential cost savings. It is assumed that the shipments arrive at any period from 1 to T, based on the estimation of a consolidation planner. Hence, he or she needs to determine whether the shipments that arrive at the current period are shipped currently or delayed to the next periods. If the shipments are delayed, waiting costs will incur. However, if the future shipment has the same destination with the current shipments, they can be combined together as a batch to ship in one TL delivery, instead of multiple separate LTLs. It might save inland transportation and handling costs. Therefore, there are trade-offs among waiting, handling and inland transportation costs.

This multi-period shipment consolidation problem is formulated as a mixed integer programming model with the objective of minimizing the total cost, including waiting, ocean container, handling, and TL and LTL costs. This model still combines a mode selection problem and a three dimensional bin packing problem. The model complexity is compared between the single- and multi-period models. We observed that the multi-period model has more variables and constraints than the single-period model. Hence, the size of model increases greatly as the periods considered increase.

Based on the natural characteristics of the model, it is not possible to solve it directly. Three heuristic algorithms are proposed to approximate the solution. All of these algorithms use the algorithm CRA in Chapter 3 as a basis, where the original multi-period model is relaxed by adding the volume factor α_j to substitute the three-dimensional bin packing constraints. The first algorithm seeks the solution of the entire planning periods at each iteration by updating the α_j of any infeasible container for the periods from 1 to T. The second and third algorithms achieve the solution of the model by iteratively obtaining the current period's solution. Specifically, the second algorithm only updates the α_j of any infeasible container for the current period. The third algorithm applies a rolling horizon technique, and the T-period model is solved by iteratively solving a 2-period model.

Computational experiments are implemented to evaluate three approximation algorithms in terms of solution quality and time. Two data sets are tested. The first data set is generated randomly considering only small-scale problems. The second data set, wherein instances for each period are selected from Chapter 3, represents large-scale problems. According to the results, we find that three algorithms can obtain good approximation solutions within a reasonable time for small-scale problems. Algorithms 1 and 2 are superior over Algorithm 3 in terms of solution quality. However, algorithm 3 is the most efficient one. Specifically, Algorithm 1 receives good solution at the expense of computational time. Algorithm 2 has a good performance in terms of solution quality and time. Although Algorithm 3 performs much worse than Algorithms 1 and 2 in terms of solution quality, it requires shorter time to achieve a solution. For large-scale problems and cases in which future information is limited, Algorithm 3 is useful. We also evaluate the value of our multi-period model over the single-period model, and we observe that the multi-period model could bring an additional 10% savings.

Chapter 5

An Integrated Consolidation Model for Single Period and Multi-Stop Delivery

5.1 Introduction

In the previous chapters, we studied integrated consolidation models using direct delivery of TL and LTL. In this chapter, TL multi-stop deliveries are taken into account since they may achieve more cost-savings in road transportation. That is, the multi-stop delivery of TL shipments could be considered when shipments are loaded into ocean containers in our proactive consolidation problem. This results in more effective loading patterns, although it is more complicated, to reduce the overall cost.

In a survey of industrial firms' consolidation practices, Jackson (1985) finds that 97% of the responding firms use multi-stop truckloads to consolidate orders domestically. The price that a multi-stop TL carrier charges is typically a function of the distance between origin and destination and the number of stops in a trip, no matter what the shipments are and how they are packed. Thus, a shipper can consolidate several shipments, going to different destinations, in a single truck. A truck takes the combined loads, makes intermediate stops, and drops shipments during the assigned one-way trip. According to Jackson (1985), 93% of the firms accepts less than four stops including the final destination per TL trip, since the more stops a route has, the less reliable its delivery time is.

The problem in this chapter can be described as follows. The same multi-commodity international network is given as described in Chapter 3. The orders are consolidated into ocean containers in China, shipped to a deconsolidation center in US by ship, and finally delivered to destinations by road transportation. We consider container cost, subsequent handling cost and inland transportation cost simultaneously. Our objective is to investigate how to transport shipments from origin to destination in the international multi-modal network with the minimum overall cost by consolidating shipments in ocean containers. In this chapter, the inland transportation modes include LTL, direct TL, and multi-stop TL, where direct TL and multi-stop TL are one-way truckload services. We assume that a consolidated TL is limited to at most three delivery stops (including the final destination). In addition, TL routes are not fixed and changed as the destinations of shipments change. The decisions addressed in this chapter consist of

1. the number of ocean containers needed
2. the assignment of multi-shipments to the ocean containers
3. the multi-stop TL and LTL mode selection
4. TL route and stop selection

The multi-stop (vehicle) consolidation model is first introduced by Hall (1987). He defines vehicle consolidation as a cost-effective transportation strategy, where trucks pick-up and drop-off items at different origins and destinations. Then, several key factors, such as the time between dispatches and the number of stops per route, are discussed. Pooley and Stenger (1992b) and Pooley (1993) present an algorithm for the mode selection on LTL versus one-way multi-stop TL problem. He finds that this problem is more complicated than a traditional vehicle routing problem. For example, for n destination points, a truck vehicle routing problem has $(\frac{n!}{2})$ possible solutions, while this problem has $\sum_{i=0}^{n}(\frac{n!}{i!})$ solutions. Finally, a heuristic algorithm is proposed using a modified Clarke and Wright savings algorithm. Brown and Ronen (1997) develop a mathematical model and implement a computerized system for consolidating customer orders into truckload while minimizing truck miles and meeting all customer service requirements. Some papers (Chu (2005), Bolduc et al. (2007), Côté and Potvin (2009)) work on the problem of routing the round-trip private trucks (TL) and making a selection of LTL by minimizing a total cost. Most of them apply a Clarke-Wright savings-based constructive heuristic followed by intra- and inter-route local improvement. Some papers (Iori and Salazar-González (2007), Gendreau et al. (2006), Moura and Olliverira (2009), Fuellerer et al. (2010), Iori and Martello (2010)) study a vehicle routing problem with two- and three-dimensional loading constraints. They integrate two difficult combinatorial optimization problem such as vehicle routing problem and bin packing problem. Iori and Salazar-González (2007) propose an exact approach, while most of others apply metaheuristics to solve this problem.

From our review of the existing literature, we find that most papers focus on classical vehicle routing problem and corresponding heuristic algorithms. There is very little research which examines the integration of mode selection, TL one-way routing and three-dimensional bin packing problem in the context of multi-modal international logistics network. Our approach in this chapter tries to fill this gap.

The remainder of this chapter is organized as follows. In Section 4.2, a mixed integer programming is developed for our problem. In Section 4.3, a heuristic approach is described. It is followed by numerical validations in Section 4.4. Finally, we provide a summary of our conclusions in Section 4.5.

5.2 Mathematical Model

This section presents a mathematical model for the problem. It is based on the model in Chapter 3 with an addition of the TL multi-stop consideration. Since at most three delivery stops are assumed for one assigned TL trip, we enumerate all the possible routes from US deconsolidation center to shipments' destinations via one-, two-, and three-stops. Hence, given K destinations, the total number of routes is equal to $\binom{K}{1} + \binom{K}{2} + \binom{K}{3}$ in the model. In the model, it is assumed that all the shipments are rectangular-shaped.

5.2.1 Variables and Parameters

In order to develop a mathematical formulation, the definitions of all the parameters and variables are described as follows.

Given Parameters:

I: a set of shipments;

J: a set of available ocean containers;

K: a set of destinations;

R: a set of pre-established routes;

S_r: a set of stop locations in route $r \in R$. For $\forall r \in R$, $S_r \subseteq K$ and $|S_r| \leq 3$;

e_i: the volume of shipment $i \in I$;

f_i: the weight of shipment $i \in I$;

(s_i^l, s_i^w, s_i^h): length, width and height of shipment i;

E: the volume capacity of the standard ocean container;

F: the weight capacity of the standard ocean container;

(L, W, H): length, width and height of a standard ocean container;

$d_{ik} = 1$: if shipment $i \in I$ to destination $k \in K$, and 0 otherwise;

C^{OC}: unit ocean container cost from China to US;

C^{H}: handling cost for shipments to one destination within a container;

C_r^{TL}: the fixed cost for each route $r \in R$ using TL;

$C_k^{LTL}(v, w)$: LTL transportation cost from the US deconsolidation center to destination $k \in K$ for a shipment with volume v and weight w;

M: an arbitrary large number;

Decision variables:

x_{ij}: a binary variable equal to 1 if shipment $i \in I$ is loaded into container $j \in J$, and 0 otherwise;

y_j: a binary variable equal to 1 if container $j \in J$ is used, and 0 otherwise;

z_{jk}: a binary variable equal to 1 if handling cost to destination $k \in K$ is incurred in container $j \in J$, and 0 otherwise;

u_{jr}: a binary variable equal to 1 if the shipments in container $j \in J$ are transported by TL on route $r \in R$, and 0 otherwise;

v_{jk}: the total volume of the shipments in container $j \in J$ to destination $k \in K$, which are transported by LTL;

w_{jk}: the total weight of the shipments in container $j \in J$ to destination $k \in K$, which are transported by LTL;

(cx_i, cy_i, cz_i): continuous variables indicating the coordinates of the front-left bottom corner of shipment $i \in I$;

$a_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the left of shipment $i' \in I$, and 0 otherwise;

$b_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the right of shipment $i' \in I$, and 0 otherwise;

$c_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the behind of shipment $i^{'} \in I$, and 0 otherwise;

$o_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the front of shipment $i^{'} \in I$, and 0 otherwise;

$p_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the below of shipment $i^{'} \in I$, and 0 otherwise;

$q_{ii'}$: a binary variable equal to 1 if shipment $i \in I$ is on the above of shipment $i^{'} \in I$, and 0 otherwise;

5.2.2 Model Formulation

The problem can be formulated as follows:

Minimize

$$\sum_{j \in J} C^{OC} y_j + \sum_{j \in J} \sum_{k \in K} C^H z_{jk} + \sum_{j \in J} \sum_{r \in R} C_r^{TL} u_{jr} + \sum_{j \in J} \sum_{k \in K} C_k^{LTL}(v_{jk}, w_{jk}) \tag{5.1}$$

subject to:

$$\sum_{j \in J} x_{ij} = 1 \qquad \forall i \in I \tag{5.2}$$

$$x_{ij} \leq y_j \qquad \forall i \in I, \quad \forall j \in J \tag{5.3}$$

$$\sum_{i \in I} x_{ij} f_i \leq F \qquad \forall j \in J \tag{5.4}$$

$$cx_i + s_i^l \leq cx_{i'} + (1 - a_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.5}$$

$$cx_{i'} + s_{i'}^l \leq cx_i + (1 - b_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.6}$$

$$cy_i + s_i^w \leq cy_{i'} + (1 - c_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.7}$$

$$cy_{i'} + s_{i'}^w \leq cy_i + (1 - o_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.8}$$

$$cz_i + s_i^h \leq cz_{i'} + (1 - p_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.9}$$

$$cz_{i'} + s_{i'}^h \leq cz_i + (1 - q_{ii'})M, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.10}$$

$$a_{ii'} + b_{ii'} + c_{ii'} + o_{ii'} + p_{ii'} + q_{ii'} \geq x_{ij} + x_{i'j} - 1, \quad \forall i, i^{'} \in I, i < i^{'}, \quad \forall j \in J \tag{5.11}$$

$$cx_i + s_i^l \leq L, \qquad \forall i \in I \tag{5.12}$$

$$cy_i + s_i^w \leq W, \qquad \forall i \in I \tag{5.13}$$

$$cz_i + s_i^h \leq H, \qquad \forall i \in I \tag{5.14}$$

$$Mz_{jk} \geq \sum_{i \in I} x_{ij} d_{ik}, \qquad \forall j \in J, \quad \forall k \in K \tag{5.15}$$

$$M \sum_{r: k \in S_r} u_{jr} + v_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} e_i, \qquad \forall j \in J, \quad \forall k \in K \tag{5.16}$$

$$M \sum_{r: k \in S_r} u_{jr} + w_{jk} \geq \sum_{i \in I} x_{ij} d_{ik} f_i, \qquad \forall j \in J, \quad \forall k \in K \tag{5.17}$$

$$x_{ij}, y_j \in \{0, 1\}, \qquad \forall i \in I, \quad \forall j \in J \tag{5.18}$$

$$z_{jk} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall k \in K \tag{5.19}$$

$$u_{jr} \in \{0, 1\}, \qquad \forall j \in J, \quad \forall r \in R \tag{5.20}$$

$$a_{ii'}, b_{ii'}, c_{ii'}, o_{ii'}, p_{ii'}, q_{ii'} \in \{0, 1\}, \qquad \forall i, i^{'} \in I, i < i^{'} \tag{5.21}$$

$$v_{jk}, w_{jk} \geq 0, \qquad \forall j \in J, \quad \forall k \in K \tag{5.22}$$

$$cx_i, cy_i, cz_i \geq 0, \qquad \forall i \in I \tag{5.23}$$

In this formulation, the objective function (4.1) minimizes the total costs which include the ocean container shipping cost, handling cost and inland transportation cost. The first term in (4.1) is a linear ocean container shipping cost where $\sum_{j \in J} y_j$ is the total number of ocean containers used. The second term in (4.1) is handling cost. The handling cost occurs proportionally to the number of destinations shipped in each container. The last two terms in (4.1) are inland transportation costs. $\sum_{j \in J} \sum_{r \in R} C_r^{TL} u_{jr}$ is the cost of the multi-stop TL routes. $C_k^{LTL}(v_{jk}, w_{jk})$ represents the LTL cost of shipments with volume v_{jk} and weight w_{jk} delivered to destination k.

Constraints (4.2) state that each shipment is assigned to exactly one container. Constraints (4.3) ensure that shipment i cannot be loaded into container j unless container j is used. Constraints (4.4) guarantee the shipments in container j cannot exceed the container weight limit. Constraints (4.5)-(4.10) imply that any two shipments in the same container do not occupy the same space. Constraints (4.11) shows that the placement relationship between any two shipments only exists if they are loaded into the same container. Constraints (4.12)-(4.14) ensure that all the shipments loaded in a container do not violate the geometric dimensions (length, width and height) of the container. Constraints (4.15) impose the condition of handling costs incurred because $\sum_{i=1}^{n} x_{ij} d_{ik}$ is the number of shipments in container j to destination k, its positive value necessitates the handling if there are shipments to destination k in container j. Therefore, $\sum_{i=1}^{n} x_{ij} d_{ik} > 0$, $z_{jk} = 1$. Constraints (4.16) and (4.17) state the mode selection of inland transportation. LTL and TL are mutually exclusive for shipments in container j to destination k. If TL transportation is selected, there is a route r such that $u_{jr} = 1$, where $k \in S_r$. Thus the total volume of those shipments cannot violate the volume capacity constraints of the container. Also it enforces that $v_{jk} = 0$ since the total cost is minimized. Each destination k

	Direct-delivery model	Multi-stop model
Given Parameters		
the number of shipments	m	m
the number of containers	n	n
the number of destinations	k	k
Model Complexities		
the number of binary variables	$3m^2 + mn + 2nk + n - 3m$	$\frac{1}{6}nk^3 + 3m^2 + mn + \frac{11}{6}nk + n - 3m$
the number of continuous variables	$2nk + 3m$	$2nk + 3m$
the number of constraints	$\frac{1}{2}m^2n + 3m^2 + \frac{7}{2}mn + 3nk - 2m$	$\frac{1}{2}m^2n + 3m^2 + \frac{7}{2}mn + 3nk - 2m$

Table 5.1: Model complexity comparison

belongs to one or zero route in each container. Because the shipments to destination k have to be shipped by a multi-stop TL or LTL deliveries. Also each location can be served by multiple routes because because each container can have different routes. Constraints (4.18)-(4.23) define types of decision variables.

5.3 Model Complexity Analysis

The mathematical model (4.1)-(4.23) is an extension of the model in Chapter 3. The comparison of model complexity between two models is listed as shown in Table 5.1. Two models have the same number of continuous variables and constraints, but the multi-stop model has approximately $\frac{1}{6}nk^3$ more binary variables since $\binom{K}{3}$ is dominant in the number of routes $\binom{K}{1} + \binom{K}{2} + \binom{K}{3}$. Thus, it would take potentially more computational time as k increases.

5.4 Solution Approaches

The model presented in this chapter is a non-linear mixed-integer programming. It integrates a three-dimensional bin packing problem, a mode selection problem and a route selection problem into one model. Any one of these problem is a difficult combinatorial problem to solve exactly. Thus, approximation algorithms are still necessary to solve our model. Since the model in this chapter is an extended version of previous model, we apply the same solution methodology presented earlier. A brief description of the solution methodology is explained as follows.

1. Disaggregate the problem into two subproblems such as a mode and route selection and a bin packing problem.

2. Solve a mode and route selection problem with relaxed capacity constraints replacing bin packing constraints.

3. Check the solution with the three-dimensional packing feasibility. If feasible, the solution is final. Otherwise, go to the previous step with tightened capacity constraints. The procedure is repeated until a solution is found.

To tighten the container capacity, the algorithm GCRA proposed in Chapter 3 is used in this chapter, because it showed superior solution quality in the single stop model. The details of the algorithm are given in Section 3.4.3.

5.5 Computational Experiments

In the previous sections, we have developed a mathematical model for our problem and proposed a solution approach (algorithm GCRA) to find good feasible solution to our model. Theoretically, the multi-stop model can achieve bigger cost-savings than the one-stop model, but may take significantly more computational time. In this section, a numerical test is implemented to evaluate cost savings and computational time.

5.5.1 Data and Model Parameters

The detailed process of generating test instances was introduced in Section 3.5.1. There are ten typical commodity classes with the density from 1 lb/ft^3 to 100 lb/ft^3,

Dataset	Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)	Dataset	Instance No.	No. of Destinations	No. of shipments	Average Volume (ft^3)
Subset1	1	5	1,395	3.60	Subset3	11	10	925	3.94
	2	5	995	3.75		12	10	850	3.46
	3	5	1,025	3.79		13	10	882	4.89
	4	5	1,018	3.74		14	10	828	5.50
	5	5	1,075	3.66		15	10	965	4.19
Subset2	6	5	166	31.93	Subset4	16	10	213	33.26
	7	5	130	30.58		17	10	259	25.93
	8	5	138	24.89		18	10	204	26.54
	9	5	154	28.80		19	10	244	27.11
	10	5	144	26.67		20	10	183	26.69

Table 5.2: Details on the instance generation

Parameters	**Value**
Ocean container cost (C^{OC})	\$2,000
Handling cost (C^H)	\$80
TL one stopover cost	\$100
Route cost (C_r^{TL})	$1.5 \times route\_distance + 100 \times the\_number\_of\_stops$
LTL cost (C^{LTL})	calculated by Czar program for each type of shipment
Ocean container weight capacity (F)	59,000 *lbs*
Ocean container volume capacity (E)	2,560 ft^3
Ocean container dimensions ($L \times W \times H$)	40ft×8ft×8ft

Table 5.3: Parameters of multi-stop model

which represent varieties of shipments. They are the same commodity types, shown in Table 3.1. New dataset including 4 subsets with 20 instances in total listed in Table 5.2. The first and the second subsets consider the small- and big-volume shipments with five destinations. The third and fourth subsets take those shipments with ten destinations. The order quantities are assumed to be somewhat smaller in this dataset so that they are more appropriate for multi-stop consolidation.

The parameters to set up numerical tests are summarized in Table 5.3. The value of parameters are mostly the same with those in Section 3.5.1. It is noted that the route cost C_r^{TL} is computed using the following formula

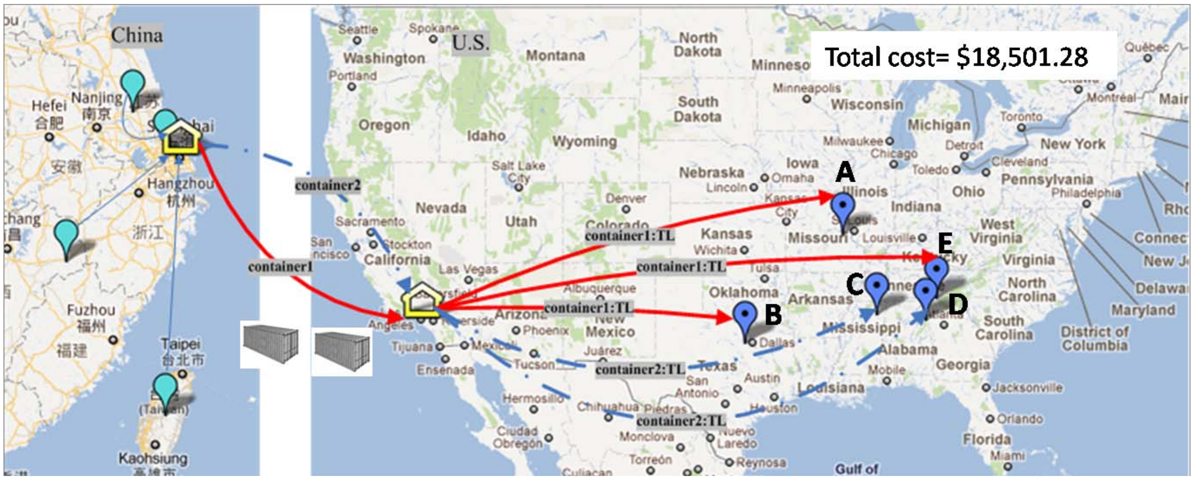
$$C_r^{TL} = TL\_rate \times route\_distance + TL\_one\_stopover\_cost \times the\_number\_of\_stops \tag{5.24}$$

where TL_rate is assumed to be \$1.5 per mile and $TL\_one\_stopover\_cost$ is \$100, estimated based on Flatbed Truckload Market Price Index and US Domestic Freight Policy, respectively. The route distance is the shortest distance of the route based on the predetermined destinations.

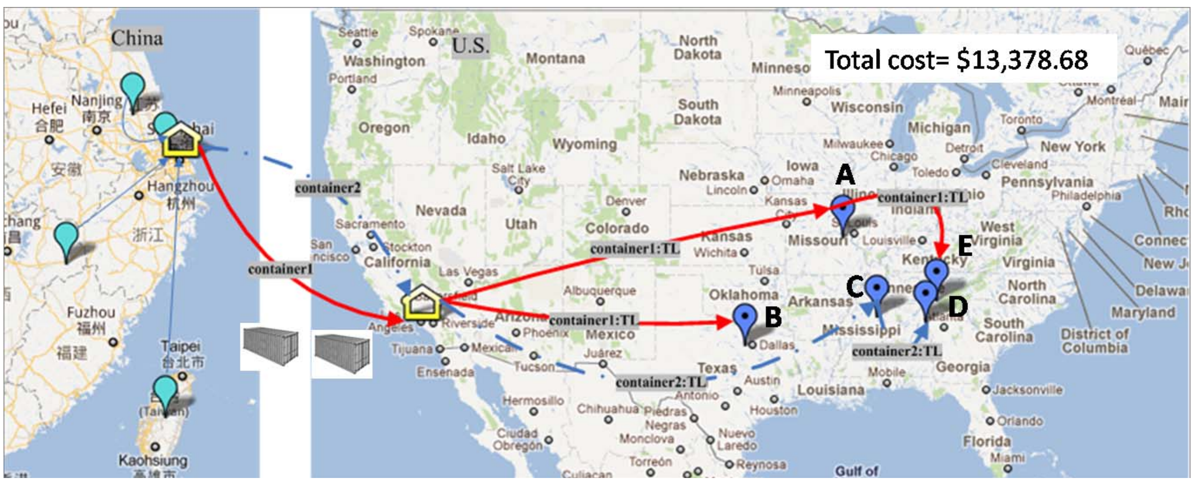
5.5.2 Results

We implemented the solution approach using MatLabR2009a on a computer with Intel Core 2 Duo CPU L7500 1.60GHz processor and 1GB RAM under Windows 32. The inner solver for optimization is Gurobi 4.0.1.

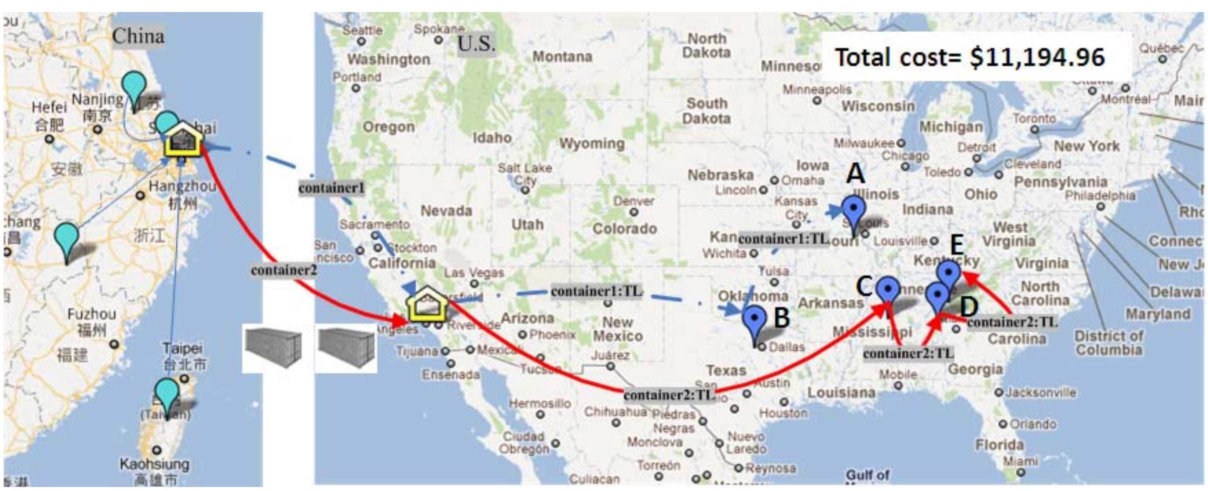
Before we present the complete results of numerical examples, we illustrate three different scenarios. Figure 5.1 shows the first scenario of the multi-stop model. In Figure 5.1(a), only direct delivery (i.e., one stop) of the inland transportation is considered. In this situation, two containers are packed in China: one container with destinations of A, B, and E and the other with C and D. The optimal inland transportation plan is to separate shipments to five batches based on destinations and send them using TL deliveries. The total cost associated with the operation is \$18,501.



(a) One stop deliveries



(b) Two stop deliveries



(c) Three stop deliveries

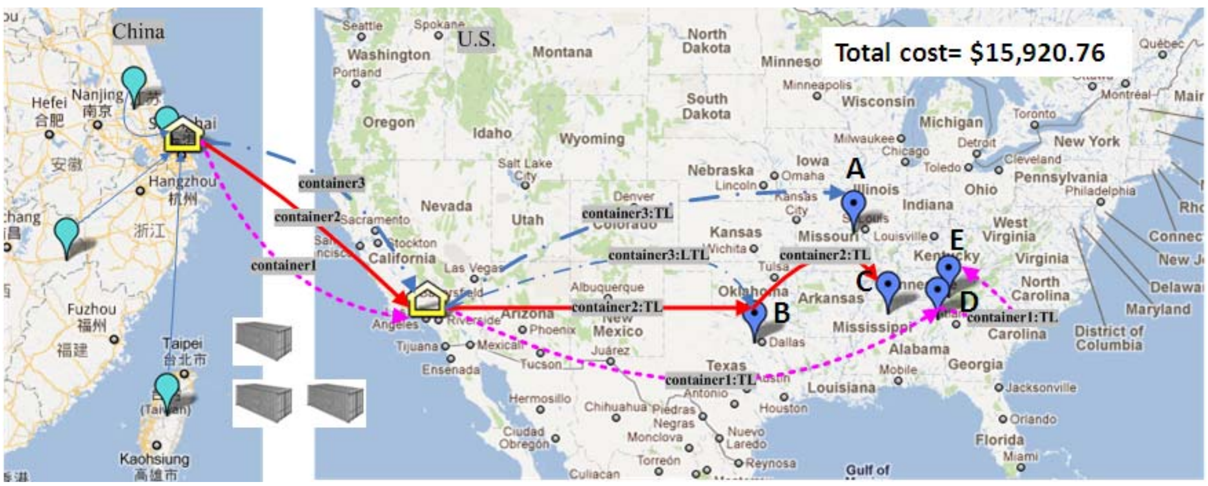
Figure 5.1: Scenario 1

Figure 5.1(b) shows the case when two stops are considered. It uses the same packaging of two containers from China, but their inland transportation is different. Shipments in the first containers are separated into two inland deliveries. The shipments to destinations A and E are delivered in a single two-stop TL route, and the shipments to B are transported by another direct TL delivery. Shipments in the second container are sent to C and D using a two-stop TL route. In this case, the total cost is $13,379, which saves 27.69% over the one stop deliveries.

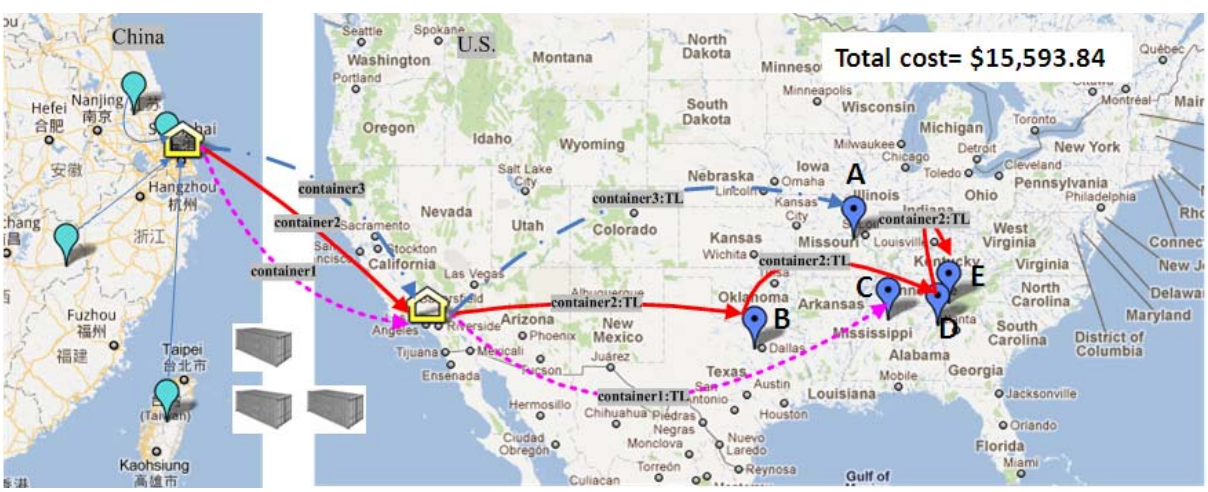
The three stop deliveries are considered in Figure 5.1(c). Although the same two containers are used in China, their original loading patterns are changed in this case. The shipments to destinations A and B are consolidated in one container in the China, and delivered in a two-stop TL route. The other container has shipments to C, D and E and is delivered in a three-stop route. Because destinations C, D and E are located close to each other, shipments to those are packed together in China and delivered together in a single three-stop route. The total cost is $11,195 , which represents additional cost savings of 16.32% over the two-stop model.

Figure 5.2 illustrate the second scenario. Figure 5.2(a) shows the consolidation with only direct deliveries. Two containers are loaded in China: one container with destinations of A, B and D and the other with C and E. The optimal inland transportation plan is to separate shipments to five TL deliveries based on destinations with the total cost of $18,501. Note that the total cost is the same as that of case in 2.1(a) even though shipments are different because TL used for inland transportation is charged by miles instead of the quantity of shipments.

(a) One stop deliveries



(b) Two stop deliveries



(c) Three stop deliveries

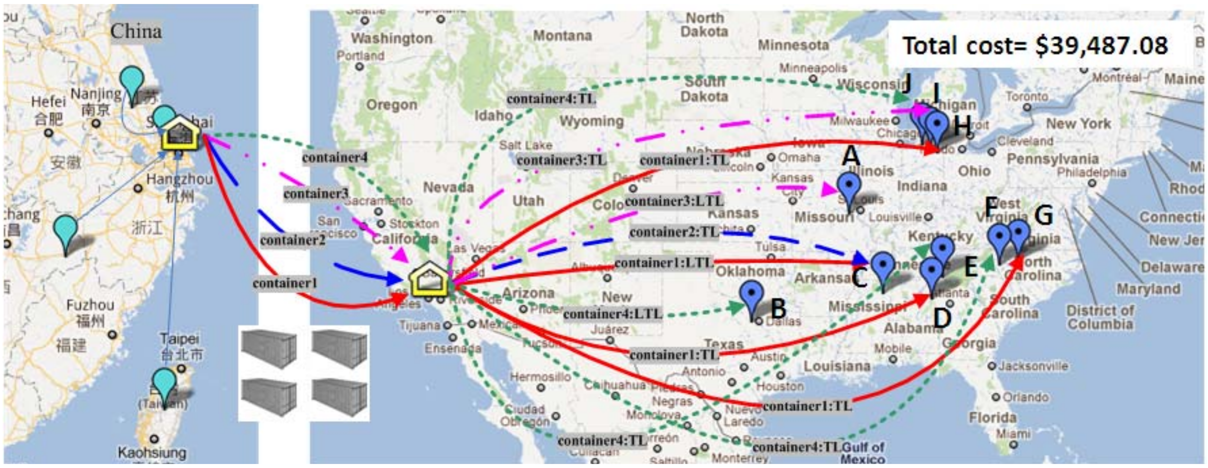
Figure 5.2: Scenario 2

In Figure 5.2(b), two stop deliveries are taken into account. In this case, three containers are packed in China, and the shipments to destination B are separated into two containers. a part of them is loaded with shipments to destination A and the remaining shipments consolidated are with those to C. The shipments to D and E in the first container are delivered in a two-stop TL route. In the second container, the shipments to B and C are also sent using a two-stop TL route. The shipments in the third container are sent to B by LTL and to A by a direct TL delivery. The total cost is \$15,921, which saves 13.95% over one stop deliveries. This loading and transportation planning increase handling cost compared with one stop deliveries. However, this saves the overall cost by creating multi-stop TL and LTL deliveries, because the cost of multi-stop TL deliveries are much cheaper than multiple separate LTL or TL deliveries.

The case of three-stop deliveries is shown in Figure 5.2(c). Three containers are still used. The shipments in the first container are sent to C by a direct TL delivery. In the second container, the shipments to B, D and E are delivered by a three-stop TL route. The shipments in the third container are delivered to A by using a direct TL delivery. The total cost is \$15,594, which achieves additional savings of 2.1% over two stop deliveries. Note that although the destinations of C, D and E are located closely, the shipments of these destinations are not put one containers for a multi-stop TL delivery. That happens because the total volume of the shipments violate the capacity of one container.

In this scenario, the consolidations with two- and three-stop deliveries consume one more ocean container than the consolidation with only direct delivery. However, the total costs associated with multi-stop deliveries are still lower because the cost savings from inland road transportation are bigger.

Figure 5.3 represents a more complicated scenario with 10 destinations. Figure 5.3(a) shows the situation with only direct deliveries. Four containers are used in



(a) One stop deliveries

(b) Two stop deliveries

(c) Three stop deliveries

Figure 5.3: Scenario 3

this case. The first one with destinations C, D, G and H, the second one with C, the third one with A and I, and the last one with B, E, F and G. The shipments in the four containers are separated to nine TL direct deliveries and two LTL deliveries. The shipments to B and part of shipments to C are sent by using LTL and all the others are shipped by direct TL deliveries. The total cost involved in the operation is $39,487.

In Figure 5.3(b), two stop deliveries are considered. Four containers are still needed. The shipments to B, D, G and F are loaded in the first container and sent to two separate two-stop TL deliveries. The shipments in the second container are sent to C and E using a two-stop TL delivery. In the third container, the shipments to A and H are delivered in a two-stop TL route, and the shipments to C are transported by LTL. The last container are loaded with the shipments to I and J, which are delivered in a two-stop TL route. The total cost in this case is $26,893, which reaches 31.90% cost savings over one stop deliveries. The shipments originally shipped separately using LTL and TL in the Figure 5.3(a) are loaded into one ocean container because two-stop TL deliveries are allowed. For example, the shipments to B, D, G and F are now loaded into one container and sent to two separate two-stop TL deliveries, while they were delivered by using one LTL and three TL separately in the previous case. This type of TL consolidation achieves significant inland transportation cost savings.

Figure 5.3(c) considers three stops deliveries. The shipments to C are separated into two containers and two three-stop TL deliveries. In the first container, the shipments to C, D and E are packed together and sent by using a three-stop TL delivery. The shipments to C, F, and G in the second container are also delivered in a three-stop TL route. The third container has shipments to A, B and H, which are delivered in another three-stop TL route. In the last container, the shipments to I and J are delivered in a two-stop TL route. The total cost associated with this operation is $23,786, which represents additional 11.55% cost savings over two stops deliveries. Hence, three-stop TL deliveries could reduce the total cost significantly.

Based on these scenarios, it is observed that the proactive consolidation with multiple stops could significantly save the total cost involved in the supply chain. In addition, it is seen that the loading pattern can change substantially.

In Table 5.4 we present more extensive computational analysis on the multi-stop model. The first column in Table 5.4 shows the index of subset. The second column in Table 5.4 reports the index of the instance. The upper bounds such as $UB_{one-stop}$, $UB_{two-stop}$, $UB_{three-stop}$ are the solutions of GCRA on one-stop, two-stop and three-stop models, respectively. Associated runtimes are the termination time of the algorithm. The last two columns give the percentage savings of two-stop and three-stop models compared with one-stop model, evaluated as

$$\%saving_{two-stop} = 100((U_{one-stop} - U_{two-stop})/U_{one-stop}), \tag{5.25}$$

and

$$\%saving_{three-stop} = 100((U_{one-stop} - U_{three-stop})/U_{one-stop}) \tag{5.26}$$

AVG1∼4 give the average values of each subset. The last row gives the average values of each column.

In Table 5.4, we find that two- and three-stop models achieve lower costs than one-stop model, which validates our conjecture. The average costs of two- and three-stop models are \$22,135 and \$20,644, which represent savings of 21.27% and 25.99%, respectively, over the one-stop cost of \$28,694. It is also observed in Table 5.4 that the three-stop model does not improve over the two-stop model in some cases. That is, the three-stop routes were not beneficial because the shipments to three destinations cannot be filled into one container due to their physical dimensions. Overall, the significant cost saving was mostly achieved by using the two-stop model. The usage of the three-stop model improved solutions only a little more. This tendency will

Dataset	Instance No.	One-stop Model $UB_{one-stop}$ (\$)	Runtime (*seconds*)	Two-stop Model $UB_{two-stop}$ (\$)	Runtime (*seconds*)	Three-stop Model $UB_{three-stop}$ (\$)	Runtime (*seconds*)	Savings Two-stop (%)	Three-stop (%)
Subset1	1	20,501	55	15,680	90	15,680	159	23.52	23.52
	2	18,501	3	15,921	669	15,594	717	13.95	15.71
	3	20,501	26	15,590	298	15,590	298	23.95	23.95
	4	20,501	28	13,379	17	11,521	332	34.74	43.80
	5	21,761	27	16,768	833	16.768	833	22.95	22.95
	AVG1	20,353	28	15,467	391	15,031	468	23.82	25.99
Subset2	6	24,527	16	22,638	64	22,451	69	7.70	8.46
	7	18,238	5	15,934	6	15,641	26	12.63	14.24
	8	17,906	6	16,213	9	15,819	12	9.46	11.66
	9	20,937	23	19,264	62	19,025	69	7.99	9.13
	10	20,702	8	18,370	18	15,929	25	11.26	23.05
	AVG2	20,462	12	18,484	32	17,773	40	9.80	13.30
Subset3	11	37,803	265	23,977	350	20,104	875	36.57	46.82
	12	35,803	25	21,977	30	18,104	22	38.62	49.43
	13	39,943	549	26,893	641	24,092	3,603	32.67	39.68
	14	39,487	561	26,893	415	23,786	3,603	31.89	39.76
	15	38,228	308	24,893	360	21,160	3,607	34.88	44.65
	AVG3	38,253	342	24,926	359	21,449	2,342	34.93	44.07
Subset4	16	38,542	97	29,115	18	27,290	1,239	24.46	29.19
	17	40,569	910	33,578	31	32,759	11,261	17.23	19.25
	18	32,725	29	28,101	78	26,543	203	14.13	18.89
	19	37,951	291	31,733	263	31,969	7,482	16.38	15.76
	20	28,761	24	25,777	19	23,048	80	10.37	19.86
	AVG4	35,710	270	29,661	82	28,322	4,053	16.52	20.59
Total	AVG	28,694	163	22,135	216	20,644	1,726	21.27	25.99

Table 5.4: Cost savings for multi-stop model

continue if we consider more than three stop routes, because the consolidation of shipments is limited due to their physical dimensions. By comparing average savings of subset1 and subset3 with subset2 and subset4, we find that small-size shipments could achieve more cost savings than large-size shipments. For example, for the small-size shipments with 5 destinations, the average savings of two- and three-stop model are 23.82% and 25.99%, which is two and three times bigger than those of large-size shipments. That's because small-size shipments can realize the higher utilization of ocean containers than those big-size ones according to their geometric dimensions, which could decrease the inland transportation costs by using more multi-stop TL transportation instead of separate TL and LTL deliveries. It is also observed that the savings achieved in the 10-destination network is bigger than that in the 5-destination network, because more multi-stop TL routes are can be utilized. Hence, the industrial practice of using multi-stop deliveries is a good practical approach. In terms of computational time of each subset, it is observed that the solution time rises as the number of stops and the number of destinations increase, which is consistent with the theoretical proofs provided in Section 1.3, that is, the solution time of multi-stop models largely depends on the number of destinations and stops. For example, the average solution time for two- and three-stop models are 216 and 1,680 seconds respectively, which is about two and ten times higher than one-stop model. By observing the computational time of the three-stop model, we found that the solution time for 10 destinations (subset3∼4) are 2342 and 4053 seconds, which is about 100 times larger than the solution time for 5 destinations.

5.6 Summary

In this chapter, we examined the multi-stop consolidation problem in the international logistics network. Different from the previous model in Chapter 3, the proactive consolidation strategy considers multi-stop TL deliveries when shipments are consolidated into containers in China. In addition, a three-dimensional packing problem and a mode selection problem are still taken into account in the mathematical model. Multi-stop delivery, due to its commercial value, has been widely applied in the freight distribution. On the other hand, the problem is also of academic interest, and the literature investigate the problem in some aspects. However, few papers have so far studied the integration of the three difficult combinatorial problems.

We developed a mixed integer programming model for the multi-stop consolidation problem. Because no exact solution can be found due to the complicated nature of the model, the approximation algorithm (GCRA), the same solution methodology used in Chapter 3, is applied to solve the model. The proposed algorithm is successfully tested on 20 instances, involving up to 10 destinations and 1,395 items. All the instances can be solved within an acceptable computational time. In addition, we evaluate the cost savings of the multi-stop model by comparing the costs of one-stop, two-stop and three-stop models. The results show two- and three-stop models achieve 21.27% and 25.99% more cost savings on average than the one-stop model. Moreover, it is also observed that the savings of multi-stop consolidation could be more significant for small-size shipments and more destinations.

Chapter 6

Summary and Concluding Remarks

6.1 Summary of the Dissertation

With increasing competition in global trades, many US companies purchase parts and finished products overseas in a just-in-time and low-inventory operation. Therefore, effective management of a distribution system to transport items from overseas vendors to US destinations is a key and challenging problem for most companies. The objective of this study is to design a cost-effective consolidation and distribution method to transport shipments in a global network.

This research work is first motivated by a real-world world project with a US manufacturing company. The problem in our work is described as follows. A manufacturing company operates several manufacturing factories in the US. Each factory purchases parts and finished products from China, according to a given replenishment policy, which frequently orders small-volume shipments to maintain low inventory. Their current distribution strategy is called the "consolidation-deconsolidation" strategy. The commodities ordered by each factory are collected and consolidated into ocean containers in the China consolidation center. Currently, items are packed into containers as much as possible to save the ocean transportation cost. They are then shipped to the US deconsolidation center, where commodities are separated and delivered to their final destinations by road transportation (TL or LTL). This practice requires extensive shipment handling, such as sorting and packing at the deconsolidation center, and items might have to be stored at the center for the arrival of the next ocean containers to have larger road shipments transportation, incurring unnecessary inventory costs.

In order to save costs, a proactive consolidation strategy is proposed. Differing from current practices, our approach consolidates items at the early stage in China, considering inland transportation to final destinations in the US. Consequently, once ocean containers arrive at the US, commodities already grouped in China could be directly reloaded onto trucks for final delivery based on the pre-determined distribution plan. No additional sorting or storage procedures are needed; hence, the delivery operation can be performed without the US deconsolidation center. Furthermore, this eliminates operation costs, such as handling and storage costs, which could be significant at the expensive US deconsolidation sites. This strategy saves transit time and ensures timely delivery to the final destinations. If shipments are fully loaded in China to maximally utilize the container capacity without a carefully designed consolidation planning, handling/sorting processes and the road transportation costs in the US will significantly increase due to more frequent LTL deliveries. Therefore, an effective and proactive order consolidation could achieve significant cost savings compared to other strategies.

By looking into this problem, we find that this research topic is related to five important models, which are consolidation models, integrated inventory and transportation models, bin packing models, mode selection and routing models, and capacitated vehicle routing problems with loading constraints models. Due to the relevance, a wide array of literature is reviewed in order to better understand the nature of the problem, the available research methodologies, and solution algorithms in the field. By reviewing the relevant literature, we find that there is very little research work that investigates the integrated problem of consolidation, three dimensional bin packing, and mode and route selection, although each problem is studied separately. Therefore, in this dissertation, a series of mathematical models and algorithms are developed to study this problem extensively.

Based on the proposed strategy, a mixed integer programming model is first developed to solve a single-period and direct delivery consolidation problem. The objective of this model is to minimize the total cost involved in the global supply chain, including ocean container, handling, TL and LTL costs. Two difficult combinatorial problems are combined into the model. One is a transportation mode (TL or LTL) selection problem; the other one is a three-dimensional bin packing problem. Hence, we cannot expect to solve the model directly. Three approximation algorithms (GCRA, SCRA and SRA) are developed to solve the model. The solution method starts with the model relaxation, where a new parameter α_j, a volume load factor, is added to relax the three-dimensional bin packing constraints. GCRA and SCRA achieve the solution by iteratively updating α_j of infeasible containers, while SRA seeks the solution by iteratively reducing the shipments from infeasible containers. All of the algorithms can obtain good solutions in a reasonable time. We also investigate the value of the proposed proactive strategy over a traditional "consolidation-deconsolidation" strategy. Based on the results of numerical examples, we find that our strategy can achieve up to 30% cost savings.

Although the single-period model provides valuable insights into the shipment consolidation problem, it does not reflect the value of a long-term planning. Hence, we extend our first model to solve a multi-period problem. A finite planning horizon $t = 1, 2, \cdots, T$ is considered. It is assumed that shipments arrive at each period. Additionally, a consolidation planner needs to determine whether the shipments arriving at the current period are shipped currently or delayed to the next periods. Waiting costs incur if the shipments are delayed. However, if the future shipments have the same destination as the current shipments, inland transportation costs might be saved by using one TL delivery, instead of multiple LTLs. Handling costs are also reduced correspondingly. Therefore, there is a trade-off between waiting, ocean container, TL and LTL costs.

We present a mixed integer programming model for the multi-period problem. Due to the computational complexity, three heuristic algorithms are developed to approximate the solution. All of these algorithms use the algorithm GCRA in Chapter 3 as a basis for relaxing the model similarly with the volume factor α_j. The first algorithm seeks the solution by adapting α_j of infeasible containers for the entire planning horizon. The second algorithm obtains the solution of each period by only updating the α_j of any infeasible container for the current period. The third algorithm applies a rolling horizon technique and the T-period model is solved by iteratively solving a 2-period model. Numerical examples are tested to evaluate the performances of three heuristics. The first two algorithms perform better than the third algorithm in terms of solution quality. Algorithm 3 is the most efficient algorithm. Additionally, it is a good alternative if only limited shipment information is available. We also compare the total cost of the single- and multi-period models. We found that the multi-period model can obtain an approximate additional 10% cost savings on average over the single-period model.

In order to explore more opportunities to reduce the cost, the TL multi-stop delivery is taken into account when shipments are loaded into ocean containers in our proactive consolidation problem. This results in more effective loading patterns, although these patterns are more complicated, to save the overall cost. Therefore, the shipments of the destinations that are close to each other can be loaded into the same container with regard to the container capacity and packing constraints. Once the ocean containers arrive at the US, the batch of shipments to the same area can be loaded into trucks for multi-stop deliveries, instead of multiple LTL and TL direct deliveries, which can save the inland transportation and handling costs largely.

The basic model is extended to solve the multi-stop consolidation problem. In this new model, we consider only three stops at most for TL multi-stop deliveries because 93% of the firms accept less than four stops including the final destination per TL trip; since the more stops a route has, the less reliable its delivery time is (Jackson (1985)). Hence, we enumerate all the routes, including one-, two-, and three-stop routes in the model. The algorithm GCRA is used to solve the multi-stop model. Twenty instances, which include small- and large-size shipments with 5 and 10 destinations, are generated to test the algorithm. All of the instances can be solved within an acceptable time. We also compare the cost savings of the multi-stop model (including two- and three-stop models) with the single-stop model. The results show two- and three-stop models achieve 21.27% and 25.99% more savings on average, respectively, than the one-stop model. It is also observed that the savings of multi-stop consolidation could be more significant for small-size shipments and more destinations.

6.2 Contributions

The major contributions of this dissertation are summarized as follows:

1. *A proactive consolidation strategy.* This research provides new insights into the global supply chain management area. As we know, consolidation strategies have been studied since the 1980s. However, the concept of "proactive" is still rarely discussed in the area of consolidation. Additionally, they can achieve significant cost savings. This idea can be used for other companies with similar distribution structures.

2. *A series of integrated consolidation models.* This work provides mathematical modeling approaches to solve complicated shipment consolidation problems faced by most international companies. The problem we investigate in the dissertation integrates many issues, such as three-dimensional bin packing problem, as well as mode and route selection problem, which occur commonly in practice. However, there is little literature that studies the integrated problem. Our models, methodologies, and results can provide some insights for academic and commercial industries.

3. *Approximation solution methodologies.* Because all of our models combine several difficult combinatorial problems, no exact solution can be obtained, even for small-size problems. We propose a variety of approximation solution methodologies to disaggregate the problem into subproblems, and then to solve them iteratively. The solution methods obtain good solutions within a satisfactory computational time. The solution methods are helpful in solving other optimization problems with similar structures.

6.3 Future Work

The current research work in this dissertation can be extended in the future to the following aspects:

1. *An efficient algorithm for the multi-stop model.* In Chapter 5, we develop a mixed integer programming model to solve a consolidation problem with multi-stop deliveries. In the mathematical model, we enumerate all of the possible routes including one-, two-, and three-stop routes. Next, an approximation algorithm is proposed to solve the multi-stop model. Currently, vehicle routing problems have been studied extensively. A variety of models and algorithms have been developed to solve various problems in this area. Hence, it might

be a good extension to combine an efficient Vehicle Routing Problem algorithm into our model.

2. *An integrated inventory and shipment consolidation model.* The main cost that we focus on so far in the dissertation is transportation cost, including trans-ocean cost and inland distribution cost. However, inventory cost is a very important cost term for the international consolidation problem that we studied. This is because inventory policy of each branch, such as order quantity and order frequency, can affect not only the decisions on the consolidation planning, but also the total cost in the system. Therefore, incorporating inventory cost into our consolidation model is of importance in order to reduce the total logistics cost in the international network. Our models can be extended to include inventory issues.

3. *Meta-heuristic algorithms.* In our solution methodologies, the relaxed models are solved by using the commercial solver Gurobi. The solution quality and time of the proposed algorithms are restricted by the performance of the solver. Currently, meta-heuristic algorithms, such as simulated annealing, Tabu search, and genetic algorithms, are becoming good alternatives to solve large-scale mixed integer programming models due to their high computational performance. Therefore, applying meta-heuristic skills to solve our models is a potential future extension of our methodologies.

4. *Time window constraints.* Most companies have time window constraints to transport the shipments from vendors to destinations. This is an important measurement for customer service. In our consolidation models, time window constraints are not included. Future extensions of our models can be extended to address time window constraints.

Bibliography

H. Agrahari. *Models and solution approaches for intermodal and less-than-truckload network design with load consolidation.* Phd dissertation, Texas A&M University, Department of Industrial Engineering, 2007.

S. Alumur and B. Y. Kara. Network hub location problems: the state of the art. *European Journal of Operational Research*, 190:1–21, 2008.

J. S. K. Ang, C. Cao, and H. Q. Ye. Model and algorithms for multi-period sea cargo mix problem. *Journal of Operational Research*, 180:1381–1393, 2007.

B. C. Arntzen, G. G. Brown, T. P. Harrison, and L. L. Trafton. Global supply chain management at digital equipment corporation. *Interface*, 25:69–93, 1995.

A. Attanasio, A. Fuduli, G. Ghiani, and C. Triki. Integrated shipment dispatching and packing problems: a case study. *Journal of Mathematical Modelling Algorithms*, 6: 77–85, 2007.

N. Ben-Khedher and C. A. Yano. The multi-item joint replenishment problem with transportation and container effects. *Transportation Science*, 28:37–54, 1994.

J. O. Berkey and P. Y. Wang. Two dimensional finite bin packing algorithms. *Journal of the Operational Research Society*, 38:423–429, 1987.

L. Bertazzi, G. Paletta, and M. G. Speranza. Minimizing the total cost in an integrated vendor-managed inventory system. *Journal of Heuristics*, 11:393–419, 2005.

D. E. Blumenfeld, L. D. Burns, C. F. Daganzo, M. C. Frick, and R. W. Hall. Reducing logistics costs at general motors. *Interfaces*, 17:26–47, 1987.

M. C. Bolduc, J. Renaud, and F. Boctor. A heuristic for the routing and carrier selection problem. *European journal of operational research*, 183:926–932, 2007.

J. H. Bookbinder and J. K. Higginson. Probabilistic modeling of freight consolidation by private carriage. *Transportation Science Part E*, 38:305–318, 2002.

Marco A. Boschetti. New lower bounds for the three-dimensional finite bin packing problem. *Discrete Applied Mathematics*, 140:241–258, 2004.

D. J. Bowersox. *Logistics Management.* Macmillan Publishing, New York, second edition, 1978.

GG Brown and D. Ronen. Consolidation of customer orders into truckloads at a large manufacturer. *Journal of the operational research society*, 48:779–785, 1997.

L. D. Burns, R. W. Hall, D. E. Blumenfeld, , and C. F. Daganzo. Distribution strategies that minimize transportation and inventory costs. *Operations Research*, 33:469–490, 1985.

J. F. Campbell. Location and allocation for distribution systems with transshipments and transportation economies of scale. *Annals of Operations Research*, 40:77–99, 1992.

J. F. Campbell. A survey of network hub location. *Studies in Locational Analysis*, 6: 31–49, 1994a.

J. F. Campbell. Integer programming formulations of discrete hub location problems. *European Journal of Operational Research*, 72:387–405, 1994b.

J. F. Campbell. Hub location and the p-hub median problem. *Operations Research*, 44:1–13, 1996.

J. F. Campbell, A. T. Ernst, and M. Krishnamoorthy. Hub arc location problems: Part1 - introduction and results. *Management Science*, 51:1540–1555, 2005a.

J. F. Campbell, A. T. Ernst, and M. Krishnamoorthy. Hub arc location problems: Part2 - formulations and optimal algorithms. *Management Science*, 51:1556–1571, 2005b.

S. Cetinkaya. Coordination of inventory and shipment consolidation decisions: a review of premised, models, and justification. *Applications of supply chain management and e-commerce research*, 92:3–51, 2005.

S. Cetinkaya and J. Bookbinder. Stochastic models for the dispatch of consolidated shipments. *Transportation Science Part B*, 38:747–768, 2003.

S. Cetinkaya and C. Y. Lee. Stock replenishment and shipment scheduling for vendor managed inventory systems. *Management Science*, 46:217–232, 2000.

S. Cetinkaya and C. Y. Lee. Optimal outbound dispatch policies: modeling inventory and cargo capacity. *Naval Research logistics*, 49:531–556, 2002.

S. Cetinkaya, F. Mutlu, and C. Y. Lee. A comparison of outbound dispatch policies for integrated inventory and transportation decisions. *European Journal of Operational Research*, 171:1094–1112, 2006.

P. Chandra and M. L. Fisher. Coordination of production and distribution planning. *European Journal of Operational Research*, 72:503–517, 1994.

C. S. Chen, S. M. Lee, and Q. S. Shen. A analytical model for the container loading problem. *European Journal of Operational Research*, 80:68–76, 1995.

F. Y. Chen, T. Wang, and T. Z. Xu. Integrated inventory replenishment and temporal shipment consolidation: a comparison of quantity-based and time-based models. *Annals of Operations Research*, 135:197–210, 2005.

C. W. Chu. A heuristic algorithm for the truckload and less-than-truckload problem. *European journal of operational research*, 165:657–667, 2005.

F. K. R. Chung, M. R. Garey, and D. S. Johnson. On packing two-dimensional bins. *Journal of Algebraic and Discrete Methods*, 3:66–76, 1982.

G. Clarke and J. W. Wright. Scheduling of vehicles from a central depot to a number of delivery points. *Operations Research*, 12:568–581, 1964.

D. J. Closs and R. L. Cook. Multi-stage transportation consolidation analysis using dynamic simulation. *International Journal of Physical Distribution and Materials Management*, 17:28–45, 1987.

E. G. Coffman Jr., M. R. Garey, and D. S. Johnson. *Approximation algorithms for bin packing : a survey.* Approximation algorithms for NP-hard problems. PWS Publishing Co,, Boston, MA, USA, first edition, 1997.

J. A. Cooke. Logistics costs under pressure. *Logistics Management*, 45:35–38, 2006.

M. Cooper. Freight consolidation and warehouse location strategies in physical distribution systems. *Journal of Business Logistics*, 4:53–74, 1983.

Jean-Francois Côté and Jean-Yves. Potvin. A tabu search heuristic for the vehicle routing problem with private fleet and common carrier. *European Journal of Operational Research*, 198:464–469, 2009.

T. G. Crainic, S. M. Marcotte, W. Rei, and P. L. Takouda. Proactive order consolidation in the retail supply chain. *Publication CIRRELT*, 37, 2009.

C. B. Cunha and M. R. Silva. A genetic algorithm for the problem of configuring a hub-and-spoke network for a ltl trucking company in brazil. *Journal of the Operational Research Society*, 179:747–758, 2007.

P. P. Dornier, R. Ernst, M. Fender, and P. Kouvelis. *Global operations and logistics: text and cases.* John Wiley & Sons, Ltd, New York, first edition, 1998.

Guenther Fuellerer, Karl F. Doerner, Richard F. Hartl, and Manuel Iori. Metaheuristics for vehicle routing problems with three-dimensional loading constraints. *European Journal of Operational Research*, 201:751–759, 2010.

Michel Gendreau, Manuel Iori, Gilbert Laporte, and Silvano. Martello. A tabu search algorithm for a routing and container loading problem. *Transportation Science*, 40: 342–350, 2006.

G. Ghiani, G. Laporte, and R. Musmanno. *Introduction to logistics systems planning and control.*, volume 1. John Wiley & Sons, Ltd, New York, first edition, 2004.

D. Gilmore. State of the logistics union 2010 - not good. *Supply Chain Digest*, http://www.scdigest.com/assets/FirstThoughts/10-06-10.php?cid=3520, 2010.

S. K. Goyal and S. G. Deshmukh. Integrated procurement-production systems: a review. *European Journal of Operational Research*, 62:1–10, 1992.

ITL Consulting Group and LLC. Freight Audit Services. Flatbed truckload market price index @OTHER, January 2012. URL `http://www.flatbedsource.com/truckload-market-price-index`.

Y. P. Gupta and P. K. Bagchi. Inbound freight consolidation under just-in-time procurement: application of clearing models. *Journal of Business Logistics*, 8: 74–94, 1987.

G. C. Hadjinicola and K. R. Kumar. Modeling manufacturing and marketing options in international operations. *International Journal of Production Economics*, 75: 287–304, 2002.

R. W. Hall. Consolidation strategy: inventory, vehicles and terminals. *Journal of Business Logistics*, 8:57–73, 1987.

J. K. Higginson and J. H. Bookbinder. Policy recommendations for a shipment consolidation program. *Journal of Business Logistics*, 15:87–112, 1994.

J. K. Higginson and J. H. Bookbinder. Markovian decision process in shipment consolidation. *Transportation Science*, 29:242–255, 1995.

R. M. Hill and M. Omar. Another look at the single-vendor single-buyer integrated production-inventory problem. *International Journal of Production Research*, 44: 791–800, 2006.

H. Hwang, B Choi, and M. J. Lee. A model for shelf space allocation and inventory control considering location and inventory level effects on demand. *International Journal of Production Economics*, 97:185–195, 2005.

Manuel Iori and Silvano. Martello. Routing problems with loading constraints. *Top*, 18:4–27, 2010.

Manuel Iori and Juan-José. Salazar-González. An exact approach for the vehicle routing problem with two-dimensional loading constraints. *Transportation Science*, 41:253–264, 2007.

G. C. Jackson. Evaluating order consolidation strategies using simulation. *Journal of Business Logistics*, 2:110–138, 1981.

G. C. Jackson. A survey of freight consolidation practices. *Journal of Business Logistics*, 6:13–34, 1985.

Y. J. Jang, S. Y. Jang, B. M. Chang, and J. W. Park. A combined model of network design and production/distribution planning for a supply network. *European Journal of Operational Research*, 43:263–281, 2002.

V. Jayaraman and H. Pirkul. Planning and coordination of production and distribution facilities for multiple commodities. *European Journal of Operational Research*, 133:394–408, 2001.

D. S. Johnson. *Near-optimal bin packing algorithms*. Phd dissertation, MIT, Department of Mathematics, 1973.

J. H. Kang and Y. D. Kim. Coordination of inventory and transportation managements in a two-level supply chain. *International Journal of Production Economics*, 123:137–145, 2010.

R. M. Karp. Reducibility among combinatorial problems. *50 years of integer programming 1958-2008*, Part1:219–241, 2010.

J. G. Klincewicz. Heuristics for the p-hub location problem. *European Journal of Operational Research*, 53:25–37, 1991.

A. M. Lambert and H. Luss. Production planning with time-dependent capacity bounds. *European Journal of Operational Research*, 9:275–280, 1982.

A. Lodi, S. Martello, and M. Monaci. Two-dimensional packing problems: a survey. *European journal of operational research*, 141:241–252, 2002.

A. Lodi, S. Martello, and D. Vigo. Tspack: a unified tabu search code for multi-dimensional bin packing problems. *Annals of operations research*, 131:203–213, 2004.

B. L. MacCarthy and W. Atthirawong. Factors affecting location decisions in international operations-a delphi study. *International Journal of Operations & Production Management*, 23:794–818, 2003.

S. Martello and P. Toth. Lower bounds and reduction procedures for the bin packing problem. *Discrete applied mathematics*, 28:59–70, 1990.

S. Martello, D. Pisinger, and D. Vigo. The three-dimensional bin packing problem. *Operations Research*, 48:256–267, 2000.

S. Martello, D. Pisinger, D. Vigo, E. den Boef, and J. Korst. Algorithm 864: Algorithms for general and robot-packable variants of the three-dimensional bin packing problem. *ACM Transactions on Mathematical Software*, 33:12, 2007.

J. M. Masters. The effects of freight consolidation on customer service. *Journal of business logistics*, 2:55–74, 1980.

M. J. Meixell and V. B. Gargeya. Global supply chain design: a literature review and critique. *Transportation Research Part E*, 41:531–550, 2005.

H. Min and G. Zhou. Supply chain modeling: past, present and future. *Computers & Industrial Engineering*, 43:231–249, 2002.

H. D. Mittelmann. Performance of optimization software. scip.zib.de.

N. H. Moin and S. Salhi. Inventory routing problems: a logistical overview. *Journal of the operational research society*, 58:1185–1194, 2007.

C. B. Moon and J. Park. The joint replenishment and delivery scheduling of the one-warehouse n-retailer system. *Transportation Research Part E*, 44:720–730, 2008.

I. K. Moon, B. C. Cha, and C. U. Lee. The joint replenishment and freight consolidation of a warehouse in a supply chain. *International Journal of Production Economics*, 133:344–350, 2011.

Ana Moura and José Fernando. Olliverira. An integrated approach to the vehicle routing and container loading problems. *OR Spectrum*, 31:775–800, 2009.

C. L. Munson and M. J. Rosenblatt. Coordinating a three-level supply chain with quantity discounts. *IIE Transactions*, 33:371–384, 2001.

F. Mutlu and S. Cetinkaya. An integrated model for stock replenishment and shipment scheduling under common carrier dispatch costs. *Transportation Research Part E: Logistics and Transportation Review*, 46:844–854, 2010.

M. E. O'Kelly. The location of interacting hub facilities. *Transportation Science*, 20: 92–105, 1986a.

M. E. O'Kelly. Activity levels at hub facilities in interacting networks. *Geographical Analysis*, 18:343–356, 1986b.

M. E. O'Kelly. A quadratic integer program for the location of interacting hub facilities. *European Journal of Operational Research*, 32:393–404, 1987.

David Pisinger. Heuristics for the container loading problem. *European Journal of Operational Research*, 141:382–392, 2002.

J. Pooley. Exploring the effect of LTL pricing discounts in the LTL versus multiple-stop TL carrier selection decision. *International Journal of logistics management*, 4:85–94, 1993.

J. Pooley and A. J. Stenger. A vehicle routing algorithm for the less-than-truckload vs. multi-stop truckload problem. *Journal of Business Logistics*, 13:239–258, 1992a.

J. Pooley and A. J. Stenger. Modeling and evaluating shipment consolidation in a logistics system. *Journal of Business Logistics*, 13:153–174, 1992b.

D. A. Popken. An algorithm for the multiattribute, multicommodity flow problem with freight consolidation and inventory costs. *Operations Research*, 42:274–286, 1994.

W. B. Powell and Y. Sheffi. Design and implementation of an interactive optimization system for network design in the motor carrier industry. *Operations Research*, 37: 12–29, 1989.

W. W. Qu, J. H. Bookbinder, and P. Iyogun. An integrated inventory-transportation system with modified periodic policy for multiple products. *European Journal of Operational Research*, 115:254–269, 1999.

Z. J. Shen. Integrated supply chain design models: a survey and future research directions. *Journal of Industrial and management optimization*, 3:1–27, 2007.

E. A. Silver and H. C. Meal. A heuristic for selecting lot size quantities for the case of a deterministic time-varying demand rate and discrete opportunities for replenishment. *Production and inventory management*, 14:64–74, 1973.

Page Siplon. Logistics market snapshot @OTHER, May 2011. URL `http://www.slideshare.net/bschoenbaechler/logistics-market-snapshot-may-2011`.

D. J. Thomas and P. M. Griffin. Coordinated supply chain management. *European Journal of Operational Research*, 94:1–15, 1996.

R. J. Trent and R. M. Monczka. International purchasing and global sourcing - what are the differences? *Journal of Supply Chain Management*, 39:26–37, 2003.

J. C. Tyan, F. K. Wang, and T. C. Du. An evaluation of freight consolidation policies in global third party logistics. *Omega*, 31:55–62, 2003.

Tonya Vinas. `IW` value-chain survey: A map of the world @OTHER, 2005. URL `http://www.industryweek.com/companies-amp-executives/iw-value-chain-survey-map-world`.

H. M. Wagner and T. M. Whitin. Dynamic version of the economic lot size model. *Management Science*, 5:89–96, 1958.

D. F. Wood, A. P. Barone, P. R. Murphy, and D. L. Wardlow. *International Logistics.* AMACOM, New York, first edition, 2002.

P. C. Yang and H. M. Wee. A single-vendor and multiple-buyers production-inventory policy for a deteriorating item. *European Journal of Operational Research*, 143:570–581, 2002.

M. G. Yoon and J. Current. Network hub location problems: the state of the art. *Journal of the Operational Research Society*, 59:80–89, 2008.

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